12-2015

Development and Implementation of Hay Yield Monitoring Technology

Henry Ramsey
Clemson University, hgramse@g.clemson.edu

DEVELOPMENT AND IMPLEMENTATION OF HAY YIELD MONITORING TECHNOLOGY

A Thesis
Presented to
the Graduate School of
Clemson University

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

---

by
Henry Guy Ramsey IV
December 2015

Accepted by:
Young J. Han, Ph.D., Committee Co-Chair
Kendall R. Kirk, Ph.D., Committee Co-Chair
John G. Andrae, Ph.D.

ABSTRACT

Three independent technologies related to hay yield monitoring were developed and studied. One technology involved comparison of infrared and ultrasonic sensors on a self-propelled forage harvester. Sensor response related to grass height and was used to estimate yield. Plots that were harvested ranged from 20-40 ft. in length while a bin mounted on the back of the mower collected the crop for weighing and sampling. The infrared sensors data demonstrated accuracies across plots between 5.9% and 9.5% error. The infrared sensors quickly deteriorated and eventually proved to be useless for data acquisition. As for the ultrasonic sensors, they demonstrated similar accuracy to the infrared sensors but the sensor response did not deteriorate like that of the infrared sensors. It was concluded that the standing crop method of yield monitoring would be difficult to adapt for commercial adoption but could potentially be beneficial in crop and machinery research.

The same model sensors that were used on the self-propelled forage harvester were installed on a boom that was mounted to the tongue of a round hay baler to measure windrow height, which was then used to estimate mass flow rate and therefore crop yield. The infrared sensors proved to not be suitable for the environment from the beginning of testing due to the dusty atmosphere. Each hay bale was individually weighed by placing them on a platform that was sitting on truck scales. Samples were also taken from bales and dried to calculate moisture content. In year one, 59 bales of a Tifton 85 and Coastal mix were baled along with 57 bales of Tifton 85 and 9 bales of alfalfa. Average absolute

error as calculated from sensor data acquired from the ultrasonic sensors ranged from 3.1% to 23.86%. Although the range is large, most of the average absolute errors stayed around approximately 10%. Year two data was also collected from ultrasonic sensors of a different model. The average absolute errors for those ultrasonic sensors ranged from 5.11% to 9.27%.

In the third technology presented, a pressure transducer was installed on the hydraulic bale kicker circuit on two different round balers. The pressure transducer data was collected and correlated to bale weight to provide on-the-go bale weight estimates. Analyses were conducted to compare different size bales and bales that use different methods of wrapping. Average absolute errors for comparison of wrapping methods ranged from 1.1% to 7.28%. When combining the two methods, average absolute errors ranged from 2.44% to 9.46%. Average absolute errors ranged from 1.1% to 5.79% when data was analyzed within particular bale sizes.

DEDICATION

I would like to dedicate this thesis to a few people. Of these people are my daddy, who has stood behind me and taught me to be the man that I am and instilled good faith and principles in me. Also, my mama who always made sure I had everything I needed and most of what I wanted. I want to thank my sisters, Beth and Becky for trying to keep me on the right path as I grew up. Had it not been for Beth, I never would have been a Clemson graduate in the first place. Becky, for being a good sister to me, and for trying to keep me out of trouble growing up. Lastly, I want to thank Cameron for being with me pretty much all through graduate school, for listening to me rant about several things, but most of all, for the love and support that was shown to me through the long days and sleepless nights when I just wanted to give up.

ACKNOWLEDGMENTS

I want to thank my graduate committee, Dr. Kendall R. Kirk, Dr. Young J. Han, and Dr. John G. Andrae for contributing to the research that was conducted and for giving me guidance throughout graduate school. Thanks especially to Dr. Kirk for the sleepless nights spent working on papers and presentations and the long and tiring days spent in a hay field collecting data. I would also like to thank the entire cattle crew at Edisto Research and Education Center in Blackville, SC for making accommodations for me to be able to collect data and for the assistance with the collection of said data. I want to thank Dr. John D. Mueller, Director at EREC, for allowing my project to take place on the station.

TABLE OF CONTENTS

Table of Contents (Continued)

Page

LIST OF TABLES

List of Tables (Continued)

LIST OF FIGURES

List of Figures (Continued)

Figure Page

List of Figures (Continued)

CHAPTER ONE

INTRODUCTION

Introduction

Yield monitoring technology for small grains, corn, and cotton have been available for two decades but one crop that plays an important role in the agriculture industry has seen limited commercial applications of precision agriculture technology. This crop is hay. Hay and forages are an important part of the agricultural infrastructure because hay is harvested and fed to livestock which makes up a great deal of agricultural industry worldwide.

Throughout this study, different methods of yield monitoring technologies for hay production were analyzed. Remote sensing technology was to be implemented on different types of machinery in order to provide yield data for hay production. Different types of sensors were analyzed on a mowing machine and sensors were implemented on a round hay baler to provide yield data. Providing yield data to hay and forage producers has the ability to be beneficial to them in that different fields and crops can be analyzed and better managed from a yield and profit standpoint. Given the ability to generate yield maps for hay fields, a producer can have the option of making management based decisions based on what is learned from the yield data. The yield data can be used to generate profit maps, suggesting that parts of a field that are not profitable can be improved or totally removed from all farming practices in order to increase cash flows and overall farm profit. The management based decisions that have the ability to be employed as a function of historical and spatial yield knowledge consists of, but are not limited to, variable rate nitrogen application, variable rate lime applications, and variable rate irrigation in order to increase efficiency and decrease costs for the producer.

The first part of the study consisted of using a Carter Research mower, which is a self-propelled forage harvester. Sensing technology was installed on the front of the mower in front of the cutter head in order to determine grass height at time of mowing. The initial thought process behind this technology was that grass height could be correlated to yield and that the technology could be implemented on larger hay mowers and mower-conditioners. Infrared and ultrasonic sensors were installed on the mower to provide comparative data between sensor types and to determine which was more suitable for this application.

The second part of the study consisted of installation of the same sensors used on the Carter mower on a round hay baler to measure windrow volume and relate it to hay yield and hay mass flow rate into the baler. Design intentions were that, if successful, the technology could be retrofitted to any baler or offered as a factory option from the manufacturer. In the first year of research, the same ultrasonic and infrared sensors were implemented on the baler. They were attached to a boom in front of the header of the baler in order to measure windrow height to calculate windrow volume and correlate that to bale weight and mass flow. Many changes were made throughout design, fabrication, and data analysis to refine the system. Year two of testing consisted of only ultrasonic sensors from different manufacturers to determine which were best suited to use in such a dusty and dirty environment.

The third and last part of this study was to provide the operator with an indication of the weight of a bale of hay as it was ejected from the bale chamber. To achieve this, a pressure transducer was fixed to the hydraulic system for the bale kicker of the round baler. Pressure transducer sensor response was correlated to hay bale weights to develop an algorithm structure for weighing bales. Some hay balers already have the ability to provide weights of bales but they generally employ load cell technology. The technology developed here is more cost effective, but is only relevant for round balers with hydraulic bale kickers.

CHAPTER TWO

DEVELOPMENT AND TESTING OF A FORAGE AND HAY YIELD MONITOR FOR USE ON MOWERS

Abstract

Yield monitoring technology has been beneficial to farmers in past years because it has helped to reduce input costs through variable rate prescriptions based on yield data and produced the basis for zone-based managerial decisions. Yield monitoring technology is readily available for corn, soybeans, small grains, and cotton. Yield monitoring has not been widely implemented for forage and hay production. This research focuses on development and testing of a yield monitor for hay crops that remotely measures the height of the grass on-the-go during mowing. A Carter research plot flail mower was outfitted with infrared and ultrasonic sensors that measured the grass height prior to entering the throat of the mower. Heights were acquired at 10 in travel intervals throughout the plots, which were 20-40 ft in length. A bin mounted on the back of the mower was used to catch the cut crop so it could be weighed and samples were taken from each plot to measure moisture content through oven drying. Regression models were developed for the prediction of yield weights as a function of grass height data. Infrared sensor data from 12 plots of oats demonstrated 9.5% error in wet weight and 5.9% error in dry weight predictions. Infrared sensor data from 34 plots of hybrid pearl millet and 33 plots of Tifton 85 bermudagrass demonstrated similar levels of accuracy, but the sensor response deteriorated with time to a level that rendered them unacceptable and in some cases nonresponsive. Ultrasonic sensor data from 17 plots of

Tifton 85 bermudagrass demonstrated lower resolution, but similar accuracy to that of the infrared sensors with reduced deterioration in sensor response. The sensors used for the prototype in this study were not rated for exposure to dust or moisture, which is suspected to have had the greatest effect on drift in sensor response. The technology developed under this study provides the capability to demonstrate relative yield differences throughout a field. However, typical hay and forage harvest systems present challenges for calibration, as well as for absolute quantification of both on-the-go and post-processed yield data.

Introduction

Yield monitoring technology has been revolutionary in the agricultural industry, credited as among the most critical components in precision agriculture (Vellidis et al., 2004). Since the implementation of precision agriculture over numerous parts of the globe, yields have been increased and more efficient farming practices have been implemented. Yield monitors were introduced in the early 1990's (University of Nebraska-Lincoln, 2013) and are becoming more prevalent, especially in the production of grains. Yield monitors in the grain industry have allowed farmers to make yield maps, which quantify in-field variability and let the farmer know what parts of the field are more or less productive than others. This knowledge can be used to assist the farmer in determining rates of application for fertilizer and lime to maximize efficient use. Also, these yield maps may be evaluated and turned into profit maps, which can be used by the farmer to determine which parts of his farm are or are not profitable. A profit map allows him to make management-based decisions to increase profits from his crop. Yield monitors are now regularly implemented for most small grains, including corn, wheat and soybeans, and cotton. Yield monitoring technology in peanuts has been researched but has not yet been made commercially available.

There are many technologies that have been used for crop mass flow sensing in yield monitoring. One important technology that has been used is optical flow sensing. The optical flow sensors have been employed in the cotton yield monitoring process (Thomasson and Sui, 2003) and are used in the Ag Leader cotton yield monitor system. The grain yield monitor provided by Trimble also uses optical technology. Another technology that has been used for yield monitoring technology is the impact plate method that is used for grain yield monitoring in the Ag Leader and John Deere systems. It used an impact plate that measures the force of the grain as it leaves the clean grain elevator and correlates it to a mass flow. A microwave mass flow sensing technology is also used by John Deere for their cotton yield monitor.

Presently, a yield monitor is not readily available for hay yield prediction although there is a system that is commercially available for forage harvesters. For a high value crop requiring more intense management such as alfalfa and other various hay crops, a yield monitor could be beneficial to the farmer. Without such a technology, a farmer can only determine the number of bales per acre but has no definition of the spatial variability. There are numerous variables that can affect the yield of a field that cannot be easily identified with this method. Among these variables are forage moisture content, the undergrowth density of the hayfield and the amount of hay left in the field (hay that did not get raked up). A hay yield monitor could factor in the moisture content variability of the study crop and give an accurate representation of the final dry weight of the hay from the field. Also, the yield monitor would be able to provide mass yield such as tons per acre (weight per unit area) and bales per acre. The yield monitor, paired with GPS technology, would be able to generate a yield map of the field, and specifically identify where the hay within each bale originated within the field. By generating the yield map, the farmer can then determine what types of management practices should be implemented so as to increase yield and/or profits.

The market potential of yield monitoring technology in the forage and hay industry can be assessed by observing the acreages used for different farming practices. The following statistics are all for the 2014 year and are nationwide for the U.S. (NASS, 2015). The total acreage used for all hay production consisted of 57,092,000 acres. Of this acreage, 18,445,000 acres or 32% were devoted only to the production of alfalfa which is a high value forage crop. Hay production ranks third in the nation for acreage used for crop production behind corn and soybeans, but leads cotton, peanuts, and sorghum. Corn was grown for grain on 83,136,000 acres and for silage on 6,371,000 acres. Soybeans were planted on 83,701,000 acres while cotton was planted on 11,037,000 acres. Peanuts accounted for 1,354,000 planted acres and grain sorghum occupied 6,401,000 acres. Sorghum for silage was grown on 315,000 acres. These statistics justify the need for a yield monitor for forage and hay crops. With hay being the third most produced crop in the country, the implementation of yield monitoring technology and precision agriculture could lead to millions of dollars saved in fertilizer and lime usage, and has the potential to significantly boost farmer's profits.

Forage harvesters can employ a commercially available yield monitoring method in which feedrollers are used to monitor the throughput of crop. Pressure on the feedrollers is measured to determine how much crop is passing through the machine. If there is no crop, then the pressure would signal zero throughput. As the instantaneous crop harvest increases, the pressure increases (Digman and Shinners, 2012). This yield monitoring technology is capable of producing a yield map, but the technology used is different from the technology to be used on the proposed standing crop yield monitor presented in this study. There is also a commercially available yield monitor that can be installed on a hay baler available from Harvest Tec (Hudson, WI). According to their website, the Harvest Tec yield monitor is only available for large or small square balers; not round balers. This yield monitor uses “star wheels” that are mounted in the bale chute that measure moisture in the bale and the speed in which the bale is passing by the star wheels. This in turn will give the user a measure of tonnage. The tonnage or mass baled paired with GPS can later be used to generate yield maps. The data that is obtained from this yield monitor is stored to a data card. This yield monitor is claimed to be accurate with a plus or minus 2-4% accuracy (Holin, 2006).

There are methods monitoring forage density in a field that are used by grazers to determine the amount of grass in a field for their cattle which could likely also be used in a estimate what the yield of a hay would be, although none are readily adaptable to mounting onto a machine. The University of West Virginia Extension service carried out research on pastureland using three different methods to measure forage mass, or present forage. The methods carried out throughout their research included using a ruler to measure forage height, a falling plate meter, and a rising plate meter (Rayburn and Lozier, 2003.) In the ruler method, the forage heights in different places throughout a forage area were measured and averaged to correlate to forage mass. With the falling plate meter, a yard stick was inserted through a hole in a square plate. The square plate indicated the measure of the forage. The falling plate method was similar to the rising plate meter. With the rising plate meter, a plate was mounted to a rod. As the rod was inserted into the crop, the plate would rise up the rod and a digital readout was given from the meter. The density of the forage crop had to be estimated with all three methods (Rayburn and Lozier, 2003.) The rising plate meter was evaluated by an experiment conducted in 2001 along with a pasture ruler and capacitance meter. The capacitance meter consisted of a probe that calculates forage mass according to equations that were developed prior to implementation of the tool. This meter could reportedly sense 400 mm tall by an area of 100 mm diameter (Sanderson et al., 2001). According to this study, it was determined that these three methods of predicting forage mass and biovolume were relatively inaccurate, with errors ranging from 26 to 33% (Sanderson et al., 2001).

Objectives

The objectives of this study were to:

- Design and build prototype remote, on-the-go standing crop height measurement system using infrared distance and ultrasonic sensors;
- Evaluate hay yield prediction capability and accuracy using infrared and ultrasonic sensing technologies for measuring crop height at the time of cutting.

Methods and Materials

Fabrication and Mounting

It was determined that in order to sense the height of the standing crop and correlate it to volume, there had to be a way to sense from above. A boom was built using square tubing and angle iron and mounted to the front of a Carter research mower. The boom was positioned so the angle iron would be approximately 91 cm (36 in.) from the ground when the head of the mower was in a position to mow the crop. This height was decided upon because it was hypothesized that the crop being cut would most likely be less than three feet tall. The boom was eventually raised after harvesting oats. The heads of the oats touched the angle iron and interfered with sensor response. There were eight pieces of 5x5 cm (2x2 in.) angle iron approximately 5 cm (2 in.) long mounted to the boom. One model 3521_0 infrared sensor (Phidgets Inc., Calgary, Alberta, Canada) was mounted to each piece of angle iron. Infrared sensors were used to estimate the height of the crop that was being harvested. The infrared sensors initially used were medium range sensors (10-80 cm), but were replaced with longer range (20-150 cm) model 3522_0 infrared sensors (Phidgets Inc., Calgary, Alberta, Canada) when the boom was raised to 102 cm (40 in.) Model 1128_0 ultrasonic sensors (Phidgets Inc., Calgary, Alberta, Canada) were later added to the boom, mounted in plastic boxes that were 5 cm (2 in.) wide by 10 cm (4 in.) long by 2.5 cm (1 in.) deep. The infrared sensors were removed from the angle iron and mounted to the outside of the plastic boxes. The plastic boxes were then mounted to the angle iron. A model LJC18A3-B-Z/AX capacitance-based proximity switch was mounted near one of the wheel hubs on the Carter mower.

The purpose of the proximity switch was to trigger the data acquisition system to take readings on a distance traveled basis rather than on the basis of a timer. This sensor was mounted behind the wheel hub and sensed the ends of the studs that held the wheel on to the hub. Each time a stud passed the proximity switch, infrared and ultrasonic target distances were taken, which equated to 25 cm (10 in.) travel intervals.

Electrical System

The infrared sensors were connected to model 1101_0 infrared distance adapters (Phidgets Inc., Calgary, Alberta, Canada). The distance adapters were connected to the analog inputs on a model 1019_0 interface kit or I/O board (Phidgets Inc., Calgary, Alberta, Canada). Harnesses were soldered to the ultrasonic sensors and attached to the analog inputs of a model 1018_2 interface kit (Phidgets Inc., Calgary, Alberta, Canada). Each ultrasonic sensor had a wire connected to the digital output side of the I/O board, which was used to toggle ranging of the sensors. This facilitated pulsing of the ultrasonic sensors to avoid echo effects and interference between sensors. A model 1040_0 GPS receiver (Phidgets Inc., Calgary, Alberta, Canada) was included to indicate position. The proximity switch was connected to a digital input of the I/O board so it could be used to trigger when the sensors should take readings of crop height. A data acquisition program was written using Microsoft Visual Basic and executed on a Panasonic CF-74 Toughbook laptop computer. The program that was written was designed to take readings for crop height and was self-calibrating based on the height of the boom in relation to the baseline used. The baseline was the height of the crop after it had been harvested. Before data logging could be started, the calibration routine of the program had to be executed to provide the baseline used in calculating grass height as a function of sensed target height, where grass height was equal to baseline height minus sensed target height.

Field Testing

A calibration equation was available for the infrared sensors (Phidgets Inc., Calgary, Alberta, Canada), but it was determined to be generally inaccurate when considering variability across sensors. A calibration equation was built by keeping the sensors a specified distance from the ground and moving a piece of plywood under and parallel to the sensors. The known height of the plywood was increased for each trial and a calibration equation for target height was developed as a regression function of target height versus sensor response. A calibration equation was also available for the ultrasonic sensors from Phidgets (Phidgets Inc., Calgary, Alberta, Canada) but it also was determined to be inaccurate. The same operation was carried out to determine a calibration equation for the ultrasonic sensors.

Plots were 30 ft long. The first plots harvested were composed of mixed grasses at the Clemson University Cherry Farm in Clemson, SC. The mixed grass consisted primarily of vetch and fescue. The Carter Mower functions as a flail mower that propels the crop through a duct to the rear of the machine so that it can be accumulated in a box situated on a platform at the rear of the mower. For each plot that was harvested during this initial test, crop height measurement events were driven by a timer, rather than using the proximity switch. Readings were collected at 10 Hz and the average of these readings were logged at 1 Hz. Once the plot was harvested, the accumulated crop was weighed using a Weigh Tronix Model 615 scale (Avery Weigh-Tronix, LLC., Fairmont, Minnesota, USA). A sample was then taken from the crop and was also weighed for use in determining moisture content from the harvested crop. Moisture samples that were acquired were dried at 100 degrees Celsius for 24 hours (Undersander et al., 1993). These samples were reweighed after being removed from the drying oven and wet basis moisture content was determined by subtracting dry weight from wet weight and then dividing by the wet weight of the sample. After analyzing data from the first testing, the program that had been written was modified to work with the aforementioned proximity switch to trigger readings only when the Carter Mower was in motion and at a set travel distance, rather than being triggered by a timer. After the first testing, a scale head communicating with load cells on the platform at the rear of the mower was also mounted on the Carter Mower to replace using the portable scale.

