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Development and Evaluation of a Yield Monitor for Round Hay Balers

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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.*

Keywords. *Hay and forage, yield monitor, mower, precision agriculture*

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. 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 also 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. 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 40.6 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, Wisonsin) 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 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.

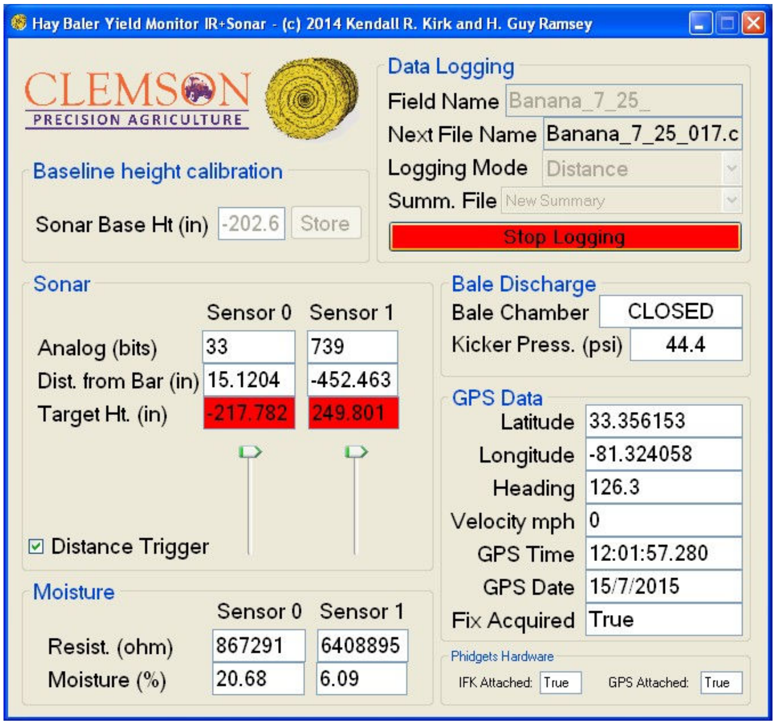


Figure 1. Screenshot of program display for data acquisition software showing dynamically updated values for sonar sensor output, bale chamber position, hydraulic pressure at kicker, moisture sensor output, and GPS position information.

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 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.

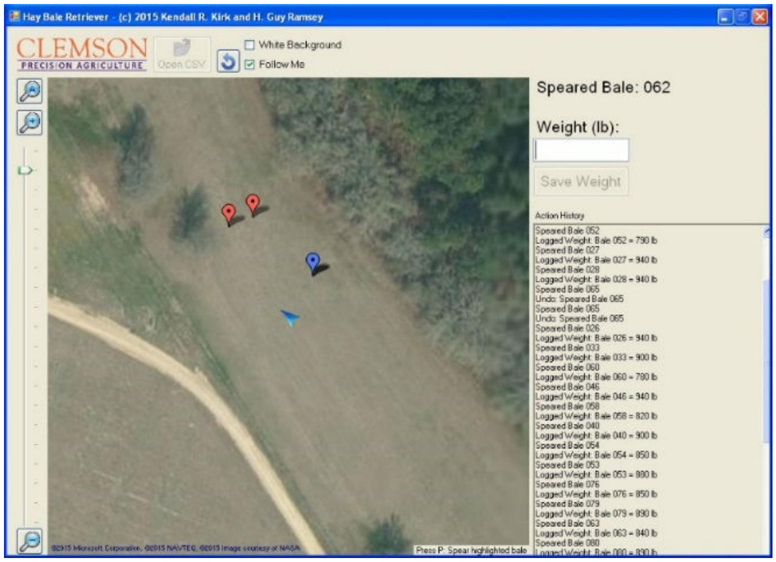


Figure 2. Screenshot showing display for Bale Chaser program that was written to collect and weigh bales.