Subsequent to the initial testing on 7 plots of mixed grass harvested at the Clemson University Cherry Farm, and after making the noted changes to the system, 12 plots of oats were harvested at Clemson University Simpson Station Research Farm in Pendleton, SC, 33 plots of Tifton 85 bermudagrass and 34 plots of hybrid pearl millet were harvested at Clemson University Edisto Research and Education Center in Blackville, SC.

Data Analysis

Linear regression models were developed for prediction of harvested weight from each plot using average sensed grass height to predict mass flow rate and using sum of sensed grass height to predict total mass. Mass flow models were constructed with non-zero y-intercepts and mass models were constructed through the origin because of the inability to distribute the y-intercept across the point data without on-the-go knowledge of the number of points for each plot. There were instances in the point data where a given sensor response indicated a negative grass height. These negative grass height values were converted in separate analyses to zeros and blanks, providing an analysis of which method provided the least yield prediction error.

In addition to modeling as a function of grass height (Ht), each of these general model types (mass flow and mass predictions) were constructed across the following mathematical transformations of the sensed grass heights to correct for potential non-linearity: $Ht^{0.5}$, Ht^{2}, Ln(Ht), Exp(Ht), $Ht^{0.25}$, and Ht^{4}. The mathematical transformations were applied to the point data for each sensor, prior to averaging or summing across entire point data from each plot. As discussed, the point data was that which was generated at each proximity switch trigger event. Single linear regression models as functions of grass height and its transformations were developed as well as multiple linear regression models, with the first regressor being grass height or one of its transformations and the second regressor being moisture content. Transformations of moisture content to assess for non-linearity were not conducted in the analyses presented here. The tables in the results section show means comparisons developed using student's t-tests (α=0.05) and connecting letters reports are for within sections (between divisions) of each table.

Results and Discussion

When the tests initially started, the infrared distance sensors appeared to be the ideal sensor for the standing crop yield monitor. These sensors displayed a high level of resolution along with a high degree of accuracy. After running several tests with only the infrared sensors, the obtained data started to deteriorate and the sensors started to report erratic readings. After observing the erratic response of the sensors, it was thought that heat was possibly the problem affecting the I/O board so a 12 VDC fan was mounted to its box in order to keep the I/O board cooled. This appeared to have no effect on the erratic operation of the sensors. Another problem that was observed that potentially could cause erratic operation was that the Carter Mower expelled some harvested crop forward in front of the header and propelled it toward the sensors. The sensors were observed to have dirty lenses. They were then cleaned and once again displayed a high level of resolution and accuracy. The sensor data soon deteriorated once again. The sensors were replaced with new sensors that were the same brand and model number. The new sensors were calibrated as discussed earlier but quickly deteriorated after operation during harvest and it was concluded that the infrared distance sensors would not be well-suited for use on the standing crop yield monitor.

The ultrasonic sensors, when mounted on the Carter mower, displayed a lower level of resolution than that of the infrared sensors but more consistency between the sensors was observed, presumably because the area of influence was about twice as large as that of the infrared sensors. The ultrasonic sensors were set up to range sequentially because in preliminary testing there was an echo noted between the sensors. The ultrasonic sensors did not have a problem with getting dirty or clouding over, as did the infrared sensors.

To assess the relative performance of eight, four, and two sensor arrangements, regression models were developed for each using two different methods. In the first method, table 2.1, negative grass height values in the point data were replaced with values of zero. In the second method, table 2.2, negative grass height values in the point data were replaced with blank values. For each dataset in tables 2.1 and 2.2, the model applied that produced the lowest average absolute prediction error was selected for means comparisons analysis. There were no statistical differences between eight, four, and two sensor arrangements for any of the models within any of the forage types. Because the data collected in this study suggests that two sensor arrangements would be statistically as accurate as four and eight sensor arrangements, the two sensor arrangement would be the best choice for reduction of cost and complexity without reducing accuracy.

Table 2.1. Comparison of average absolute errors for best 2, 4, and 8 sensor wet prediction models where negative sensed grass heights were replaced with values of zero.

Forage Type	N[1]	Model[2]		Avg. Abs. Error, %[3]
	8 IR	Wt = f[Ht^4,MC]	A	18.03
All grasses[4]	4 IR	Wt = f[Ht^4,MC]	A	17.67
	2 IR	Wt = f[Ht^4,MC]	A	17.57
	8 IR	Wt = f[Exp(Ht),MC]	A	7.24
Oats	4 IR	MF = f[Ht^2,MC]	A	5.99
	2 IR	MF = f[Exp(Ht),MC]	A	7.61
	8 IR	Wt = f[Ht^4,MC]	A	13.76
H. pearl millet	4 IR	Wt = f[Ht^4,MC]	A	13.98
	2 IR	Wt = f[Ht^4,MC]	A	14.98
	8 IR	MF = f[Exp(Ht),MC]	A	9.19
Bermudagrass	4 IR	MF = f[Ht^2,MC]	A	9.15
	2 IR	MF = f[Ht^2,MC]	A	9.15
	8 Son	MF = f[Ht^(0.25),MC]	A	8.32
Bermudagrass	4 Son	MF = f[ln(Ht),MC]	A	8.05
	2 Son	MF = f[Ht^(0.25),MC]	A	9.63

[1] Number of sensors used, where IR = Infrared and Son = Ultrasonic
[2] Best model based on least average absolute error across plots, where Wt = plot weight,
MF = mass flow rate, and MC = moisture content
[3] Average absolute prediction error across plots within specified group
[4] Includes a single regression model across all plots, irrespective of type

Table 2.2. Comparison of average absolute errors for best 2, 4, and 8 sensor wet prediction models where negative sensed grass heights were replaced with blanks.

Forage Type	N	Model		Avg. Abs. Error, %
	8 IR	Wt = f[Ht^4,MC]	A	18.59
All grasses	4 IR	Wt = f[Ht^4,MC]	A	18.16
	2 IR	Wt = f[Ht^4,MC]	A	17.87
	8 IR	MF = f[Ht^(0.25),MC]	A	6.43
Oats	4 IR	MF = f[Ht,MC]	A	5.62
	2 IR	MF = f[exp(Ht),MC]	A	7.57
	8 IR	MF = f[Ht^4,MC]	A	12.54
H. pearl millet	4 IR	MF = f[Ht^4,MC]	A	12.41
	2 IR	MF = f[Ht^2,MC]	A	14.34
	8 IR	MF = f[Exp(Ht),MC]	A	9.19
Bermudagrass	4 IR	MF = f[Ht^(0.5),MC]	A	9.09
	2 IR	MF = f[Ht,MC]	A	9.15
	8 Son	MF = f[Ht^(0.5),MC]	A	10.26
Bermudagrass	4 Son	MF = f[ln(Ht),MC]	A	9.58
	2 Son	MF = f[Ht^(0.25),MC]	A	9.79

To compare model accuracy when replacing negative grass height values in the point data with zeros or blanks, a similar analysis was conducted (table 2.3). Means comparisons tests were conducted across the average absolute errors of the most accurate models for two sensor arrangements within each forage type using processed data where negative values were replaced with zeros and blanks. As shown in table 2.3, there were no statistical differences between using blanks or zeros, suggesting that both methods produce equally acceptable results.

Table 2.3. Best 2-sensor wet prediction models, comparing replacement of negative sensed grass heights with zeros and blanks.

Forage Type	Type[1]	Sensor Type	Model		Avg. Abs. Error
All grasses	Zeros	IR	Wt = f[Ht^4,MC]	A	17.57
	Blanks		Wt = f[Ht^4,MC]	A	17.87
Oats	Zeros	IR	MF = f[exp(Ht),MC]	A	7.61
	Blanks		MF = f[exp(Ht),MC]	A	7.57
H. pearl millet	Zeros	IR	Wt = f[Ht^4,MC]	A	14.98
	Blanks		MF = f[Ht^2,MC]	A	14.34
Bermudagrass	Zeros	IR	MF = f[Ht^2,MC]	A	9.15
	Blanks		MF = f[Ht,MC]	A	12.03
Bermudagrass	Zeros	Son	MF = f[Ht^(0.25),MC]	A	9.63
	Blanks		MF = f[Ht^(0.25),MC]	A	9.79

[1] "Zeros" represents models where negative grass height values for any given sensor at any given point were converted to values of zero and "Blanks" represents those where negative values were converted to blanks.

The relative performance for 8, 4, and 2 sensor configurations was also examined on a basis of dry mass and dry mass flow prediction. There were no statistical differences between the different sensor configurations across forage types for data where negative values were replaced with zeros (table 2.4) For data where negative values were replaced with blanks, there were also no statistical differences between yield prediction models (table 2.5). Based on the lack of statistical differences between 8, 4, and 2 sensor configurations in tables 4 and 5 and for the same justification as provided for the wet prediction models, these data suggest that the two sensor configuration should also be used for dry yield prediction.

Table 2.4. Comparison of average absolute errors for best 2, 4, and 8 sensor dry prediction models where negative sensed grass heights were replaced with values of zero.

Forage Type	N	Model		Avg. Abs. Error
All grasses	8 IR	MF = f[exp(Ht),MC]	A	21.45
	4 IR	MF = f[exp(Ht),MC]	A	21.43
	2 IR	MF = f[exp(Ht),MC]	A	21.55
Oats	8 IR	MF = f[Ht^4]	A	7.56
	4 IR	MF = f[Ht^4]	A	6.94
	2 IR	MF = f[Ht]	A	7.52
H. pearl millet	8 IR	MF = f[Ht^4,MC]	A	16.59
	4 IR	MF = f[Ht^4,MC]	A	16.41
	2 IR	MF = f[Ht^4,MC]	A	17.30
Bermudagrass	8 IR	MF = f[Ht^(0.25),MC]	A	9.15
	4 IR	MF = f[Ht,MC]	A	9.08
	2 IR	MF = f[Ht,MC]	A	9.10
Bermudagrass	8 Son	MF = f[Ht^4,MC]	A	9.26
	4 Son	MF = f[Ht^4,MC]	A	9.03
	2 Son	MF = f[Ht^4,MC]	A	9.27

Table 2.5. Comparison of average absolute errors for best 2, 4, and 8 sensor dry prediction models where negative sensed grass heights were replaced with blanks.

Forage Type	N	Model		Avg. Abs. Error
All grasses	8 IR	MF = f[Ht^(0.25),MC]	A	20.87
	4 IR	MF = f[Ht^(0.25),MC]	A	21.16
	2 IR	MF = f[exp(Ht),MC]	A	21.54
Oats	8 IR	Wt = f[Ht^2,MC]	A	7.02
	4 IR	MF = f[Ht]	A	6.56
	2 IR	Wt = f[Ht]	A	7.62
H. pearl millet	8 IR	MF = f[Ht^4,MC]	A	14.40
	4 IR	MF = f[Ht^4,MC]	A	14.62
	2 IR	MF = f[Ht^2,MC]	A	16.01
Bermudagrass	8 IR	MF = f[Ht]	A	9.17
	4 IR	MF = f[ln(Ht)]	A	9.05
	2 IR	MF = f[Ht]	A	9.09
Bermudagrass	8 Son	Wt = f[ln(Ht)]	A	8.82
	4 Son	Wt = f[Ht^(0.25),MC]	A	9.37
	2 Son	MF = f[ln(Ht),MC]	A	9.38

Displayed in table 2.6, the dry prediction models had no statistical differences using data where negative values were replaced with zeros or blanks, suggesting that either method of data processing would be sufficient. In the interests of simplifying the analyses and comparisons set forth in this study, the remainder of the models considered utilize two sensor configurations with negative target heights converted to blanks.

Table 2.6. Best 2-sensor dry prediction models, comparing replacement of negative sensed grass heights with zeros and blanks.

Forage Type	Type	Sensor Type	Model		Avg. Abs. Error
All grasses	Zeros	IR	MF = f[exp(Ht),MC]	A	21.55
	Blanks		MF = f[exp(Ht),MC]	A	21.54
Oats	Zeros	IR	MF = f[Ht]	A	7.52
	Blanks		MF = f[Ht]	A	8.35
H. pearl millet	Zeros	IR	MF = f[Ht^4,MC]	A	16.16
	Blanks		MF = f[Ht^2,MC]	A	16.01
Bermudagrass	Zeros	IR	MF = f[Ht,MC]	A	9.17
	Blanks		MF = f[Ht]	A	9.09
Bermudagrass	Zeros	Son	MF = f[Ht^4,MC]	A	8.57
	Blanks		MF = f[ln(ht),MC]	A	9.38

Using the data where negative values were replaced with blanks, the models that numerically demonstrated the lowest average absolute prediction error for each forage type for mass and mass flow were selected for inclusion in table 2.7. The table shows the yield prediction models on a wet basis, comparing use of mass versus mass flow models. There was no statistical difference between models across each forage type, although mass flow models were numerically superior to mass models for all grass types, excepting the general or “all grasses” forage type. Table 2.8 demonstrates the same analysis, but on a dry prediction basis. There were also no statistical differences between dry prediction models across forage types. In short, the data presented here suggests that mass and mass flow models are equally accurate in predicting wet and dry hay yields. In the interests of simplifying ensuing analyses, since the “all grasses” consisted of all the underlying forage types, the model in this category with the lowest average absolute error was selected to use for further analyses. Moving forward, the model that will be used for wet yield prediction predicts mass and the model that will be used for dry yield prediction predicts mass flow.

Table 2.7. Best 2-sensor wet prediction models replacing negative values with blanks, comparing mass flow to mass prediction.

Forage Type	Type	Sensor Type	Model		Avg. Abs. Error
All grasses	Mass Flow	IR	MF = f[exp(Ht),MC]	A	21.55
	Mass		Wt = f[Ht^4,MC]	A	17.87
Oats	Mass Flow	IR	MF = f[exp(Ht),MC]	A	7.57
	Mass		Wt = f[Ht^4,MC]	A	9.51
H. pearl millet	Mass Flow	IR	MF = f[Ht^2,MC]	A	14.34
	Mass		Wt = f[Ht^4,MC]	A	14.39
Bermudagrass	Mass Flow	IR	MF = f[Ht,MC]	A	9.15
	Mass		Wt = f[ln(Ht),MC]	A	12.62
Bermudagrass	Mass Flow	Son	MF = f[Ht^4,MC]	A	10.58
	Mass		Wt = f[Ht^(0.25),MC]	A	11.04

Table 2.8. Best 2-sensor dry prediction models replacing negative values with blanks, comparing mass flow to mass prediction.

Forage Type	Type	Sensor Type	Model		Avg. Abs. Error
All grasses	Mass Flow	IR	MF = f[exp(Ht),MC]	A	21.54
	Mass		Wt = f[exp(Ht),MC]	A	29.28
Oats	Mass Flow	IR	MF = f[ln(Ht)]	A	8.26
	Mass		Wt = f[Ht]	A	7.62
H. pearl millet	Mass Flow	IR	MF = f[Ht^2,MC]	A	16.01
	Mass		Wt = f[Ht^4,MC]	A	18.32
Bermudagrass	Mass Flow	IR	MF = f[Ht]	A	9.09
	Mass		Wt = f[Ht^(0.25),MC]	A	10.33
Bermudagrass	Mass Flow	Son	MF = f[ln(Ht),MC]	A	9.38
	Mass		Wt = f[Ht^(0.25),MC]	A	9.41

Table 2.9 compares wet yield prediction error of a single linear regression model against a multiple linear regression model, which uses moisture content as the second regressor. Within the independent forage types, there was no statistical difference between the two model structures. For "all grasses", there was a significant difference between single and multiple linear regression models. The statistical difference showed that moisture as a second regressor was important to the accuracy of wet yield prediction when applying a single calibration to span grass types. Within specific grass types, there were numerical differences for the average absolute error; these differences coincided with the statistical difference for "all grasses," further suggesting that inclusion of moisture content in the regression model improves prediction accuracy. The results and arguments are synonymous for dry yield prediction on a mass flow basis (table 2.10). For the following analyses in this manuscript, models applied will be in the form of multiple linear regressions.

Table 2.9. Best 2-sensor wet mass prediction models replacing negative values with blanks, comparing single to multiple linear regression models.

Forage Type	Type	Sensor Type	Model		Avg. Abs. Error
All grasses	Single	IR	Wt = f[Ht^(0.25)]	A	24.21
	Multiple		Wt = f[Ht^4,MC]	B	17.87
Oats	Single	IR	Wt = f[Ht]	A	13.52
	Multiple		Wt = f[exp(Ht),MC]	A	9.51
H. pearl millet	Single	IR	Wt = f[Ht]	A	17.22
	Multiple		Wt = f[Ht^4,MC]	A	14.39
Bermudagrass	Single	IR	Wt = f[Ht^(0.25)]	A	16.15
	Multiple		Wt = f[ln(Ht),MC]	A	12.62
Bermudagrass	Single	Son	Wt = f[ln(Ht)]	A	14.54
	Multiple		Wt = f[Ht^(0.25),MC]	A	11.04

Table 2.10. Best 2-sensor dry mass flow prediction models replacing negative values with blanks, comparing single to multiple linear regression models.

Forage Type	Type	Sensor Type	Model		Avg. Abs. Error
All grasses	Single	IR	MF = f[Ht^2]	A	38.10
	Multiple		MF = f[exp(Ht),MC]	B	21.90
Oats	Single	IR	MF = f[ln(Ht)]	A	11.74
	Multiple		MF = f[exp(Ht),MC]	A	7.57
H. pearl millet	Single	IR	MF = f[Ht^2]	A	17.99
	Multiple		MF = f[Ht^2,MC]	A	16.01
Bermudagrass	Single	IR	MF = f[Ht]	A	9.09
	Multiple		MF = f[ln(Ht),MC]	A	9.16
Bermudagrass	Single	Son	MF = f[Ht^(0.25)]	A	10.06
	Multiple		MF = f[ln(Ht),MC]	A	9.38

After selecting use of multiple regression for both wet and dry basis predictions, comparison of transformations of the target heights were conducted (tables 2.11 and 2.12). In tables 2.11 and 2.12, the comparison between datasets only compares plots where infrared and ultrasonic sensing methods were used. For the seven transformations applied in the data analysis, there were no significant differences in wet or dry prediction models, across the transformations within use of IR and ultrasonic sensing methods. This finding suggests that there may be no need to correct for non-linearity in the sensed grass height.

**Table 2.11. Comparison of grass height and transformations of grass height as regressors for 2-sensor wet mass,
multiple linear regression prediction models replacing negative values with blanks.**

Sensor Type	Transformation		Avg. Abs. Error
IR	Exp(Ht)	A	15.75
	$Ht^{0.25}$	A	15.78
	Ln(Ht)	A	15.99
	$Ht^{0.5}$	A	16.29
	None	A	16.90
	Ht^4	A	16.93
	Ht^2	A	17.21
Ultrasonic	$Ht^{0.25}$	A	14.28
	Ln(Ht)	A	14.40
	$Ht^{0.5}$	A	14.75
	None	A	15.64
	Exp(Ht)	A	15.75
	Ht^2	A	17.02
	Ht^4	A	18.00

Table 2.12. Comparison of grass height and transformations of grass height as regressors for 2-sensor dry mass flow, multiple linear regression prediction models replacing negative values with blanks.

Sensor Type	Transformation		Avg. Abs. Error
IR	Exp(Ht)	A	15.02
	$Ht^{0.25}$	A	14.05
	Ht^4	A	17.04
	Ln(Ht)	A	14.15
	$Ht^{0.5}$	A	14.30
	Ht^2	A	16.21
	None	A	15.09
Ultrasonic	Ln(Ht)	A	9.38
	$Ht^{0.25}$	A	9.42
	$Ht^{0.5}$	A	9.45
	None	A	9.60
	Ht^2	A	9.76
	Ht^4	A	10.23
	Exp(Ht)	A	10.26

When comparing IR to ultrasonic technologies for sensing grass height, the only plots where ultrasonic and infrared sensors were used simultaneously were the Bermudagrass plots. The data demonstrated that there were no statistical differences when using ultrasonic or infrared to predict wet or dry yield. Although there were no statistical differences between the IR and ultrasonic sensors, the ultrasonic sensors functionally performed better. For the IR sensors, the raw grass heights had more readings that contained negative numbers that had to be converted into zeros or blanks. The ultrasonic sensors demonstrated a better consistency throughout sensor readings and observations during this testing suggested that they were better suited for the environment.

Conclusions

Because they demonstrated higher resolution with statistically similar accuracy, the infrared sensors would be the best choice for the standing crop yield monitor if they were tolerant enough to withstand the dirt and dust. Although the resolution of the ultrasonic sensors was not as high as that of the infrared sensors, they displayed greater functional longevity throughout the research. The ultrasonic sensors did not have the trouble with getting dirty or demonstrating erratic responses as the trials progressed. After some length of service, the infrared sensor data was quickly determined to be useless for yield prediction because of the sporadic readings exhibited. The grass height readings would go from high to low extremes when the Carter mower was not moving, while under the same conditions the ultrasonic sensors would maintain relatively consistent readings. When the Carter mower was in motion during harvest, the infrared sensors would still give erratic readings while the ultrasonic sensor readings appeared to be relatively consistent with the grass heights observed.

Using the crop height sensing technologies discussed here, yield prediction errors within crops were generally less than 9%, depending on model structure, with the exception of the hybrid pearl millet grass type, which exhibited errors of around 15%, depending on model structure. When a common, or universal calibration was applied across all of the grass types evaluated, yield prediction errors were in the range of about 20%, depending on model structure. Statistically, there was no difference in yield prediction error for 2-sensor, 4-sensor, and 8-sensor configurations, suggesting that a simplified system consisting of two sensors could be used instead of an eight sensor configuration without sacrificing prediction error. Inclusion of moisture content as a regressor proved to improve the predictions, but only when it was applied to the universal calibration that covered all grass types. Analysis of mathematical transformations of the sensor response did not provide evidence that correction for non-linearity in sensor response should be applied for prediction of yield.

For this study, the standing crop height yield monitor was applied to a research plot mower, with intentions of designing the system so that it could be easily adapted to commercial field mowers used for hay and forage production. If applied to a commercial field mower, there will be inherent challenges in calibrating systems as described here. Specifically, the sensor response data is collected on one machine, the mower, but another machine is used to complete the final harvest. Because of this, calibration would likely need to be conducted over an entire field or region of the field, comparing sensor responses within that region or field to the amount of harvested material removed from that field or region. This data could then be post-processed to generate yield maps, and the relationship determined could be applied to subsequently harvested areas. This is not altogether unlike the methods used for calibration of grain and cotton yield monitors, but the process is much simpler for grain and cotton harvest because the mass flow sensors are mounted on the same machine from which harvested quantities are collected.

Acknowledgments

Special thanks goes to Chanse Rayfield and Blake Watkins for assisting with fabrication and field testing, Reid Miller for assistance with field testing, and to Philip Fravel for assisting with field testing and photography.

References

Digman, M. and K. Shinners. 2012. Technology Background and Best Practices: Yield Mapping in Hay and Forage. In Proceedings, 2012 California Alfalfa and Grain Symposium, Sacramento, CA. UC Cooperate Extension.

"Equipment & Products for Quality Hay." Harvest Tec. Hudson, WI. Web. 26 Jan. 2015.

Holin, Fae. "Yield Monitors For Balers." Hay and Forage Grower. Hay and Forage Grower, 1 May 2006. Web. 26 Jan. 2015.

"NASS - National Agricultural Statistics Service." *NASS - National Agricultural Statistics Service*. USDA, Web. 26 Jan. 2015.

Rayburn, Ed, and John Lozier. "Estimating Pasture Forage Mass From Pasture Height." *Extension Service West Virginia University* (2003)

Sanderson, Matt A., C. Alan Rotz, Stanley W. Fultz, and Edward B. Rayburn. "Estimating Forage Mass with a Commercial Capacitance Meter, Rising Plate Meter, and Pasture Ruler." Agronomy Journal 93.6 (2001): 1281-286. Web.

Thomasson, J. A., and R. Sui. "Mississippi Cotton Yield Monitor: Three Years Of Field-Test Results." Applied Engineering in Agriculture 19.6 (2003): 631-36. Web.

Undersander, Dan, David R. Mertens, and Nancy Thiex. "Forage Analysis Procedures." *The National Forage Testing Association*. Foragetesting.org, July 1993. Web.

Vellidis, G., C. Perry, and T. Wells. 2004. Cotton Incorporated. Retrieved from http://www.cottoninc.com/fiber/AgriculturalDisciplines/Engineering/Precision-Crop-Management-for-Cotton/Cotton-Yield-Monitors/cottonyieldmonitors.pdf.

CHAPTER THREE

DEVELOPMENT AND EVALUATION OF A YIELD MONITOR FOR ROUND BALERS

Abstract

Corn, grain and cotton yield monitoring technologies have been widely implemented since their development and throughout the past twenty years. Yield monitoring has been indicated to be the second most applied precision agriculture technology, behind auto-steer. However, commercially available technologies are for yield monitoring crops other than corn, cotton, and grain have not been widely available, if available at all. Yield monitoring for hay and forages has not been broadly implemented but it can be a beneficial management and inventory tool for farmers in the cattle and hay industries. This research focused on development and testing of a yield monitor installed on a John Deere model 458 round hay baler, but adaptable to any type of hay baler. The yield monitor was built using on-the-go remote sensing technology to measure the height of the windrow as it was being collected by the baler. Bales were individually weighed using a platform placed on truck scales, and samples from each bale were oven dried to calculate dry weights. For year 1, sensor data across 77 bales of a mixed hybrid bermudagrass (Tifton 85 and Coastal), 23 bales of Tifton 85 bermudagrass, and 9 bales of alfalfa were used to develop regression models predicting bale counts, baled wet weights, and baled dry weights. Data analysis indicates that yield prediction error, when applying the proper regression model, ranges between 3% and 15%. For year 2, 21 bales of mixed hybrid Bermuda (Tifton 85 and Coastal) and 20 bales of Tifton 85

bermudagrass were analyzed to formulate prediction errors ranging between 5% and 9.5%. The technology developed under this project provides the capability of generating hay yield maps with an acceptable level of accuracy for guidance in making variable rate prescriptions and zone management applications across a variety of hay crops.

Introduction

The agricultural industry is ever changing, whether it be through increasing of yields and herbicide resistance through genetically modified crops or technological advances and more intense management practices through precision agriculture. Machinery and technological advancements have proven to be profitable to growers throughout all aspects of agricultural production. Notable advancements that can be attributed to precision agriculture are variable rate applications of lime and fertilizers using zone management, and yield monitoring technology. Yield monitoring technology has been important to agricultural production since its development. A yield monitor is a system that can be implemented on agricultural harvesters to monitor mass flow rates of crops. The yield monitor, when paired with GPS, has been used to develop yield maps of fields to show the yield per unit acre. These yield maps have been important to farmers in that they show where high yields and low yields are throughout different fields. When the yield maps are viewed by the grower, management practices can be developed and modified to improve production efficiency of the farm. Yield maps can also be converted into profit and revenue maps to show the grower which parts of the farm are the most costly or the most profitable.

Yield monitoring technology has been extensively implemented for small grains, like corn, soybeans, and wheat, and cotton. These yield monitoring systems use different mass flow sensing technologies. Small grain yield monitors generally use an impact plate, which grain is propelled against as it leaves the elevator. Optical sensors are used for both grain and cotton to measure interceptance of light by the flowing crop material. Microwave reflectance sensors are also used in cotton to indicate the kinetic energy of the pneumatically conveyed material. Research and development of peanut yield monitors have been underway for well over a decade, although a commercial product is not yet offered. Among the top ten U.S. crops by acreage and the top six U.S. crops by value of production, hay is the only one that does not have a commercially available yield monitor (NASS, 2015.)

However, there is one company that offers a system that makes it possible to develop yield maps from a hay field when baled using a large square baler. Harvest Tec (Hudson, WI) has a system that can be implemented on a large square baler that weighs the bale as it comes out the back of the baler. When paired with GPS, a yield map can be developed through post-processing by taking the GPS coordinates of where the bale was dropped, the weight of the bale, and the distance travelled between bales. Moisture is accounted for in the bales by using “star wheels” in the bale chute (Harvest Tec). There are downfalls to this method though. When developing the yield map, the hay cannot be accurately distributed across the field. Windrow height and volume is not accounted for so a consistent volume of hay is assigned to the windrow for a certain bale, reducing map resolution substantially. Another problem with this yield monitoring technology is that it does not provide on the go yield data for the producer.   The post-processing of data for a yield monitor can be problematic for a producer in that the process that has to be followed to generate the yield map may not be known be the grower, or the data may have to be sent off or processed by someone else in order to generate the map. It is more desirable to have on-the-go yield data for a hay yield monitor, similar to that of the grain and cotton yield monitors. Another yield monitor technology that has been employed for forage harvesting is through the usage of feedrollers on a silage chopper. As crop passes between feedrollers, the amount of spring force is sensed and correlated to yield (Shinners et al., 2003).   On some self-propelled forage harvesters, such as a hay windrower, impact force measure on a hinged plate have been used on the area where hay passes from the rear of the machine, correlating to yield at mowing (Savoie et al., 2002.)

One study implemented yield monitoring technology on a self-propelled windrower to obtain yield data using five parameters. These parameters consisted of impact force at the swath forming shield, crop flow at the swath forming shield, roller speed, platform pitch, and pressure of platform drive motor. The results for this study consisted of average absolute error of 13.4% (Shinners et al., 2003). On a forage harvester for silage, a study was conducted where five sensors were installed. A torquemeter was installed on the PTO shaft and at the cutterhead. A load cell was implemented on the duct with a vertical displacement transducer on the feedrollers. A capacitance-controlled oscillator, which exhibites frequency drop, proportional to moisture flow, was installed at the end of the duct where the crop exits. Each of these sensors' responses were correlated to wet matter flow rate (Savoie et al., 2002).

Feedroller pressure and displacement is used on self-propelled silage choppers to monitor yield (Digman and Shinners, 2012) on a patented system (Shinners et al., 2002). Some hay baler manufacturers have systems that can be implemented on the baler to weigh the bales after they are baled. This method utilizes load cells on the axle and the tongue of the baler.

By implementing hay yield monitoring technology and having the ability to generate on-the-go yield data and yield maps, a producer can have the capability of knowing tons per acre or bales per acre. This knowledge allows the producer to investigate and attempt to remedy yield limiting factors on low yielding areas, or implement, for instance, variable rate application of fertilizers proportionate to expected yields. Another example of a management practice that can be implemented is by looking at the maps and seeing which parts of a field are possibly not at all profitable. If money is being lost on certain parts of fields, then those parts can be removed from production entirely so as to increase overall profitability.

The market potential of yield monitoring technology in the forage and hay industry can be assessed by observing the acreages used for different farming practices. The following statistics are all for the 2014 year and are nationwide for the U.S. (NASS, 2015). The total acreage used for all hay production consisted of 57,092,000 acres. Of this acreage, 18,445,000 acres or 32% were devoted only to the production of alfalfa which is a high value forage crop. Hay production ranks third in the nation for acreage used for crop production behind corn and soybeans, but leads cotton, peanuts, and sorghum. Corn was grown for grain on 83,136,000 acres and for silage on 6,371,000 acres. Soybeans were planted on 83,701,000 acres while cotton was planted on 11,037,000 acres. Peanuts accounted for 1,354,000 planted acres and grain sorghum occupied 6,401,000 acres. Sorghum for silage was grown on 315,000 acres. These statistics suggest justification of the need for a yield monitor for forage and hay crops. With hay being the third most produced crop in the country, the implementation of yield monitoring technology and precision agriculture could lead to millions of dollars saved in fertilizer and lime usage, and has the potential to boost farmer's profits tremendously.

There are no systems for hay yield monitoring that use remotes sensing technology to measure windrow volume and correlate it to yield. By using infrared or ultrasonic sensors to measure windrow volume, an accurate mass flow can be predicted as a function of windrow height. When paired with a weighing mechanism, on-the-go yield data can be accumulated and yield maps can be created to be used for management decisions.

Objectives

The objectives of this study were to:

- Develop a yield monitor capable of being implemented on any hay baler using remote sensing technology that measures windrow height
- Test and evaluate sensors for use on the yield monitor
- Evaluate linearity of sensor response with respect to hay mass flow rate
- Characterize accuracy of the yield monitor using different algorithm structures
- Develop yield maps as a demonstration of system application and utility

Methods and Materials

The yield monitor developed in this study was designed to measure the windrow volume using remote sensing technology. The research was carried out for two growing seasons analyzing which sensors were better for determination of windrow volume. Year 1 analyzed the use of two different types of sensors (infrared and ultrasonic) while year 2 analyzed only ultrasonic sensors. Many things were changed between year 1 and year 2, from methods of mounting to methods of numbering bales. The program had some slight changes and different methods were implemented.

Year 1

Fabrication and Mounting

A boom was constructed from 2.5 cm (1 in.) square tubing and mounted to the tongue of a John Deere 458 hay baler. The boom had to be mounted to the bottom of the tongue so the tongue would not interfere with the downward facing sensors mounted to the boom. This was a design limitation in that it confined the maximum mounting height of the sensors. However, it was observed that in most cases the windrow would be no taller than the drawbar on the tractor so the boom was mounted as high on the tongue as possible without being too close the header. If the boom would have been too close to the header, then it would have been possible for the header to cause interference with the sensors by raising the hay in the field of view and giving an inaccurate reading of windrow height. On the boom, eight pieces of 5 cm x 5 cm (2 in. x 2 in.) angle iron were mounted in order to provide the sensors with a suitable mounting point. Eight 3521_0 infrared distance sensors (Phidgets Inc., Calgary, Alberta, Canada) were mounted to the angle iron. Each of the sensors was equally spaced along the 99 cm (39 in.) boom. Four Model 1128_0 ultrasonic sensors (Phidgets Inc., Calgary, Alberta, Canada) were secured to every other of piece of the angle iron. The reason for using both types of sensors was for evaluation of the sensors and determination of which was best for the application.

A model LJC18A3 B Z/AX capacitance-based proximity switch was mounted at the hub of the baler. This switch sensed each of the wheel studs as they passed by, signaling for a sensor reading to be logged. The purpose of this sensor was to make the yield monitor capable of taking readings on distance trigger events rather than timer generated events. Had the yield monitor been on a timer, sensor readings would have been inaccurate due to the constant stopping of a baler for tying and dumping purposes. An accurate GPS receiver would be an acceptable alternative to the proximity switch used in this study. When the baler was not in motion, no readings would be taken. By taking sensor readings for height and knowing the distance travelled, windrow volume of hay that had been collected by the baler could be calculated.

Electrical System

The ultrasonic and infrared distance sensors that were mounted to the boom were connected to USB interface kits or I/O Boards. For the infrared distance sensors, model 1101_0 infrared distance adapters (Phidgets Inc., Calgary, Alberta, Canada) were connected between the sensors and the input/output (I/O) board. Each I/O board had eight analog input channels and twelve were needed, so two I/O boards were utilized. The first I/O board, which was a model 1019_0 (Phidgets Inc., Calgary, Alberta, Canada) required an external 12 VDC power input to support its USB hub. In order to establish a stable power supply, a power inverter was used along with a 12 VDC transformer to power the I/O board. The wiring harnesses supplied with the infrared distance sensors were extended to go between the sensors and the distance adapters. From the adapters to the I/O board, the wiring harnesses supplied with the adapters were used. Phidgets analog input cables were soldered to the boards of the ultrasonic sensors and connected to the other I/O board, which was a model 1018_2 interface kit (Phidgets Inc., Calgary, Alberta, Canada). The ultrasonic sensor harnesses included an additional conductor, each connected to a digital output channel of the I/O board. This digital output was used to pulse the sensors in sequence so they would not get echo or interference from one another.

The capacitance switch was connected to a digital input channel of the I/O board and a 4.7 kΩ resistor was connected between ground and the digital input. The I/O boards and distance adapters were mounted in sealed PVC electrical enclosure boxes. A model 1040_0 GPS receiver (Phidgets Inc., Calgary, Alberta, Canada) was used to indicate log field position for map development, but its accuracy was not suitable for use in determining ground speeds and short distances. The 1018_2 interface kit and GPS unit were connected to the USB hub of the 1019_0 interface kit. The enclosures containing the data acquisition components for the yield monitoring system were mounted to the baler. The only wires entering the tractor cab were USB cable from the 1019_0 interface kit and the 12VDC power supply cable from the power inverter. The data acquisition software was written using Microsoft Visual Basic 2010 and data from all sensors was logged on a Panasonic CF-74 Toughook in the tractor cab at each distance trigger event from the capacitance sensor. A separate log file was generated for each bale.

Calibration and Field Testing

Generic calibration equations for the infrared distance sensors and ultrasonic sensors were available from the Phidgets website but when tested, the equations proved to be inaccurate and inconsistent across sensors. As a result, independent calibration equations were constructed for each sensor as follows. The baler was put into a stationary position on a flat surface. The height of each infrared sensor was determined to be the same in relation to the flat surface so a reference point at one of the sensors was chosen to use in the calibration process. The height of the reference point was determined and a plywood panel was extending beyond the length of the boom was placed under the sensors. Readings were taken at different incremental elevations of the plywood panel, the distance to the panel being measured from the aforementioned reference point. The distance measurements were regressed in Microsoft Excel as functions of the sensor readings to develop a distance to target equation for each sensor to be used in the data acquisition software. The same process was carried out for calibration of the ultrasonic sensors.

All baling was carried out at Clemson University Edisto Research and Education Center in Blackville, South Carolina. Hay was mowed first and after curing and drying was completed, it was raked with a V-style Bush Hog Wheel Rake. Using a wheel rake instead of a side delivery rake was determined to be the best method for obtaining yield data because of spatial consistency. When using a wheel rake, one pass is carried out in order to form a windrow whereas with a side delivery rake, more than one round is usually necessary to for the windrow. The wheel rake provided a standard distance between windrows which could then be used to distribute data back across the field, similar to that of row crop yield monitoring. The average distance between raked windrows was 4.6 m (15 ft). Prior to baling, a baseline was calibrated for the baler, which set the distance from the sensors to the sensed ground level as a target height of zero. To calibrate the baseline, the baler was driven over 5 lineal meters (15 lineal feet) of ground that had been mowed and raked to account for and eliminate the height of the cut crop from sensor response, which may otherwise suggest shallow windrow presence. Once the calibration process was carried out, the baler was ready to start baling; this calibration process was carried out in each different field prior to baling.

When the baler started to pick up hay for each bale, a “Start Logging” button on the program was clicked and at the end of a bale, when it was being wrapped or tied, a “Stop Logging” button was clicked to advance the bale count, which was incorporated into the file naming convention for the log file. Each bale was tagged with the corresponding file number so that their weights and moisture contents could be later associated with the logged sensor data. The distance travelled to complete each bale varied with the volume of the windrow. In lower yielding areas of the field, the distance travelled was higher than in higher yielding areas of the field. The capacitance switch at the wheel of the baler triggered a sensor reading to indicate height of the windrow beneath each sensor at each 41 cm (16 in.) travel distance.