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. 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, with the 5V supply and ground connected to the I/O board. In the figure, R1 was a 1 MOhm 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, Ohm

R1 = known resistance, 1 x 10^6 Ohm

V_{in} = supply voltage, 5 V

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

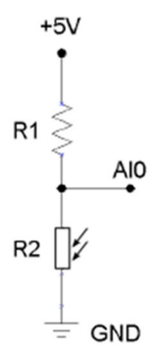


Figure 3. Diagram for voltage divider used to measure resistance across electrodes on moisture sensors

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, sonar 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 1 through 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 1, 2, 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 5-12 only consisted of models where two ultrasonic sensors were used.

Table 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 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. 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 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 5 through 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 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 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 5 through 8 generally suggest that yield prediction models are improved, if not significantly improved when knowledge of moisture is included.

Table 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 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 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 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 9 and 10 compare mass and mass flow prediction errors for wet basis (Table 9) and dry basis (Table 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 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 9 and 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 sonar 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 sonar sensor response.

Table 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 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 11 and 12 compare mass and mass flow models for wet (Table 11) and dry (Table 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 sonar sensor response and that it may be best characterized as a function of the square of sensor response.

Table 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 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 4 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 sonar 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.

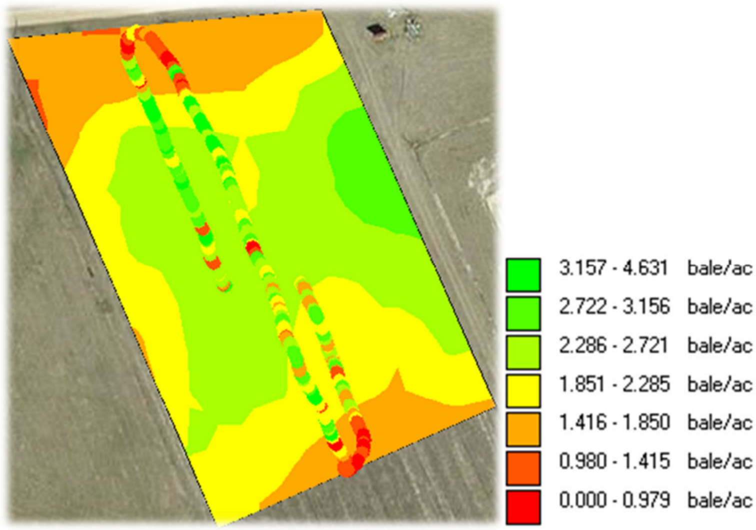
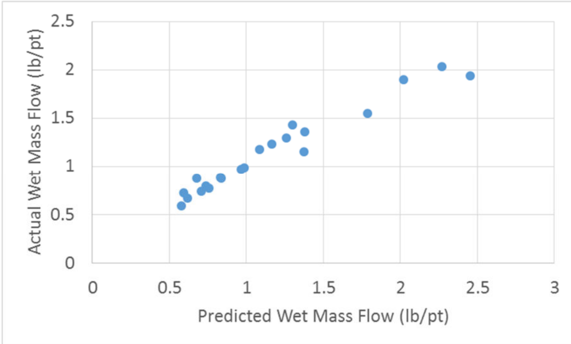


Figure 4. Yield map developed using 7-30 Alfalfa dataset, showing point datasets from two bales overlayed on a contoured yield map of point datasets from all bales.

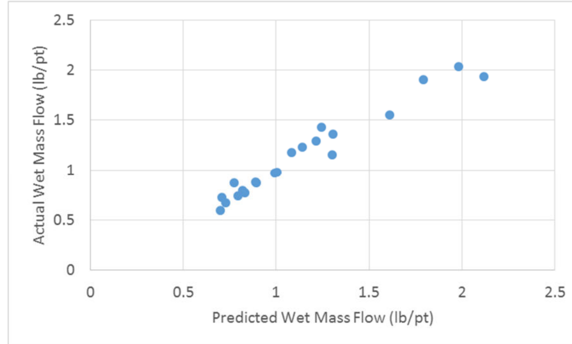
Year 2

During the second year of research and testing, efforts were focused on indentifying the best sonar 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%