After the hay was baled for the specific field, a hay wagon was positioned on truck scales to serve as a scale pad large enough on which to weigh the bales. Each bale was picked up with a front end loader-mounted bale spear transported to the scale pad for obtaining and recording weights. The bales were then sampled for moisture content using a Colorado Hay Probe (Nasco, Fort Atkinson, Wisconsin) coupled to an electric drill. Two cores were removed from each bale and placed into a bag labelled with the corresponding file number. After all moisture samples were collected, the samples were weighed using a model 8800SS scale (Seedburo Equipment Co., Des Plaines, Illinois) and the wet weight was recorded. The samples were then oven-dried for 24 hours at 100 degrees Celsius (Undersander et al., 1993). After removing samples from the oven, they were once again weighed to obtain dry weight. Moisture content was then calculated on a wet weight basis using the formula: (wet weight – dry weight)/wet weight.

Data Analysis

Analysis of the data was conducted in Microsoft Excel and involved correlating the sensor responses to hay mass and mass flow for both dry and wet bases. Analysis of nonlinearity was conducted by applying different mathematical transformations to the sensor responses, as discussed in further detail below. Investigation of nonlinearity in the mass and mass flow relationships with sensor response through application of transformations was conducted in order to suggest the most accurate model structure for the yield prediction algorithm.

Linear regression models were developed for prediction of yield across each bale using average sensed windrow height to predict hay mass flow rate and using sum of sensed windrow height to predict total mass. Mass flow models were constructed with non-zero y-intercepts and mass models were constructed through the origin with y-intercepts equal to zero because of the inability to distribute the y-intercept across the point data without on-the-go knowledge of the number of points for each plot. There were instances in the point data where a given sensor response indicated a negative windrow height. These negative windrow height values were converted to zeros and blanks, providing an analysis of which method provided the least yield prediction error.

In addition to modeling as a function of windrow height (Ht), each of these general model types (mass flow and mass predictions) were constructed across the following mathematical transformations of the sensed windrow heights to correct for potential non-linearity: $Ht^{0.5}$, Ht^2, Ln(Ht), Exp(Ht), $Ht^{0.25}$, and Ht^4. The mathematical transformations were applied to the point data for each sensor, prior to averaging or summing across entire point data from each plot. As discussed, the point data was that which was generated at each capacitance switch trigger event. Single linear regression models as functions of windrow height and its transformations were developed as well as multiple linear regression models, with the first regressor being windrow height or one of its transformations and the second regressor being moisture content. Transformations of moisture content to assess for non-linearity were not conducted in the analyses presented here. The tables in the results section show means comparisons developed using student's t-tests (α=0.05) and connecting letters reports are for within sections (between divisions) of each table.

Year 2

In year 2 of research and evaluation of the hay yield monitor, the Phidgets ultrasonic sensors were replaced by other ultrasonic sensors that had an IP 67 rating. The sensors used were Maxbotix 7060, Maxbotix 7067 (MaxBotix Inc., Brainerd, Minnesota), and model T30UXDA sensors (Banner Engineering Inc., Minneapolis, Minnesota). The 7060 sensors demonstrated problems from the very beginning due to the fact that a stable reading could not be obtained. The sensors were erratic and displayed data that did not appear to correlate to target distance. Further analysis suggested that the erratic readings were due to effects from echoes. Technical support representatives from Maxbotix suggested testing 7067 sensors because of their different firmware that was present to improve stability in sensor response. The 7067 also displayed problems from the beginning in that three consecutive readings at the same distance had to be obtained in order to update the sensed output. The data obtained from these sensors was flat-lined from the beginning to the end of a bale and would change when the tractor stopped travelling in forward motion. As soon as the tractor resumed forward travel, the sensor would once again flat-line at the sensor reading obtained when stopped. The T30UXDA sensors consistently responded proportionately with the target distance regardless of whether or not the sensor platform was in forward motion and demonstrated a higher level of resolution because the sensors were designed for a 1 meter distance range, therefore utilizing almost all of the window of sight between the baler tongue and ground.

The data acquisition program display can be seen in figure 3.1; the need for tagging hay bales was eliminated to reduce labor required for data collection and to reduce opportunities for human error. To accomplish this, the hay yield monitoring program was modified to record the GPS coordinates (latitude, longitude) of where each bale was ejected. A GPS offset opposite the direction of travel of 4.6 m (15 ft) was applied to each bale, based on visual observation of generally how far the bale rolled after ejection. Along with the coordinates, the ejection time and bale number was recorded. A limit switch installed on the baler from the manufacturer to indicate if the chamber was open or closed was used as a digital input to the I/O board to indicate bale ejection. Sometimes when baling hay, it becomes necessary to open and close the bale chamber more than once while sitting in one spot on the occasion that the baler clogs up or the bale doesn't wrap. To avoid logging points more than once or advancing the bale number more than once if the bale chamber was opened multiple times, the program was written so that the coordinates would only be logged and the bale number only be advanced if the baler had travelled in a forward motion since the prior log record; this was indicated through use of the capacitance switch. If the capacitance switch had not been triggered by the wheel lug since the last bale ejection event and the bale chamber was opened, the coordinates would not be recorded to the excel file.

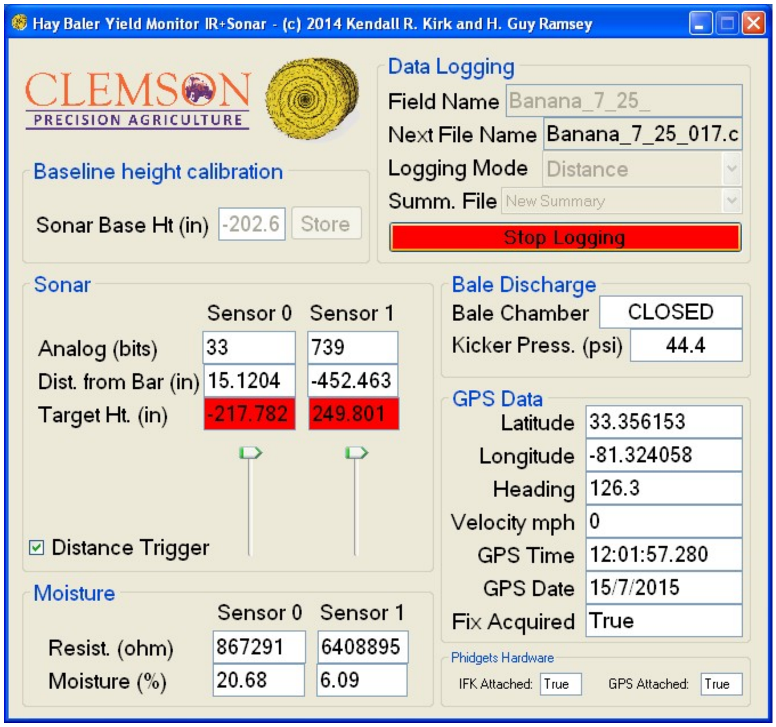


Figure 3.1. Screenshot of program display for data acquisition software showing dynamically updated values for ultrasonic sensor output, bale chamber position, hydraulic pressure at kicker, moisture sensor output, and GPS position information.

The data logged for bale position was then opened in another program, the “Bale Chaser” program that was also written with Microsoft Visual Basic (figure 3.2). The Bale Chaser program displayed markers on a map that corresponded with the GPS coordinates of the bale, along with current position and travel direction of the tractor. A GPS antenna and receiver was installed on a tractor with a front end loader. The magnetic GPS antenna was placed on the loader close to where the bale spear attached in order to get the bale spear closer to the bale without the need for applying an offset. When a bale was picked up, the user specified which bale was collected and a text box labeled weight became visible on the screen. After the bale was weighed, the weight was recorded in that box and saved to a text file, which was later merged with the mass flow, moisture, and kicker pressure sensor data for that bale.

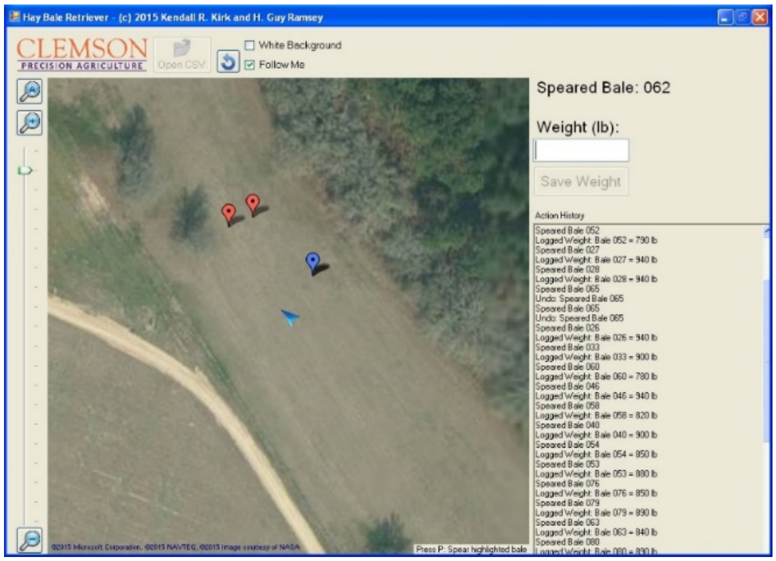


Figure 3.2. Screenshot showing display for Bale Chaser program that was written to collect and weigh bales.

Two Model BHT-2 moisture sensor pads (Agratronix, Streetsboro, Ohio) were installed in the bale chamber—one on the left side and one on the right side—according to manufacturer specifications (figure 3.3).

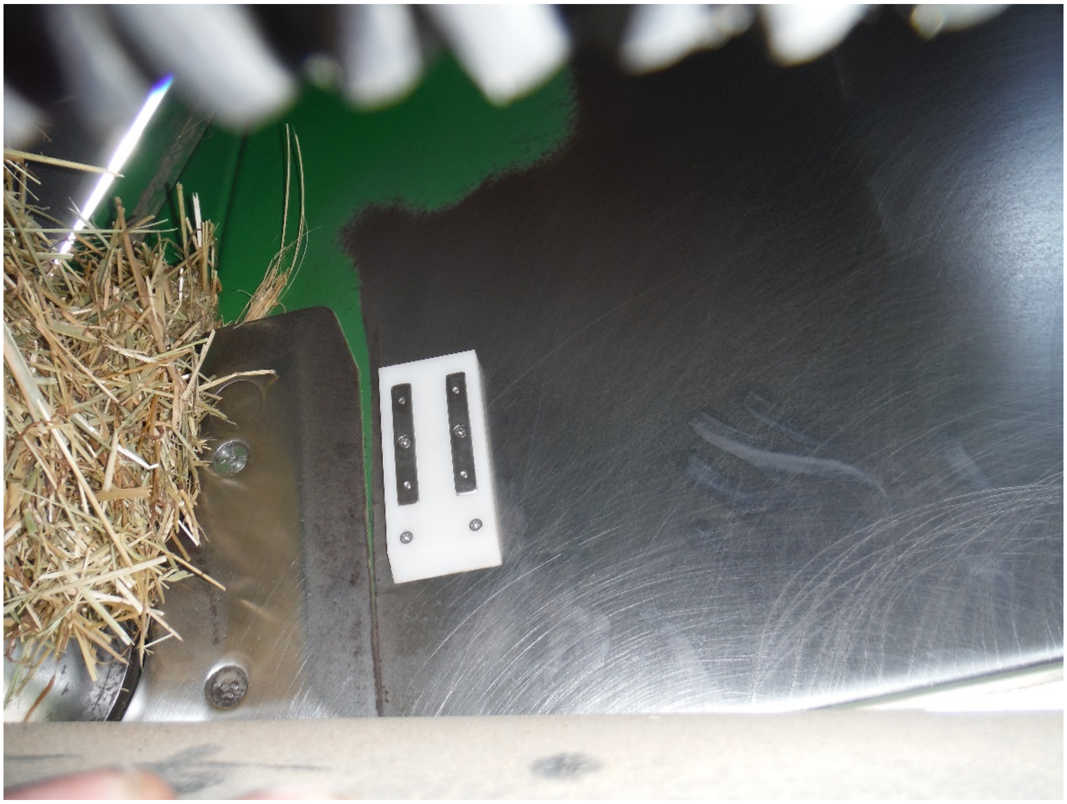


Figure 3.3. Installation of moisture sensors in the bale chamber, according to Agra-tronix specifications.

The Agritronix calibration was estimated by providing a known resistance across the electrodes and recording the moisture indicated on the display. For data logging, a voltage divider circuit was constructed for each moisture pad and wired into the analog inputs of the I/O board. The voltage divider was constructed as shown in figure 3.4, with the 5V supply and ground connected to the I/O board. In the figure, R1 was a 1 MΩ resistor and R2 represented the unknown resistance created by the hay contacting the sensor pads' electrodes. One electrode was connected directly to the ground of the I/O board and AI0 was connected to an analog input on the I/O board. The unknown resistance of the hay, or R2 was calculated as:

$$R2 = \frac{R1}{\frac{V_{in}}{V_{out}} - 1},$$

where, R2 = resistance of hay across electrodes, MΩ

R1 = known resistance, 1 MΩ

V_{in} = supply voltage, 5 V

V_{out} = measured voltage at I/O board, V

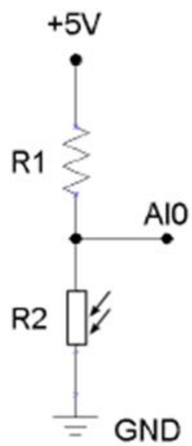


Figure 3.4. Diagram for voltage divider used to measure resistance across electrodes on moisture sensors

Results and Discussion

Year 1

The infrared distance sensors exhibited several problems from the very beginning. The data that they produced was erratic and not proportional to target distance; negative windrow volumes were regularly recorded for these sensors. This error could be attributed to many reasons, with none being specifically identified in this study. It is suspected that the most likely cause for inaccurate readings was from the high amount of dust produced from the header of the baler taking in the hay. The dust may have clouded the sensors almost immediately. Also, the sensors could have been affected by exterior heat at the sensor or at the sensed target, or the surface geometry of the target (windrow) could have resulted in an inability to obtain a sensor response proportional to distance. It is suspected that dust was the culprit because the sensors, early in the first baling, produced responses that were proportional to windrow height and because there was no trend in malfunction that could be directly linked to temperature. Sensor lenses were cleaned after the first baling, which seemed to sometimes improve their function, but not always and not for long. The infrared distance sensor data was abandoned after the data from the first and second balings were analyzed. The infrared distance sensors were evaluated to not be the sensor to use for a hay yield monitor that determined cross sectional area and volume of the windrow.

The data for the ultrasonic sensors appeared to be proportional to windrow height. There were times in early testing when data from these sensors would abruptly begin demonstrating erratic operation though. After the sensors demonstrated erratic data, all the wiring was checked and protected using wire loom. After the wires were protected, the erratic operation of the sensors seemed to cease. After analyzing the data and performing one-way ANOVA, it was determined that the absolute yield prediction error for the ultrasonic sensors for different regression models was not statistically different between the models using four ultrasonic sensors and two ultrasonic sensors. After evaluation of the ultrasonic sensors, it was determined that data from only the two inside sensors was enough to have an accurate yield monitoring system for the hay yield monitor. When processing data, individual sensor responses that had negative values were replaced with zeros through a simple logic function.

The different linear regression models tested consisted of models with one regressor through the origin, one regressor with a non-zero y-intercept, two regressors through the origin, and two regressors with a non-zero y-intercept. In all models tested, wet weight, dry weight, wet mass flow, and dry mass flow across a given bale were each set as the dependent variables. In all models tested, ultrasonic sensor response was used as a regressor, or independent variable: in the mass flow prediction models average sensor response across a bale was used and in the weight prediction models sum of sensor responses across a bale was used. The second regressor in the multiple regression models used was average moisture content in the bale as calculated from core samples that were taken from each bale and weighed, oven dried, and re-weighed. Again, mass flow prediction models used average moisture across a bale and weight prediction models used sum of moisture values across a bale. The data was also analyzed using all four ultrasonic sensors and by only using the inner two ultrasonic sensors. Mass flow was defined as the weight of the bale divided by the number of readings collected for that bale; because each reading was collected at a given travel distance by the capacitance switch, this can be translated to mass per unit travel distance. Wet weight was defined as the weight of the bale recorded from the scale immediately after baling. Dry weight was defined as the wet weight corrected by the moisture content determined from oven-drying of the collected core samples.

The data analysis to follow in tables 3.1 through 3.12 represents three sequential tests to help suggest the best model structure for using this system for hay yield monitoring: (1) comparison of two and four sensor configurations, (2) comparison of models using moisture sensor data with those not using moisture sensor data, and (3) comparison of mass and mass flow prediction models. All comparisons demonstrated by ordered letter reports were conducted in JMP 10.0 (SAS Institute Inc., Cary, North Carolina) using one-way ANOVA and Student's t-tests to evaluate pooled prediction error for each bale within the indicated dataset.

In the data presented below, the number of bales used for analysis for each dataset were: 55 bales for the 7-24 Banana baling, 9 bales for the 7-30 Alfalfa baling, 9 bales for the 7-31 Bermuda baling, 22 bales for the 9-11 Banana baling, and 14 bales for the 9-12 Bermuda baling. The 2014 All Bales dataset includes all 109 bales combined. The first analysis performed was a comparison between use of two or four ultrasonic sensors to measure the windrow. Tables 3.1, 3.2, 3.3, & 3.4 demonstrate the results of Student's t-tests between regression models using the models that had the best numerical average absolute error when using two or four ultrasonic sensors. It was found that there were no significant differences between using two or four sensors for any of the fields that were baled on wet or dry prediction basis. Not all models contained moisture as a regressor because in some cases, the best model was not a multiple linear regression model. Since there was no difference between the different sensor configurations, it was concluded that the best commercial model would be a two sensor system because of cost. Based on this conclusion, data analyses in tables 3.5-3.12 only consisted of models where two ultrasonic sensors were used.

Table 3.1. Comparison of average absolute errors for best two- and four-sensor models for wet weight prediction. Comparisons were made within datasets.

Dataset[1]	N[2]	Model[3]		Avg. Abs. Error, %[4]
	2	Wt = f[Ht,MC]	A	7.16
7-24 Banana	4	Wt = f[Ht,MC]	A	6.46
	2	Wt = f[Ht,MC]	A	3.10
7-30 Alfalfa	4	Wt = f[Ht,MC]	A	3.07
	2	Wt = f[Ht^4,MC]	A	5.98
7-31 Bermuda	4	Wt = f[exp(Ht),MC]	A	7.08
	2	Wt = f[Ht^(0.5),MC]	A	3.83
9-11 Banana	4	Wt = f[Ht^(0.5),MC]	A	3.68
	2	Wt = f[Ht,MC]	A	4.62
9-12 Bermuda	4	Wt = f[Ht^(0.5),MC]	A	4.53
	2	Wt = f[Ht^2,MC]	A	15.70
2014 All Bales	4	Wt = f[Ht^2,MC]	A	14.02

[1]Date of baling and field that was baled
[2]Number of sensors used
[3]Best model based on least average absolute error across plots, where Wt = bale weight,
MF = mass flow rate, and MC = moisture content
[4] Average absolute prediction error across plots within specified group

Table 3.2. Comparison of average absolute errors for best two- and four-sensor models for wet mass flow prediction. Comparisons were made within datasets.

Dataset	N	Model		Avg. Abs. Error, %
	2	MF = f[Ht^2]	A	10.02
7-24 Banana	4	MF = f[Ht^2]	A	7.51
	2	MF = f[Ht^(0.5),MC]	A	5.06
7-30 Alfalfa	4	MF = f[Ht^2,MC]	A	5.88
	2	MF = f[exp(Ht),MC]	A	5.90
7-31 Bermuda	4	MF = f[ln(Ht),MC]	A	7.12
	2	MF = f[Ht,MC]	A	8.54
9-11 Banana	4	MF = f[Ht^2,MC]	A	6.99
	2	MF = f[Ht^4,MC]	A	13.97
9-12 Bermuda	4	MF = f[Ht^(0.25),MC]	A	9.83
	2	MF = f[Ht]	A	22.17
2014 All Bales	4	MF = f[Ht^2]	A	19.65

Table 3.3. Comparison of average absolute errors for best two- and four-sensor models for dry weight prediction. Comparisons were made within datasets.

Dataset	N	Model		Avg. Abs. Error, %
	2	Wt = f[Ht,MC]	A	7.90
7-24 Banana	4	Wt = f[Ht,MC]	A	7.29
	2	Wt = f[Ht,MC]	A	4.01
7-30 Alfalfa	4	Wt = f[Ht^(0.5),MC]	A	3.80
	2	Wt = f[Ht^2,MC]	A	7.19
7-31 Bermuda	4	Wt = f[Ht,MC]	A	7.81
	2	Wt = f[Ht,MC]	A	3.81
9-11 Banana	4	Wt = f[Ht,MC]	A	3.42
	2	Wt = f[Ht,MC]	A	5.64
9-12 Bermuda	4	Wt = f[Ht^(0.5),MC]	A	5.42
	2	Wt = f[Ht^2,MC]	A	17.60
2014 All Bales	4	Wt = f[Ht^2,MC]	A	15.51

Table 3.4. Comparison of average absolute errors for best two- and four-sensor models for dry mass flow prediction. Comparisons were made within datasets.

Date/Field	N	Model		Avg. Abs. Error, %
	2	MF = f[ln(Ht),MC]	A	4.73
7-24 Banana	4	MF = f[exp(Ht),MC]	A	4.81
	2	MF = f[Ht^(0.5),MC]	A	4.97
7-30 Alfalfa	4	MF = f[Ht^2,MC]	A	5.10
	2	MF = f[Ht^(0.25),MC]	A	5.66
7-31 Bermuda	4	MF = f[exp(Ht),MC]	A	5.66
	2	MF = f[Ht,MC]	A	8.23
9-11 Banana	4	MF = f[Ht^2,MC]	A	6.88
	2	MF = f[Ht^4,MC]	A	13.77
9-12 Bermuda	4	MF = f[Ht^(0.25),MC]	A	9.60
	2	MF = f[exp(Ht),MC]	A	9.08
2014 All Bales	4	MF = f[Ht^(0.25),MC]	A	8.89

In tables 3.5 through 3.8 models using one regressor and models using moisture as a second regressor were compared. It was found that using moisture as a second regressor in all datasets numerically improved the average absolute error for wet mass prediction and in most cases demonstrated a significantly reduced yield prediction error. For wet mass flow prediction, there were no significant differences between using moisture as a second regressor and using a single regression model. Table 3.7 shows that in some cases, there was significant difference when using moisture but not in all cases, but the average absolute error was numerically better when moisture was used. Table 3.8, which demonstrates comparisons for dry mass flow prediction, shows for the 2014

All Bales dataset that the average absolute error was significantly lower when using moisture as a second regressor than that for the single regression model; the average absolute error, when using moisture, was less than half of that when not using moisture. This was the only analysis of number of regressors where there was a significant difference for the 2014 All Bales dataset. The data in tables 3.5 through 3.8 generally suggest that yield prediction models are improved, if not significantly improved when knowledge of moisture is included.

Table 3.5. Comparison of average absolute errors for two-sensor models using single and multiple linear regression for wet mass prediction. Comparisons were made within datasets.

Dataset	Type[1]	Model		Avg. Abs. Error, %
	Single	Wt = f[Ht^2]	A	10.16
7-24 Banana	Multiple	Wt = f[Ht,MC]	B	7.16
	Single	Wt = f[Ht^2]	A	5.44
7-30 Alfalfa	Multiple	Wt = f[Ht,MC]	A	3.10
	Single	Wt = f[Ht^2]	A	20.09
7-31 Bermuda	Multiple	Wt = f[Ht^4,MC]	B	5.98
	Single	Wt = f[Ht^2]	A	11.26
9-11 Banana	Multiple	Wt = f[Ht^(0.5),MC]	B	3.83
	Single	Wt = f[Ht^4]	A	14.35
9-12 Bermuda	Multiple	Wt = f[Ht,MC]	B	4.62
	Single	Wt = f[Ht^2]	A	17.85
2014 All Bales	Multiple	Wt = f[Ht^2,MC]	A	15.70

[1]What type of regression model was used

Table 3.6. Comparison of average absolute errors for two-sensor models using single and multiple linear regression for wet mass flow prediction. Comparisons were made within datasets.

Date/Field	Type	Model		Avg. Abs. Error, %
	Single	MF = f[Ht^2]	A	10.02
7-24 Banana	Multiple	MF = f[Ht^2,MC]	A	10.76
	Single	MF = f[Ht^4]	A	5.50
7-30 Alfalfa	Multiple	MF = f[Ht^(0.5),MC]	A	5.06
	Single	MF = f[exp(Ht)]	A	12.26
7-31 Bermuda	Multiple	MF = f[exp(Ht),MC]	A	5.90
	Single	MF = f[Ht]	A	10.41
9-11 Banana	Multiple	MF = f[Ht,MC]	A	8.54
	Single	MF = f[Ht^4]	A	15.15
9-12 Bermuda	Multiple	MF = f[Ht^4,MC]	A	13.97
	Single	MF = f[Ht]	A	22.17
2014 All Bales	Multiple	MF = f[Ht,MC]	A	23.86

Table 3.7. Comparison of average absolute errors for two-sensor models using single and multiple linear regression for dry mass prediction. Comparisons were made within datasets.

Dataset	Type	Model		Avg. Abs. Error, %
	Single	Wt = f[Ht^2]	A	9.13
7-24 Banana	Multiple	Wt = f[Ht,MC]	A	7.90
	Single	Wt = f[Ht^2]	A	5.21
7-30 Alfalfa	Multiple	Wt = f[Ht,MC]	A	4.01
	Single	Wt = f[Ht^2]	A	20.24
7-31 Bermuda	Multiple	Wt = f[Ht^2,MC]	B	7.19
	Single	Wt = f[Ht^2]	A	10.49
9-11 Banana	Multiple	Wt = f[Ht,MC]	B	3.81
	Single	Wt = f[Ht^4]	A	13.59
9-12 Bermuda	Multiple	Wt = f[Ht,MC]	B	5.64
	Single	Wt = f[Ht^2]	A	18.61
2014 All Bales	Multiple	Wt = f[Ht^2,MC]	A	17.60

Table 3.8. Comparison of average absolute errors for two-sensor models using single and multiple linear regression for dry mass flow prediction. Comparisons were made within datasets.

Dataset	Type	Model		Avg. Abs. Error, %
	Single	MF = f[Ht^2]	A	9.30
7-24 Banana	Multiple	MF = f[ln(Ht),MC]	B	4.73
	Single	MF = f[ln(Ht)]	A	4.88
7-30 Alfalfa	Multiple	MF = f[Ht^(0.5),MC]	A	4.97
	Single	MF = f[exp(Ht)]	A	12.52
7-31 Bermuda	Multiple	MF = f[Ht^(0.25),MC]	A	5.66
	Single	MF = f[Ht]	A	9.54
9-11 Banana	Multiple	MF = f[Ht,MC]	A	8.23
	Single	MF = f[Ht^4]	A	14.35
9-12 Bermuda	Multiple	MF = f[Ht^2,MC]	A	14.40
	Single	MF = f[Ht]	A	20.00
2014 All Bales	Multiple	MF = f[exp(Ht),MC]	B	9.08

Tables 3.9 and 3.10 compare mass and mass flow prediction errors for wet basis (table 3.9) and dry basis (table 3.10) predictions using moisture as a second regressor. Wet mass prediction errors were significantly lower than wet mass flow prediction errors in most cases. There was only one instance of wet mass flow prediction error being numerically lower than wet mass prediction error, but it they were not significantly different. In table 3.10, the dry mass flow prediction was significantly better than the dry mass prediction for all bales. Across the other datasets, there were also generally significant differences between errors of mass and mass flow prediction models, but the

model type with the significantly lowest error was not consistent. Tables 3.9 and 3.10 suggest that wet yield prediction models should be constructed as mass prediction models but that more work must be completed to determine the best model structure (mass or mass flow) for dry yield prediction models. General observation of the transformations of ultrasonic sensor response that yielded the most successful models within each dataset shows that Ht was the most common transformation, suggesting that when moisture is used as a regressor, hay yield may be linear in relationship to ultrasonic sensor response.

Table 3.9. Comparison of average absolute errors for two-sensor models using moisture as a second regressor predicting wet mass and wet mass flow. Comparisons were made within datasets.

Dataset	Type	Model		Avg. Abs. Error, %
	Mass	Wt = f[Ht,MC]	B	7.16
7-24 Banana	M.F.	MF = f[Ht^2,MC]	A	10.76
	Mass	Wt = f[Ht,MC]	A	3.10
7-30 Alfalfa	M.F.	MF = f[Ht^(0.5),MC]	A	5.06
	Mass	Wt = f[Ht^4,MC]	A	5.98
7-31 Bermuda	M.F.	MF = f[exp(Ht),MC]	A	5.90
	Mass	Wt = f[Ht^(0.5),MC]	B	3.83
9-11 Banana	M.F.	MF = f[Ht,MC]	A	8.54
	Mass	Wt = f[Ht,MC]	B	4.62
9-12 Bermuda	M.F.	MF = f[Ht^4,MC]	A	13.97
	Mass	Wt = f[Ht^2,MC]	B	15.70
2014 All Bales	M.F.	MF = f[Ht,MC]	A	23.86

Table 3.10. Comparison of average absolute errors for two-sensor models using moisture as a second regressor predicting dry mass and dry mass flow. Comparisons were made within datasets.

Dataset	Type	Model		Avg. Abs. Error, %
	Mass	Wt = f[Ht,MC]	A	7.90
7-24 Banana	M.F.	MF = f[ln(Ht),MC]	B	4.73
	Mass	Wt = f[Ht,MC]	A	4.01
7-30 Alfalfa	M.F.	MF = f[Ht^(0.5),MC]	A	4.97
	Mass	Wt = f[Ht^2,MC]	A	7.19
7-31 Bermuda	M.F.	MF = f[Ht^(0.25),MC]	A	5.66
	Mass	Wt = f[Ht,MC]	B	3.81
9-11 Banana	M.F.	MF = f[Ht,MC]	A	8.24
	Mass	Wt = f[Ht,MC]	B	5.64
9-12 Bermuda	M.F.	MF = f[Ht^4,MC]	A	13.77
	Mass	Wt = f[Ht^2,MC]	A	17.60
2014 All Bales	M.F.	MF = f[exp(Ht),MC]	B	9.08

Tables 3.11 and 3.12 compare mass and mass flow models for wet (table 3.11) and dry (table 3.12) yield predictions, excluding moisture as a regressor. There were no

significant differences between mass and mass flow predictions on a wet or dry basis within any of the datasets. This data is suggestive that model structure is flexible for yield predictions that do not use knowledge of moisture content for yield prediction. It should be noted that the majority of the models use the Ht^2 transformation, suggesting that weight and mass flow may be nonlinear with respect to ultrasonic sensor response and that it may be best characterized as a function of the square of sensor response.

Table 3.11. Comparison of average absolute errors for two-sensor single regressor models predicting wet mass and wet mass flow. Comparisons were made within datasets.

Dataset	Type	Model		Avg. Abs. Error, %
	Mass	Wt = f[Ht^2]	A	10.16
7-24 Banana	M.F.	MF = f[Ht^2]	A	10.02
	Mass	Wt = f[Ht^2]	A	5.44
7-30 Alfalfa	M.F.	MF = f[Ht^4]	A	5.50
	Mass	Wt = f[Ht]	A	17.98
7-31 Bermuda	M.F.	MF = f[exp(Ht)]	A	12.26
	Mass	Wt = f[Ht^2]	A	11.26
9-11 Banana	M.F.	MF = f[Ht]	A	10.41
	Mass	Wt = f[Ht^4]	A	14.35
9-12 Bermuda	M.F.	MF = f[Ht^4]	A	15.15
	Mass	Wt = f[Ht^2]	A	17.85
2014 All Bales	M.F.	MF = f[Ht]	A	22.17

Table 3.12. Comparison of average absolute errors for two-sensor single regressor models, predicting dry mass and dry mass flow. Comparisons were made within datasets.

Dataset	Type	Model		Avg. Abs. Error, %
	Mass	Wt = f[Ht^2]	A	9.13
7-24 Banana	M.F.	MF = f[Ht^2]	A	9.30
	Mass	Wt = f[Ht^2]	A	5.21
7-30 Alfalfa	M.F.	MF = f[ln(Ht)]	A	4.88
	Mass	Wt = f[Ht^2]	A	20.24
7-31 Bermuda	M.F.	MF = f[exp(Ht)]	A	12.52
	Mass	Wt = f[Ht^2]	A	10.49
9-11 Banana	M.F.	MF = f[Ht]	A	9.54
	Mass	Wt = f[Ht^4]	A	13.59
9-12 Bermuda	M.F.	MF = f[Ht^4]	A	14.35
	Mass	Wt = f[Ht^2]	A	18.61
2014 All Bales	M.F.	MF = f[Ht]	A	20.00

As a demonstration of the application of the modeling presented here, figure 3.5 shows a yield map that was developed using Farmworks™ (Trimble, Hamilton, Indiana) for the 7-30 Alfalfa dataset. Point data predicting wet weight as a function of sum of ultrasonic sensor response across each bale was converted to weight per unit area, or yield, by dividing by the field area represented by each point, which was calculated as the distance between points (as defined by the wheel lug spacing) multiplied by the windrow spacing (as defined by the hay rake used. The mass yield per unit acre was then divided by the average weight per bale to provide bales per acre. Two of several point data sets (bales) used to construct the map are shown in the figure, overlayed on a contoured yield map using all point datasets (bales). The higher yielding areas along with the lower yielding areas are indicated on this map as a demonstration for how the technology presented here could be applied for guidance of management decisions.

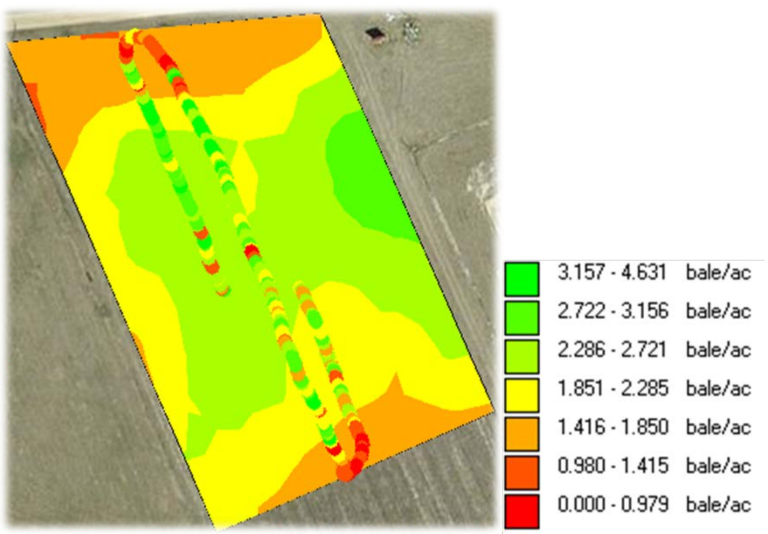


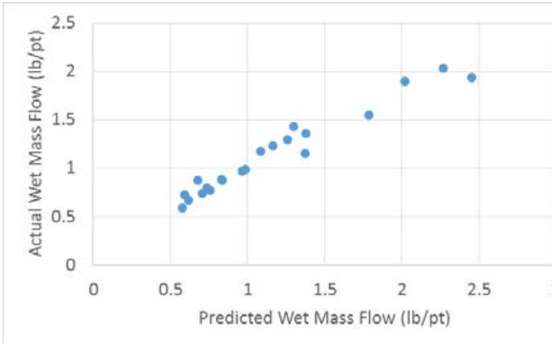
Figure 3.5. Yield map developed using 7-30 Alfalfa dataset, showing point datasets from two bales overlaid on a contoured yield map of point datasets from all bales.

Year 2

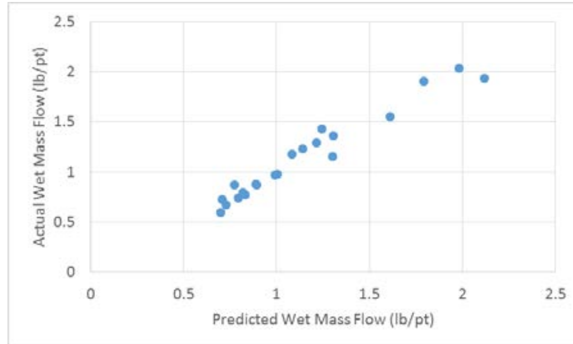
During the second year of research and testing, efforts were focused on identifying the best ultrasonic sensor to use for the yield monitoring techniques; the sensors used in the first year of research were indoor sensors and were never intended to be the final selection. Two different sensors were used from Maxbotix to no avail: models 7060 and 7067. After consultation with Maxbotix technical support, it was learned that model 7067 had a stability filter, which resulted in a sensor response that was only updated if three consecutive readings were the same. In application on the baler, these sensors returned a fixed sensor response value across all data points in a given bale, the sensor response level only changing when the baler stopped to eject a bale. Their technical support recommended a model 7060, which contained a most likely target filter, however, these sensors regularly returned values corresponding to target distances greater than that between the sensor and the ground. It was speculated that this phenomenon was a result of the range of the sensors (7 m) being much greater than the sensed range (about 1 m). The data collected during testing and calibration suggested an echo effect; the sensors were actually measuring a signal that was reflected off of the target and then off of one or more objects prior to returning to the sensor, rather than only being reflected off of the target. This echo effect was supported by stationary testing where parts of the baler near the header and tongue were physically blocked, resulting in reduction in the apparent echo effect. SunSource (Charlotte, North Carolina) technical sales representatives helped to locate model T30UXDA ultrasonic sensors with a 1 m distance range from Banner Engineering Inc. (Minneapolis, Minnesota). Because these sensors were not acquired until near the end of the growing season, there were only two datasets collected with the model T30UXDA sensors, although the data seemed to provide good results with average absolute yield prediction errors as low as 5.11% The Agra-tronix moisture sensors were added to the baler to determine if the sensors could provide on-the-go moisture data.

Evaluating the moisture sensors was not an objective of this study but moisture data was collected and preliminary analysis was performed (Appendix A), The importance of the moisture sensors was to provide on-the-go sensor responses to be factored into yield prediction as a second regressor or correction factor.

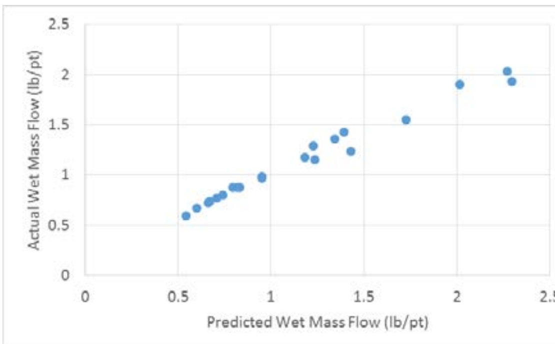
Figures 3.6 (wet basis) and 3.7 (dry basis) display charts that were developed using data from harvesting 21 bales in the Banana field on August 26, 2015. The data displayed shows wet mass flow prediction (lb/pt) for four different analysis methods, as developed in Year 1. A single regressor model was used for figure 3.6a to predict mass as a function of sum of ultrasonic sensor responses. Figure 3.6b uses a single regressor model predicting mass flow as a function of average ultrasonic sensor response. Figures 3.6c and 3.6d are two-regessor models using the same regressors as 3.6a and 3.6b, respectively, along with use of moisture content as a second regressor. Figures 3.6a and 3.6c are forced through the origin while figures 3.6b and 3.6d have a non-zero intercept. Average absolute errors for the models depicted in Figure 3.6 are displayed in table 3.13; statistical comparisons between models structures were not performed for the year two data because there were only two balings used to collect the data.



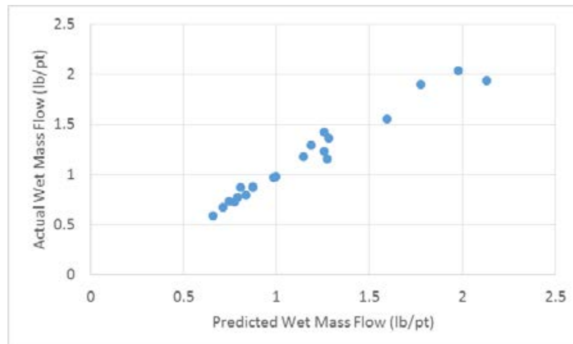
(a)



(b)



(c)



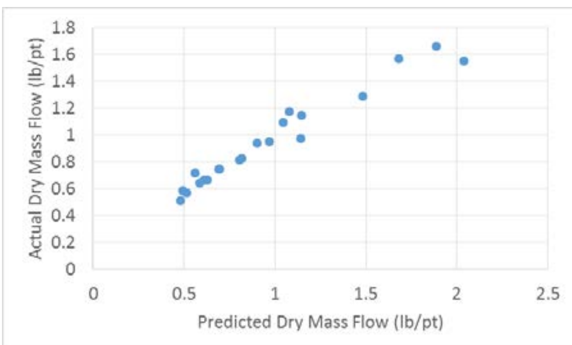
(d)

Figure 3.6. Demonstration of the relationship between wet mass flow prediction (lb/pt) and actual, or measured, wet mass flow (lb/pt) with regards to regressors used for evaluation. Models used for construction of Figures 3.6a, 3.6b, 3.6c, and 3.6d are outlined in table 3.13.

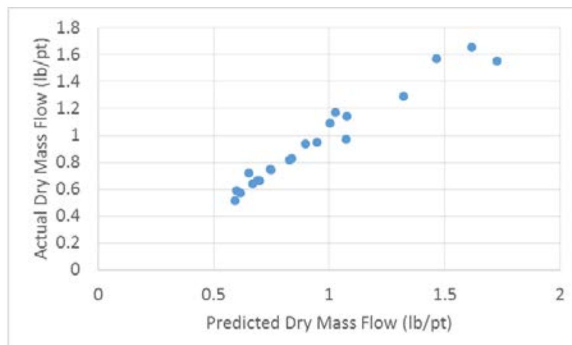
Table 3.13. Demonstration of average absolute errors for models applied to construct Figure 3.5.

Chart	y-intercept	1st Regressor	2nd Regressor	Avg. Abs. Error, %
a	Zero	Sum	None	8.62
b	Non-zero	Average	None	6.71
c	Zero	Sum	Moisture	7.53
d	Non-zero	Average	Moisture	5.11

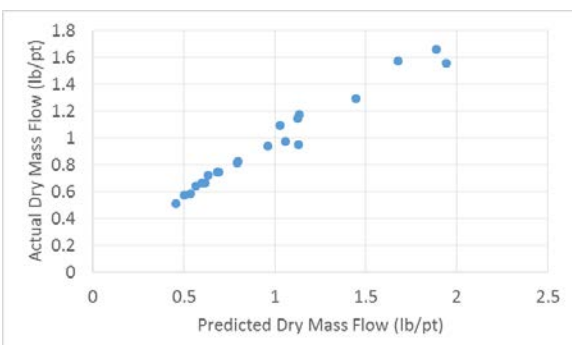
In figure 3.7, the charts shown show actual (measured) dry mass flow as a function of predicted dry mass flow, both as units of lb/pt. Models used to develop figures 3.7a, 3.7b, 3.7c, and 3.7d are the same as those described to develop figures 3.6a, 3.6b, 3.6c, and 3.6d, respectively, except that the models for figure 3.7 predict dry yield and those for figure 3.6 predict wet yield. Although statistical comparisons were not made between model types for year two, some general observations can still be made. For both wet and dry yield prediction models, models predicting mass flow as a function of average ultrasonic sensor response demonstrated numerically less error than those predicting mass as a function of sum of sensor responses. In both cases (wet and dry), inclusion of moisture knowledge slightly improved yield prediction error, but not substantially.



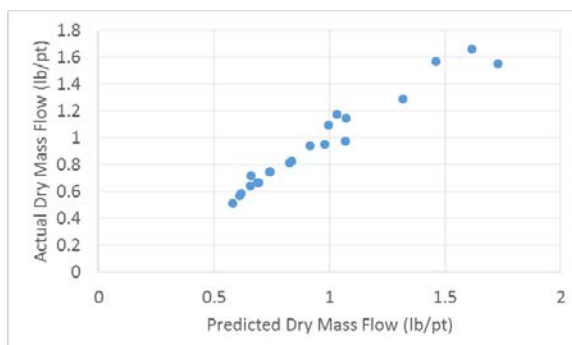
(a)



(b)



(c)



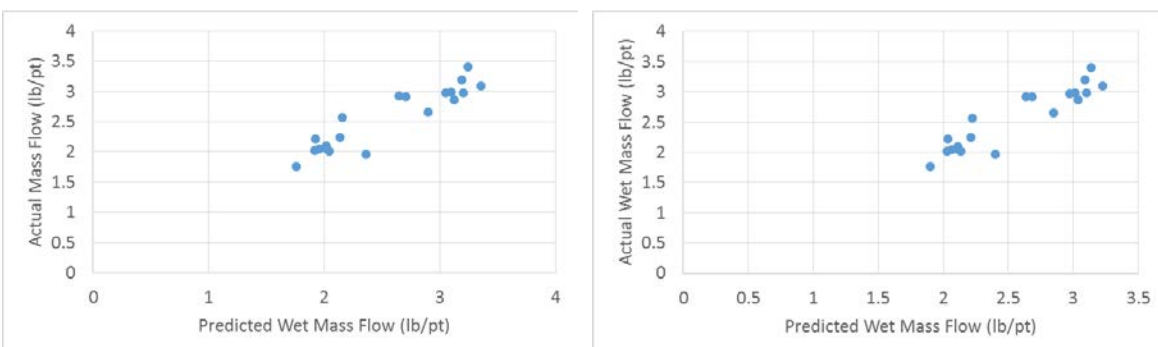
(d)

Figure 3.7. Demonstration of the relationship between dry mass flow prediction (lb/pt) and actual, or measured, dry mass flow (lb/pt) with regards to regressors used for evaluation. Models used for construction of figures 3.7a, 3.7b, 3.7c, and 3.7d are outlined in table 3.14.

Table 3.14. Demonstration of average absolute errors for models applied to construct Figure 6.

Chart	y-intercept	1st Regressor	2nd Regressor	Avg. Abs. Error, %[4]
a	Zero	Sum	None	9.27
b	Non-zero	Average	None	5.57
c	Zero	Sum	Moisture	9.16
d	Non-zero	Average	Moisture	5.39

Figure 3.8 displays data from a dataset collected from harvest on August 27, 2015 in the Bermuda field. The dataset consists of 20 bales that were harvested. No moisture data was collected for the dataset. Table 3.15 displays average absolute errors for the two methods of error determination. Figure 3.8a uses the sum of sensor readings for analysis and is forced through the origin. Figure 3.8b uses the average of sensor readings for analysis and is not forced through the origin. Table 3.15 shows the average absolute errors of the two charts.



(a) (b)

Figure 3.8 shows the relationship between predicted wet mass flow (lb/pt) and actual wet mass flow (lb/pt). Both use only one regressor

Table 3.15 Demonstrates average absolute errors for above charts as a function of regressors.

Chart	y-intercept	1st Regressor	2nd Regressor	Avg. Abs. Error, %
a	Zero	Sum	None	6.61
b	Non-zero	Average	None	5.80

Conclusions

A hay yield monitoring system was developed and evaluated using remote sensing technology to measure windrow volume and correlate it to yield. Ultrasonic sensors proved to be suitable for windrow height measurement and analyses were completed to suggest the best yield prediction algorithm structures for the application. When calibrated and applied, on-the-go yield data can be recorded and hay yield maps can be created for use in making and evaluating management decisions.

The infrared distance sensors that were tested for windrow height measurement were not suitable for the hay yield monitor due to the fact that the data collected was very erratic after a short time period of operation. Because the erratic operation of the infrared distance sensors could not be alleviated, they were abandoned for this application and removed from the data analysis entirely. The ultrasonic sensors that were used in year one displayed relatively accurate yield prediction when the best regression model was displayed for each field. The best regression model when applied across all bales, which includes datasets on different harvest dates, different fields, and different grass types, displayed an average absolute yield prediction error of approximately 9%. The rest of the fields displayed an even smaller average absolute error which suggests that separate calibrations may be appropriate for different grass types; more research should be conducted in further investigate and suggest best calibration practices for this technology.

There were some problems associated with erratic operation of the ultrasonic sensors, but they were assumed to be caused by worn insulation on wires connecting the sensors; when the sensors were rewired and loomed, the erratic operation ceased. The original sonar sensor configuration used on the baler consisted of four ultrasonic sensors, although statistical analysis indicated that there was no significant difference in yield prediction error when using the data from all four sensors versus that when using the data from only the middle two sensors. Therefore, it was concluded that only two sensors are necessary for this application, being more economically and feasible for potential commercialization.

It was confirmed in the data for year two that the sensors used have the ability to produce yield prediction errors of less than 10% with the correct analysis, with demonstrated errors in the 5-6% range when predicting mass flow rate as a function of average sensor response. Inclusion of moisture content as a regressor slightly improved the yield prediction error in the year two data, although there were instances in the year one data where its inclusion worsened the accuracy. When hay moisture was included as a regressor, hay yield generally varied directly as a function of the windrow height. When hay moisture was not included as a regressor, hay yield generally varied as a function of the square of the windrow height.

Because the sensors investigated in year two were only tested on two fields, it would be beneficial to conduct more research to evaluate if the sensors can be effectively and reliably used to provide yield data for the hay baling industry. The yield monitor developed in this study is likely suitable for commercial applications on round, small square, or large square balers; this study demonstrated its capability of providing on-the-go yield data and the ability to generate yield maps. The commercial availability of a yield monitor could be pivotal to hay production, as it has been to small grain, corn, and cotton production.Acknowledgments

Special thanks goes to Reid Miller, Andrew Warner, Gillian Tuttle, Harry McAlhany, and Jacqueline Gray for assistance with field testing.

References

Digman, M. and K. Shinners. 2012. Technology Background and Best Practices: Yield Mapping in Hay and Forage. In Proceedings, 2012 California Alfalfa and Grain Symposium, Sacramento, CA. UC Cooperate Extension.

"Equipment & Products for Quality Hay." Harvest Tec. Hudson, WI. Web. 26 Jan. 2015.

Savoie, P., P. Lemire, and R. Theriault. "Evaluation of Five Sensors to Estimate Mass-Flow Rate and Moisture of Grass in a Forage Harvester" *Applied Engineering in Agriculture* 18.4 (2002)

Shinners, Kevin J., Brian M. Huenink, and Casey B. Behringer. "Precision Agriculture As Applied To North American Hay and Forage Production." *International Conference on Crop Harvesting and Processing* (2003)

Shinners, Kevin J., Neil G. Barnett, and Walter M. Shlesser. Yield Monitor for Forage Crops. Wisconsin Alumni Research Foundation, assignee. Patent US 6431981 B1. 13 Aug. 2002.

"NASS - National Agricultural Statistics Service." *NASS - National Agricultural Statistics Service*. USDA, Web. 26 Jan. 2015.

Undersander, Dan, David R. Mertens, and Nancy Thiex. "Forage Analysis Procedures." *The National Forage Testing Association*. Foragetesting.org, July 1993. Web.

CHAPTER FOUR

IMPLEMENTATION AND EVALUATION OF USING A HYDRAULIC PRESSURE TRANSDUCER TO DETERMINE WEIGHT OF ROUND HAY BALES

Abstract

Hay yield monitoring technology has been very limited throughout the past, despite the number of acres harvested per year and the monetary value of the crop. Weighing mechanisms have been implemented on round hay balers that can provide bale weights but have been relatively expensive. A method was analyzed in this study to provide bale weight at a lower cost than commercially available technologies, while maintaining an easy installation. A pressure transducer was mounted to the hydraulic bale kicker of a John Deere round baler and its response was correlated to bale weight. Two balers were used in this study: John Deere 458 and John Deere 459 Silage Special. This method proved to be cost effective and provided a range of average absolute errors from as low as approximately 3% up to approximately 10%. A total of 180 bales, 156 from a John Deere 458 and 24 from a John Deere 459 Silage Special, were baled and analyzed using pressure transducer data to predict bale weight during the 2015 growing season. Each harvest was analyzed independently and cumulatively. Cumulative average absolute error for all bales resulted in 9.61% error in bale weight prediction. This technology has the ability to allow a grower to have the knowledge of the production of the fields at an affordable cost. It also can provide the ability to generate coarse yield maps when paired with a GPS.

Introduction

Hay, throughout the United States is one of the top six crops for land use. About 57,092,000 acres of ground were used for hay production in 2014, ranking behind only corn and soybeans (NASS, 2015). Implementation of large scale precision agriculture technology has trailed behind that of small grains, corn, and cotton although it could be highly beneficial to a producer. Research has been carried out by institutions to develop a yield monitor for round baling hay (Maughan et al., 2012), although none have been adopted by industry and commercialized. One precision agriculture technology that has been put in place within hay production has been the ability to obtain weights of hay bales on the baler rather than having to transport scales to the field and weigh bales as an additional process.

The ability to weigh hay bales has recently been implemented by many manufacturers of hay balers. One method used to weigh bales implements loads cells on the axle: Case New Holland holds a patent using load cells on the axle, along with inclinometers to determine bale weight. The inclinometers are used to compensate for gravitational forces due to the ground not being level at the location where the bale is ejected from the baler (Posselius et al., 2014). Similar methods have been adopted by other hay baler manufacturers. One specific manufacturer that has not implemented this technology is John Deere. The load cell method for weighing hay bales has also been implemented on large square balers. Harvest Tec uses the load cell weighing system and pairs it with GPS in order to develop yield maps for growers, which can be beneficial to the grower if used for making and evaluating management decisions (Harvest Tec

Hudson, WI). Although the yield map does not show an accurate distribution of where the hay came from in the field, it can suggest higher yielding versus lower yielding areas and can allow management decisions to be made. The load cell weighing system is a costly addition to a baler and would likely be hard to retrofit to an older model without expensive modifications, such as changing the entire axle or wheel spindle assembly and modifying the tongue of the baler with addition of a load bar there as well. As an alternative on-baler bale weighing technology, AGCO holds a patent that consists of load sensing devices that are used to determine bale weight on both large and small square balers. The load sensors mount in the bale chute and measure weight as the bale passes over them (Seeger et al., 2011).

A study conducted by researchers from Clemson University instrumented a pressure transducer on the basket offloading (dump) cylinder of a peanut combine. In this study, the pressure transducer was used to determine the weight of peanuts in the basket. Transducer readings were recorded throughout the angular position of the basket during dump cycles and the peanuts were offloaded into a weigh wagon, where the actual weight was recorded. The accuracy of this study resulted in average absolute error of less than 10.5% (Kirk et al., 2015).

Hydraulic circuits have been used in studies to determine the weight of hay bales. West Virginia University Extension researched this particular topic, where a pressure gauge was added to the loader. The reason a pressure gauge could be used to determine bale weight is because pressure in most hydraulic lifting circuits is predominately influenced by the load. As a bale was picked up with the loader, the hydraulic pressure increased until there was enough to sustain the load. Each time a bale was picked up and the pressure stabilized, the gauge reading was recorded and the bale was weighed in order to draw a correlation between the hydraulic pressure and the weight of the bale. A similar method, which was discussed in the same study, used hay forks on the three-point-hitch of the tractor with a hydraulic top link. The circuit that operated the top link had a pressure gauge installed to perform the same procedure. The hay bales were lifted individually with the fork on the back of the tractor and as the bale rose, hydraulic pressure increased. When the pressure stabilized, it was recorded and the bale was weighed. After weights and pressures were recorded, ratios were calculated in order to determine accuracy of using a hydraulic system as a scale. Accuracy ranges were reported between 1.3% and 8.5% error (Yohn et al., 2006).

Hydraulic pressure transducers operate much like a pressure gauge in that there is a linear sensor response as a function of pressure that can be sensed and transmitted to computer or data logger. Essentially, the signal and sensor reading can be taken without having to manually record it, although correlations have to be drawn between sensor reading, pressure, and weight. A hydraulic pressure transducer can be installed on a hydraulic circuit and relay a reading back to the interface in order to correlate sensor response to load. They have been used in many applications, from weighing peanut baskets to weighing hay bales on a tractor loader. Pressure transducers for weighing applications are not only used in the agricultural industry. They are also used on wheel loaders at rock quarries for the operator to know that a truck is not being overloaded. (Avery Weigh Tronix, Fairmont, Minnesota, US). This method consists of using a pressure transducer on a hydraulic excavator to eliminate the need to use scales to determine weight (Ehrich and Dobner, 1985).

Pressure transducer use on hay balers with hydraulic bale kickers have great market potential for hay bale weighing technology because of the relatively low cost, as compared to load cell and strain gauge technologies. The cost of a pressure transducer system versus a load cell weighing system is substantially less, perhaps as little as 10%. A limiting factor of the pressure transducer system discussed here is the fact that not all round balers have hydraulic bale kickers; many have spring loaded bale ramps, which would not be compatible with a retrofit of a pressure transducer.

The objectives of this study were to:

- Install a pressure transducer on the hydraulic bale kicker of a round hay baler and record its response throughout the cylinder stroke or kicker cycle.
- Develop an algorithm structure for predicting bale weight from pressure transducer response.
- Quantify the accuracy of using the pressure transducer for predicting bale weight.
- Evaluate the effects of bale wrap and bale size on bale weight prediction using the pressure transducer.

Methods and Materials:

A model TDH30 pressure transducer (Transducers Direct, Cincinnati, Ohio) was installed on the hydraulic circuit for the bale kicker of a John Deere 458 round baler and a John Deere 459 Silage Special round baler. The reason for implementing this on two balers was to verify that the data can be replicated between different machines. The bale kicker was actuated by a double acting hydraulic cylinder that automatically extended after the bale chamber was completely opened. A “tee” fitting was added to the hydraulic hose connected to the blind end of the cylinder and the pressure transducer was connected to the “tee.” Figure 4.1 displays the circuit that the pressure transducer was inserted into.

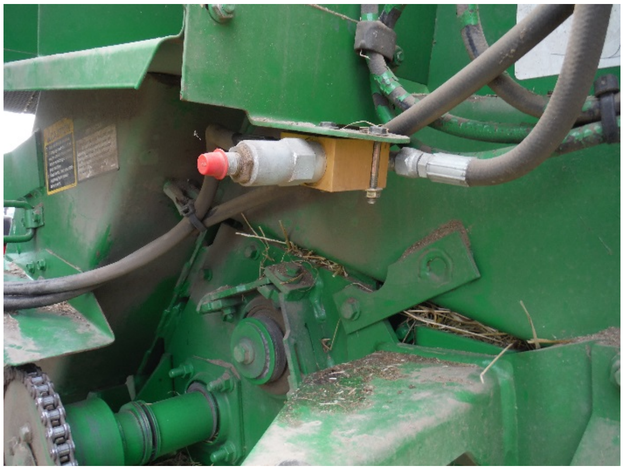
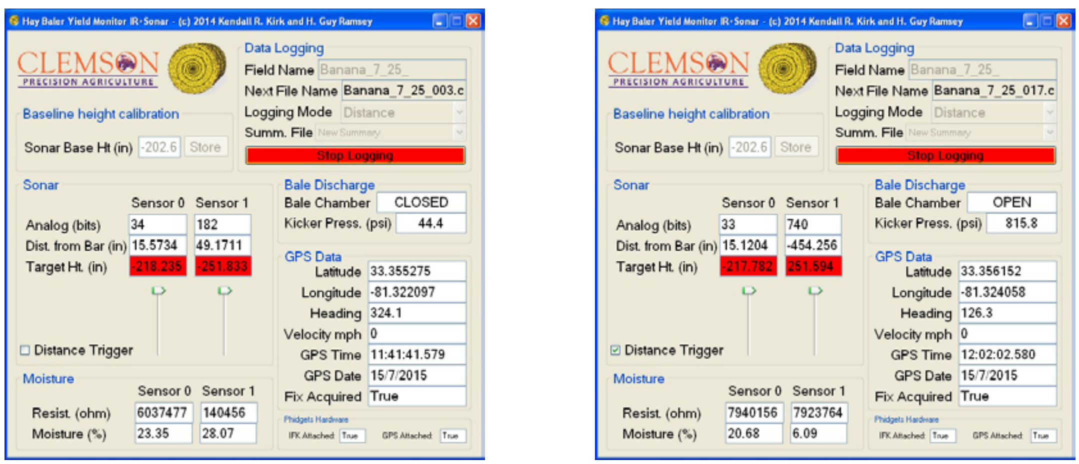


Figure 4.1. Where the pressure transducer was installed

Data acquisition was completed through use of a program written in Microsoft Visual Basic 2010 (figure 4.2). A model 1018_2 interface kit (Phidgets Inc., Calgary, Alberta, Canada) was utilized for analog and digital inputs. A model 1020_0 GPS receiver (Phidgets Inc., Calgary, Alberta, Canada) was also used to record where each bale was ejected in the field. The pressure transducer was connected to one of the analog inputs on the interface kit. The pressure transducers were calibrated against an AFC-5M-25 pressure gauge (DiscountHydraulicHose.com, Philadelphia, Penn.) using pressure generated from a model 60726 portable hydraulic power kit (Harbor Freight Tools Co., Camarillo, Calif.). The balers were also outfitted with model LJC18A3-B-Z/AX capacitance sensors at the wheel lugs that sensed movement. This was to keep the program from logging readings from the pressure transducer if the bale chamber was opened more than once in one position, such as in the event of maintenance or repairs. If the bale chamber was open and no forward motion of the baler occurred since the last bale opening event, then the data from the pressure transducer was logged at each change in sensor response that exceeded 1/1000 of the full scale of the sensor, or at about each 34.47 kPa (5 psi) change. This resulted in data logging rate generally being in the 30-50 Hz range. Each bale was then weighed using a hay wagon positioned on wireless truck scales. During harvest, the bale sizes were varied between 48 in., 54 in., and 60 in. Data was collected for bales that were net wrapped and twine wrapped, which was set with the bale monitor located in the cab of the tractor.



(a) (b)

Figure 4.2. Screen captures of the data acquisition program during harvest. Under the title, "Bale Discharge," Kicker Press. (psi) is shown: 44.4 psi (a) was the operating pressure of the system while 815.8 psi (b) was the pressure indicated while the bale was being ejected.

Data that was collected was analyzed and trimmed to eliminate data collected after full extension of the hydraulic cylinder. The pressure relief for the bale kicker was approximately 2,500 psi so anything at or about 2,500 psi was omitted from the data. A singular dataset was collected for each bale and each of these datasets was analyzed to identify “peaks” in the pressure data, meaning that the pressure at a given instance was greater than the instance(s) before and after that instant. Three types of peaks were used in the analysis of data. First, second, and third order pressure peaks were defined, respectively, as a pressure reading greater than one point immediately before and one point immediately after, a pressure greater than both of the two points immediately before and two points immediately after, and a pressure value greater than the three points immediately before and three points immediately after the peak value. Analysis of the data across multiple bales suggested that the third order peaks were most consistently present and third order peaks were therefore designated for use in bale weight prediction. In order to visualize the peaks, the points were plotted with respect to time (fig. 4.3) but a macro was written in Microsoft Excel providing the logic to identify these peaks automatically. After the pressure peaks were determined for each bale, the data was analyzed and regression models were formulated. Figure 4.3 displays raw data that was obtained from the pressure transducer. The first peak, after data analysis was attributed to mechanical friction and assumed to have no effects on bale weight. It became obvious that a bale made contact with the hydraulic bale kicker twice throughout a cycle by generally displaying two peaks. After correlations were made, it was concluded that the second peak was the best regressor to use as a predictor of bale weight.

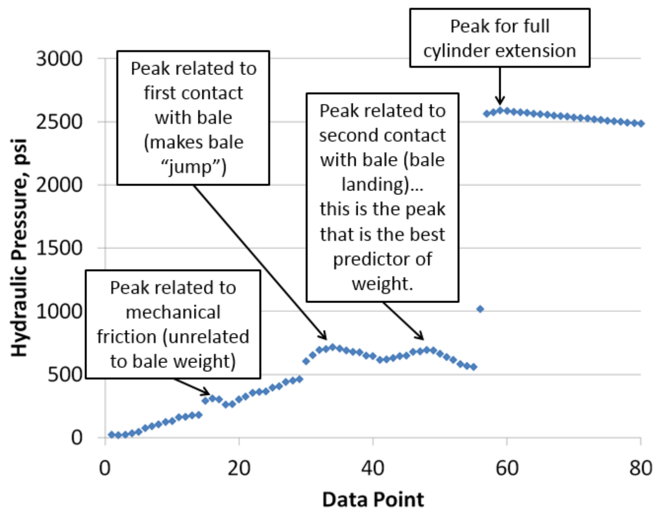
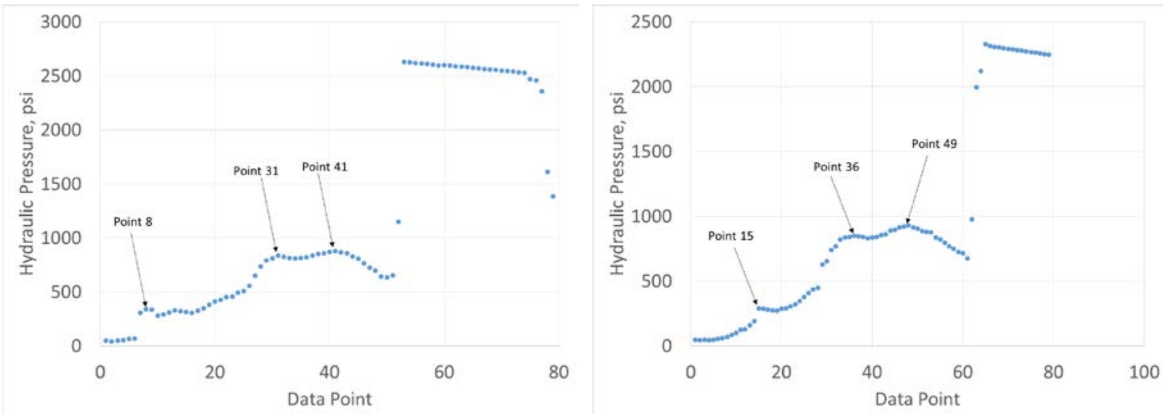


Figure 4.3. Shows how "peaks" are identified througout the obtained data. Peak for full extension coincides with the achievement of pressure relief setting.

Testing was conducted at Edisto Research and Education Center (Clemson University) in Blackville, South Carolina. Data was collected from two independent hay fields and compared to determine the accuracy across plots. The fields were referred to as the "Banana field" and the "Bermuda field." The Bermuda field was irrigated while the Banana field was not. Each field was harvested between the beginning of May 2015 and the end of August 2015 with general moisture contents ranging between 10% and 20% as determined by use of a moisture probe. Two balers, a John Deere 458 and a John Deere 459 silage specials were used to harvest a total of 180 hay bales to be used for analysis.

Results and Discussion

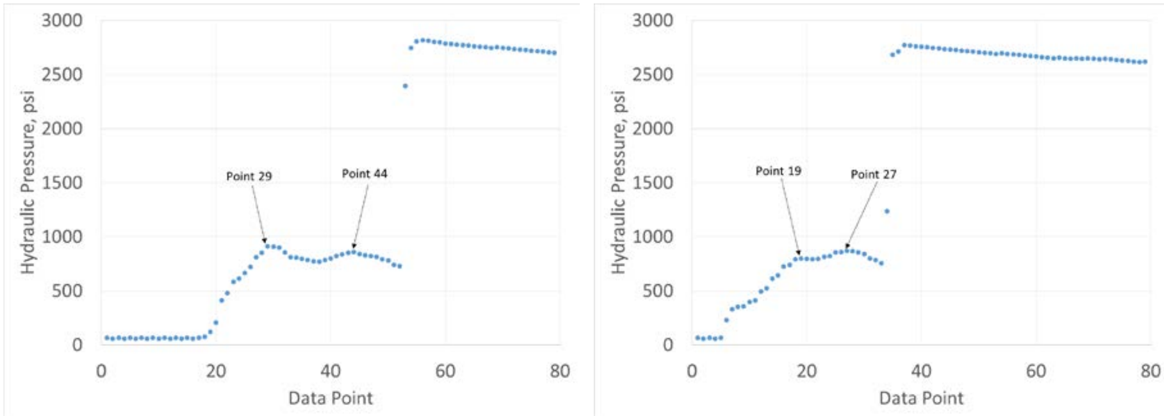
Figure 4.4a demonstrates an example of the pressure transducer response for a single bale when plotted as a function of sequentially collected data points from a bale that was net wrapped. As discussed above, third order peaks were defined when pressure at a data point was higher than that for at least three consecutive, preceding and three consecutive, subsequent data points. Third order peaks were observed for this dataset at data points 31, 41 and 8. The peak at point 8 was assumed to be linked to mechanical friction in the kicker assembly due to the fact that it was observed on virtually all bales at about the same pressure, regardless of bale weight. Although not confirmed, it is assumed that the peak at point 8 occurred prior to contact between the bale and kicker assembly. Data point 31 was considered the first associated peak and data point 41 was considered to be the second associated peak. Figure 4.4b demonstrates raw data from a bale that was twine wrapped. This same trend was demonstrated in all datasets, where it is presumed, but not confirmed that the first peak is associated with contacting of the bale with the kicker assembly, at which point the bale is momentarily lifted off of the kicker assembly, followed by the second peak where the bale once again makes contact with the kicker assembly. The time between peaks was consistently about 0.2 sec. The theory that was formulated to explain the time between peaks and first peak being present was that the bale "jumped" as it was ejected from the bale chamber and contacted the kicker plate. When the bale chamber was opened and the bale first contacted the kicker, the data suggested that the first peak that was not associated with mechanical friction was a result of a bounce of the bale and providing the 0.2 seconds between the first and second peak. The theory is supported in observing the differences exhibited between net and twine wrap for the bales. The twine wrapped bales were less dense than the net wrapped bales which caused a decrease in acceleration of the bale as it left the bale chamber and an increase in drag, causing the first peak on the twine wrapped bales to be less distinct than that on the net wrapped bales. This theory was not proven but was thought to be accurate; more research would need to be carried out to validate the theory.



(a) (b)

Figure 4.4. Displays the differences for raw data from net wrap (a) and twine wrap (b) when baled with John Deere 458.

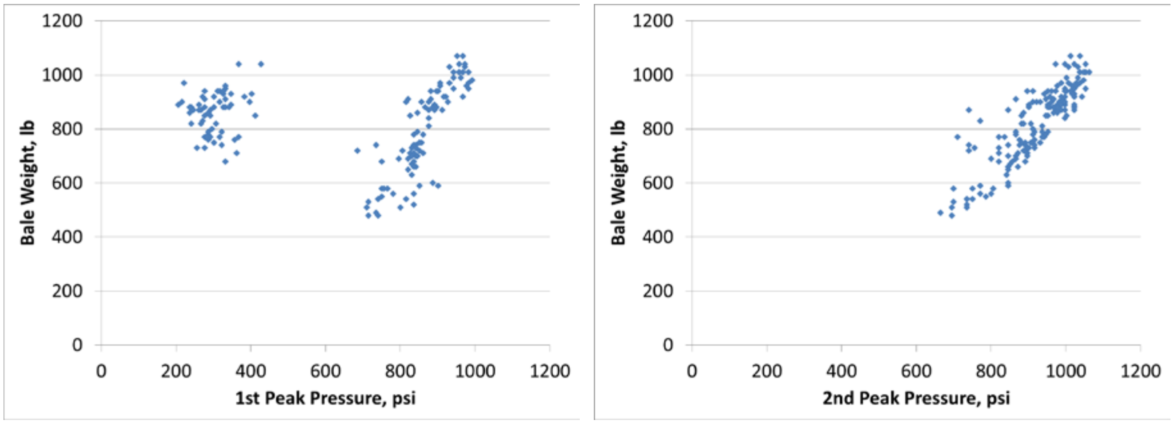
Figure 4.5 displays resulting raw data that was collected from the John Deere 459 Silage Special. Figure 4.5a was collected from a bale that was net wrapped while figure 5b came from a bale that was twine wrapped. The John Deere 459 did not display the first peak which was attributed to mechanical friction like the 458 did. The data from the two balers were similar in that there were two peaks close together within the data.



(a) (b)

Figure 4.5. Displays the differences for raw data from net wrap (a) and twine wrap (b) when baled with John Deere 459 Silage Special.

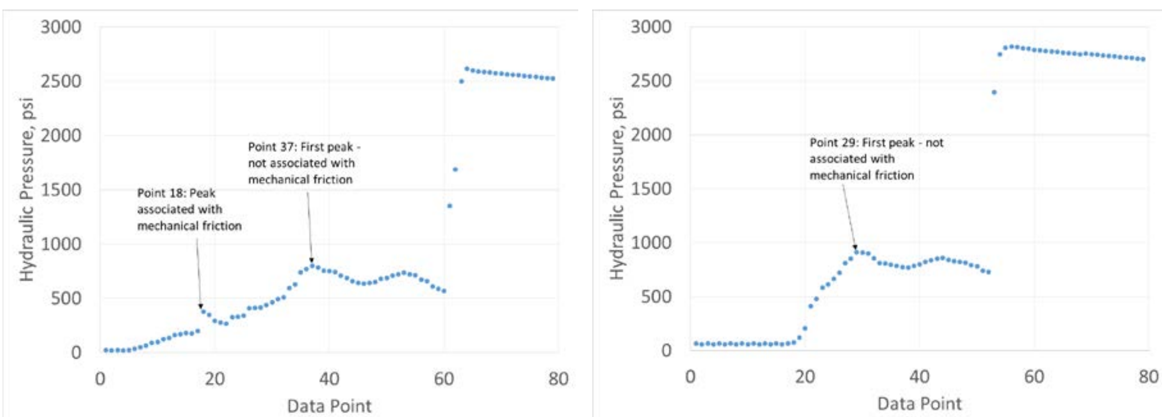
Figure 6 displays first peak (a) and second peak (b) and how each correlated to bale weight. As demonstrated in figure 4.6a, there appears to be two datasets. The first group of data, between approximately 200 and 400 psi are the peaks that were referred to as mechanical friction that could be attributed to the hydraulic system with no correlation to bale weight. Initially, the first peak in the stated range was assumed to be associated with a lower bale density because it was observed more in bales that were twine wrapped, but after further analysis, it was concluded that it was the mechanical friction that was recently stated. Without the first peak being pronounced in all bales, it was concluded that it could not be used in analysis. In figure 4.6b, there is a much tighter correlation between hydraulic pressure (psi) and bale weight (lb). The second peak was consistently observed in the data for all bales, regardless of the method used for wrapping.



(a) (b)

Figure 4.6. Demonstrates the relationship between bale weights and first peak (a) and second peak (b).

In figure 4.7, two plots of raw data are displayed. One has a pronounced peak that can be associated with mechanical friction. A point such as point 18 (a) is not displayed in figure 4.7b. Comparisons such as this give justification to the removal of the friction related peak from analysis and only using the second associated peaks.



(a) (b)

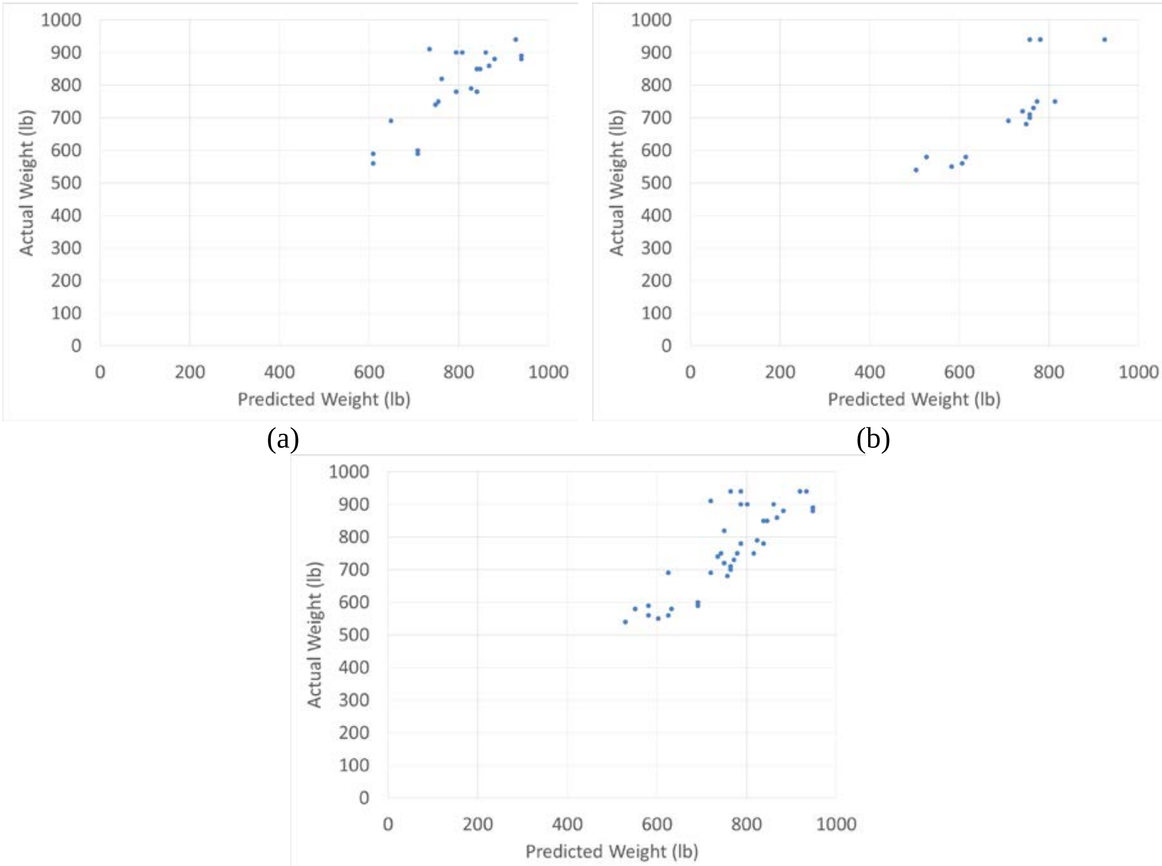
Figure 4.7. Comparison of data with and without pronounced first peak attributed to mechanical friction.

Because the 2nd pressure peak demonstrated the only consistent relationship with bale weight across all bales, it was used as an independent variable in development of linear regression models to predict bale weight. Table 4.1 demonstrates the results of bale weight prediction models across multiple breakdowns of the data collected in this study. Throughout table 4.1, the data is divided according to the dataset. Data confined between double borders come from one instance of harvest. Single borders divide the data according to bale size. It can be concluded from the table that when N is small, the data can seem to be slightly skewed to be lower than if N was greater. This table demonstrates that in most cases, analysis for a particular size or a particular method of wrapping the bale produces a lower average absolute error. It is also important to calibrate and analyze data according to the equipment used because all pieces of equipment will react differently to different loads.

Table 4.1. Displays data that has been split according to bale size, method of wrapping, and which baler was used to compare error.

Baler	Wrap Type	Bale Diameter	N	Avg. Abs. Error, %	Avg. Abs. Error,(lb)
458	Net	60”	31	5.79	39.22
458	Twine	60”	19	5.41	42.52
458	Mixed	60”	50	9.46	65.22
458	Net	48”	5	5.41	33.97
458	Twine	48”	5	2.48	13.98
458	Mixed	48”	10	4.27	25.99
458	Net	54”	4	7.28	58.44
458	Twine	54”	8	1.91	13.55
458	Mixed	54”	12	5.34	40.96
458	Net	60”	13	3.63	31.02
458	Twine	60”	3	0	0
458	Mixed	60”	16	4.66	40.32
458	Net	Mixed	22	6.42	48.89
458	Twine	Mixed	16	7.57	56.01
458	Mixed	Mixed	36	7.00	53.19
458	Net	60”	20	3.95	37.31
458	Net	60”	17	3.32	33.02
459	Net	48”	5	2.68	16.95
459	Twine	48”	4	3.28	23.34
459	Mixed	48”	9	5.65	38.19
459	Net	54”	3	1.10	8.57
459	Twine	54”	5	2.91	22.14
459	Mixed	54”	8	2.64	20.33
459	Net	60”	4	1.79	16.73
459	Twine	60”	3	3.32	30
459	Mixed	60”	7	2.44	22.13
459	Net	Mixed	11	5.31	38.23
459	Twine	Mixed	12	5.79	46.20
459	Mixed	Mixed	23	7.16	52.88

Figure 4.8 demonstrates actual vs. predicted bale weights for some of the scenarios exhibited in table 4.1 from the John Deere 458 baler. Figure 4.8a exhibits plots predicted weight (lb) against actual weight (lb) for 22 bales that were net wrapped with average absolute error of 6.42%. Figure 4.8b consists of 16 bales that were twine wrapped that produced an average absolute error of 7.57%. Figure 4.8c displays all bales from figure 4.8a and 4.8b to display a combined average absolute error of 7.00%. As mentioned before, it can be concluded that it is important to calibrate according to baling methods although the combined absolute error for all bales is less than that of the twine wrapped bales.



(a) (b)

(c)

Figure 4.8. Demonstration of the relationship between actual weight and predicted weight as a function of (a) net, (b) twine, or (c) both methods of baling for the John Deere 458.

Figure 4.9 is similar to figure 4.8 in that it is a comparison of data for net (4.9a), twine (4.9b), and all bales (4.9c) except for the fact that these bales came from the John Deere 459 Silage Special. Figure 4.9a displays an average absolute error of 5.31% for 11 net wrapped bales. Figure 4.9b contained 12 twine wrapped bales with an average absolute error of 5.79%. Figure 4.9c consisted of all bales demonstrated in 4.9a and 4.9b for a total of 23 bales and a combined average absolute error of 7.16%. Figure 4.9 demonstrates the need for calibration according to bale wrapping method.

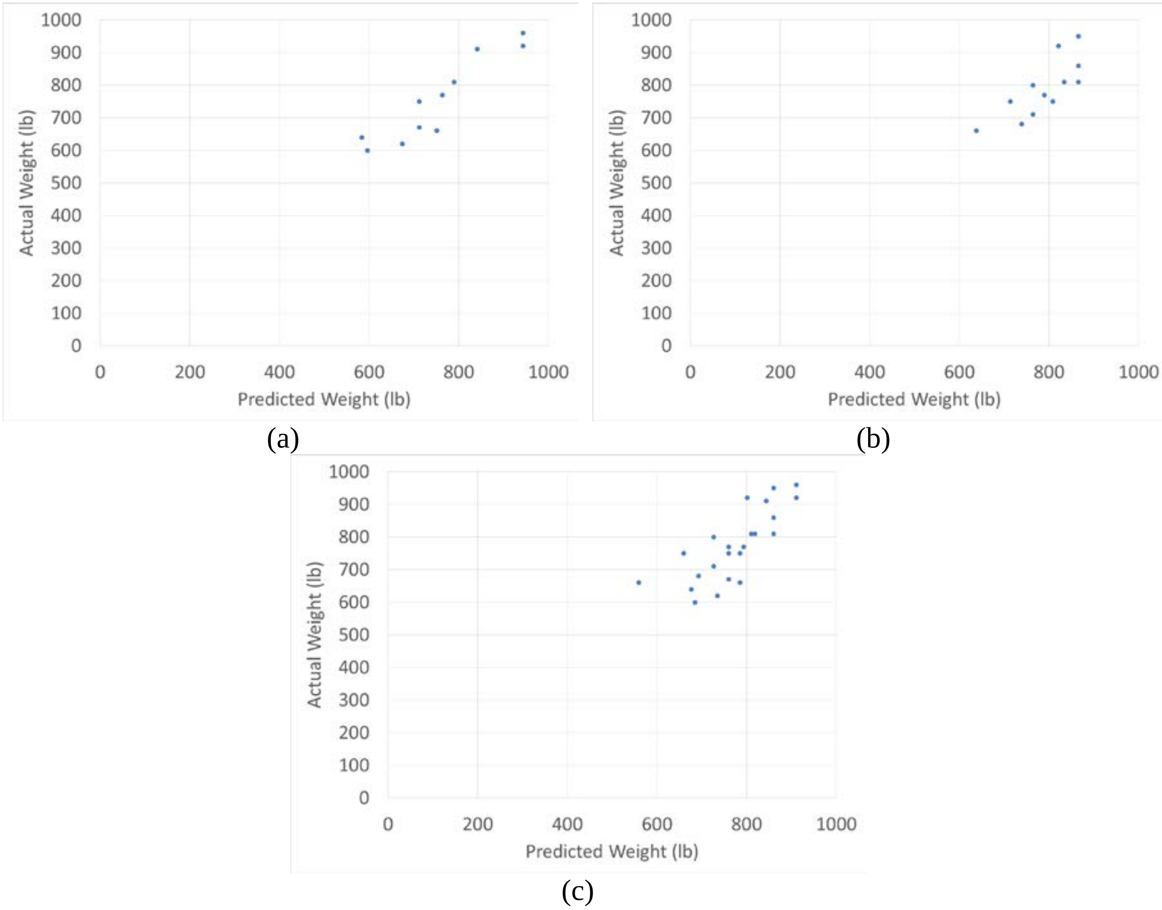


Figure 4.9. Demonstration of the relationship between actual weight and predicted weight as a function of (a) net, (b) twine, or (c) both methods of baling for the John Deere 459 Silage Special.

The necessity of calibrating according to the size of the bale was determined. In one instance of baling, three different size bales were baled. The total number of bales used for analysis was 12 but there were divided up as to whether they were net wrapped or twine wrapped and bale diameter. Among these were 9 - 48 in., 8 - 54 in., and 7 - 60 in. bales, that used net or twine. When the analysis was carried out, average absolute error was calculated for the independent sizes and for all bales. As shown in table 4.2, average absolute error is greatest for mixed bales. This data demonstrates the need for in dependent calibrations for different sized bales because typically, a producer would not be changing bale size in the same field

Table 4.2. Displays average absolute errors according to bale diameter and wrap method.

Bale Diameter, in.	N	Wrap Type	Avg. Abs. Error, %
48	5	Net	2.7
	4	Twine	3.3
54	3	Net	1.1
	5	Twine	2.9
60	4	Net	1.8
	3	Twine	3.3
Mixed	11	Net	5.3
	12	Twine	5.8

For one analysis, a field that produced 23 bales during harvest was used to determine how different calibration methods affect the weight prediction. The method used for post-processed calibration was to randomly select 3 bales of a specific size that were net wrapped and build regression models based off those 3 bales. Of the regression models built, one consisted of using 3 - 48 in. bales, one consisted of using 3 – 60 in. bales and one consisted of using 1 of each size, 48 in., 54 in., and 60 in.. Table 4.3 shows the average absolute errors produced when the different regression models consisting of only 3 bales each, were used to predict weight for the rest of the bales. The 48 in. calibration produced lower errors than that of the 60 in. calibration model. . When 3 bales of different sizes were selected for the use of calibration, average absolute error as applied across the 23 bales displayed a drastic decrease. This table demonstrates that if a field was going to consist of different bale sizes and only one calibration was to be used, the calibration should consist of bales from each size that are to be baled.

Table 4.3. Displays average absolute errors for 3 bale calibration across different models.

Bale Diameter, in.	Wrap Type	Avg. Abs. Error, %
48	Net	11.7
60	Net	26.1
Mixed	Net	7.6

Conclusion

The ability to record pressure transducer response throughout the bale kicker cycle was achieved in this study by installing the pressure transducer on the circuit for cylinder extension. By doing this, the ability to develop an algorithm for bale weight prediction was also developed to demonstrate the accuracy of using the pressure transducer for bale weight prediction. Through many analyses and calculations, average absolute errors for different methods of baling, whether it be using different types of wrap or different size bales, were calculated and displayed.

Further testing for this pressure transducer technology should further investigate the effects of twine wrap versus net wrap and how different size bales affect average absolute error. Another objective should consist of analysis of when hay is baled and ejected on flat ground versus hay that is ejected on an incline. This could have the potential to further decrease prediction error. Different bale densities should also be analyzed to determine whether that has a significant impact on pressure transducer response.

This study demonstrated the effectiveness of using a hydraulic pressure transducer to predict bale weight from a round hay baler. With average absolute errors median range remaining between 3% and 6%, the feasibility of implementing this technology commercially can be analyzed and justified. This technology has the potential to be pivotal to the hay industry for round baling because it has the ability to provide the producer with on-the-go bale weights and weight accumulation through a field, which in turn allows them to have an estimated value on a field by field basis. This technology has the ability to be much cheaper than what is presently available and less complex. There are less parts in the system when compared to a load cell weighing system. The bale weighing system has the ability to be retrofitted to any baler with a hydraulic bale kicker and can be offered from the factory.

Acknowledgements

Special thanks goes to Reid Miller, Andrew Warner, Gillian Tuttle, and Harry McAlhany for assistance with field testing

References

Ehrich, G. and E. Dobner. 1985. Method for measuring the weight of bulk goods loaded by a hydraulic excavator. U.S. Patent No. 4,499,960.

Kirk, Kendall R., D. Hollens Free, J. Warren White and Joel S. Peele. “Measurement of Offloading Cylinder Pressure for Load Weight Determination in Peanut Yield Monitoring.” Clemson University (2015)

Maughan, Justin D., Sunil K. Mathanker, Tony E. Grift and Alan C. Hansen. “Yield Monitoring and Mapping Systems for Hay and Forage Harvesting: A Review.” University of Illinois at Urbana-Champaign (2012)

"NASS - National Agricultural Statistics Service." NASS - National Agricultural Statistics Service. USDA

Posselius, John H., Kevin M. Smith, Douglas S. Fitzkee, Robrecht M.K. Dumarey, Bart M.A. Missotten, and Didier O.M. Verhaeghe. Weighing Round Bales. CNH America LLC, assignee. Patent US 2014/0174303. 26 June 2014.

Seeger, Jason, Robert Waggoner, Brian Bretz, Lawrence D. Retzlaff, Eward W. Esau, and David Eaton. Bale Chute Weighing Appartatus for Crop Balers. AGCO Corporation, assignee. Patent WO 2011/033357 A2. 24 Mar. 2011.

Yohn, Craig W., Edward B. Rayburn and Dana Porter. "Forage Management: Using Hydraulics as a Scale on the Farm." Extension Service West Virginia University (2006)

CHAPTER FIVE

CONCLUSION

Conclusion

Throughout this study, different yield monitoring methods for hay crops were developed and evaluated. Three different yield monitoring methods were employed and analyzed to determine which method had the potential to be most effective. The potential for commercialization was also discussed.

The analysis of sensors for estimating yield from grass height on the Carter Research mower resulted in conclusion that measuring standing crop at time of harvest using infrared and ultrasonic sensors is relatively inaccurate, impractical, and not likely therefore not feasible from a commercial standpoint. Had the infrared distance sensors been able to withstand the debris and dust that was expelled from the front of the mower, they would have been the best suited sensors because of resolution. Also, the infrared sensors could have potentially produced better yield predictions with lower average absolute errors if they were more rugged and less susceptible to the environmental problems. However, the ultrasonic sensors proved to be the best choice for measuring crop height on-the-go for yield prediction because they provided consistent data and did not behave erratically. This study showed that sensor response to grass height can correlate to mass flow and yield, although practical challenges such as development of a calibration protocol likely are prohibitive to its potential commercial application and adoption.

The yield monitor implementation on the hay baler proved to be effective. Infrared and ultrasonic sensors were used but the infrared sensors provided generally useless data because of fouling from dust. After analysis, the number of recommended ultrasonic sensors for the system was reduced to two; the use of two ultrasonic sensors was shown to be not significantly different from using 4 sensors. Different types of ultrasonic sensors were evaluated for the yield monitor. The reason the initial ultrasonic sensors were replaced it because they were not suitable for outdoor use. New sensors were located and installed too the yield monitor to only achieve two datasets. The two datasets, after analysis demonstrated that the new sensors had potential to provide good, useful data. More research should be carried out in the coming years to further evaluate the use of these sensors.

The last part of the study consisted of using a pressure transducer on the hydraulic bale kicker of a round baler. By analyzing the pressure change as the bale was being ejected from the bale chamber, bale weight could be calculated by correlating weight to pressure. This technology proved to be feasible and effective through demonstration of acceptable average absolute errors. Calibration methods also proved to be very important to achieve the low error percentages. Commercialization of this technology showed to be feasible and cost effective when compared to other technology. The pressure transducer can be implemented on balers with hydraulic bale kickers for a fraction of the cost of a traditional load cell based weighing mechanism.

Overall, these methods can be employed to obtain yield data for hay production. The yield data acquired from each method provides different but useful information. The standing crop method does not have as much potential for commercialization as the yield monitoring technology for the baler or the bale weighing system using the pressure transducer but it does have a place in the world of research. Although the technology has not yet been commercialized, there has been some interest displayed for commercialization of the technologies studied and developed. More research is scheduled to be carried out to further evaluate the weighing system and the yield monitoring system for the hay baler.

APPENDICES

Appendix A

Moisture Sensor Preliminary Data

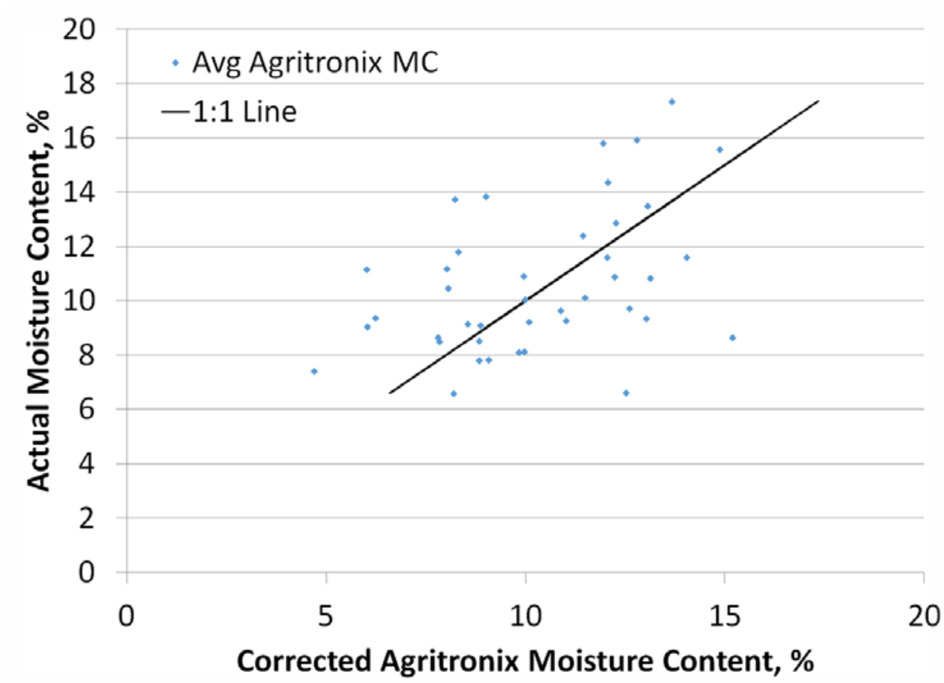


Figure A-1: Demonstration of data collected from the moisture sensors.

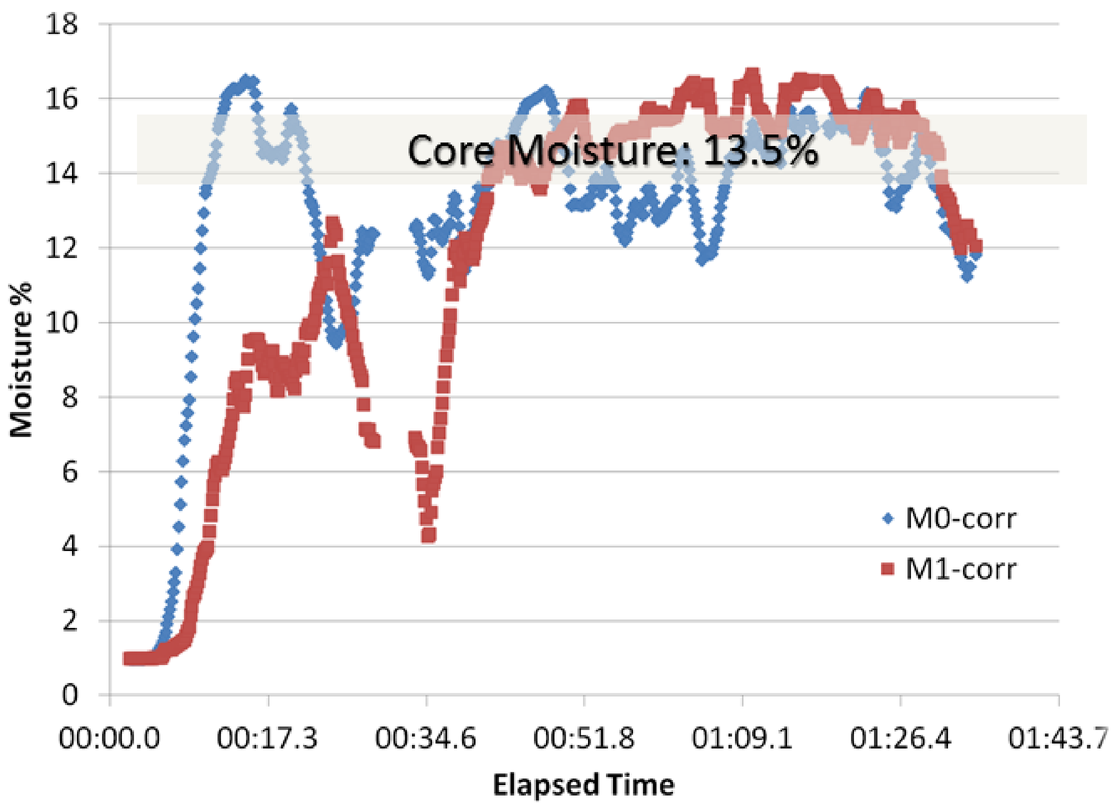


Figure A-2: Comparison of data acquired from moisture sensors compared with data obtained from core moisture sampling of one bale.