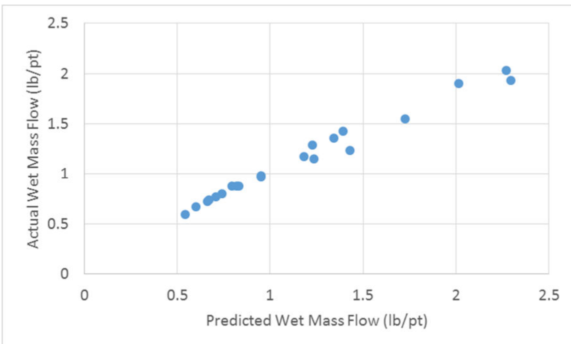
Figures 5 (wet basis) and 6 (dry basis) display charts that were developed using data from harvesting 21 bales in the Banana field on August 26, 2015. The data displayed shows wet mass flow prediction (lb/pt) for four different analysis methods, as developed in Year 1. A single regressor model was used for Figure 5a to predict mass as a function of sum of sonar sensor responses. Figure 5b uses a single regressor model predicting mass flow as a function of average sonar sensor response. Figures 5c and 5d are two-regessor models using the same regressors as 5a and 5b, respectively, along with use of moisture content as a second regressor. Figures 5a and 5c are forced through the origin while Figures 5b and 5d have a non-zero intercept. Average absolute errors for the models depicted in Figure 5 are displayed in Table 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.



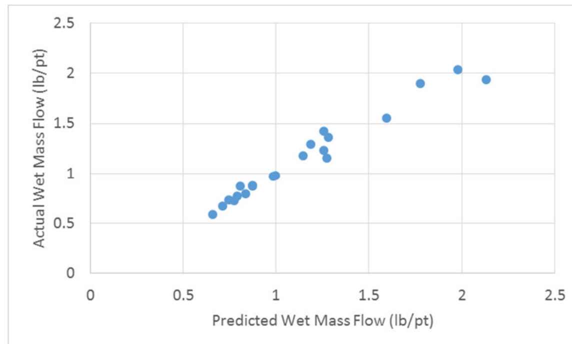
(a)



(b)



(c)



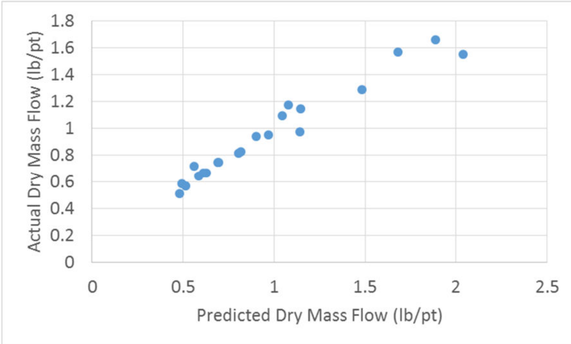
(d)

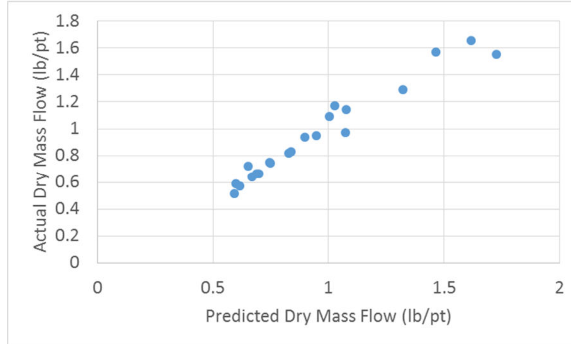
Figure 5. Demonstration of the relationship between wet mass flow prediction (lb/pt) and actual, or measured, wet mass flow (lb/pt) with regards to regressors used for evaluation. Models used for construction of Figures 5a, 5b, 5c, and 5d are outlined in Table 13.

Table 13. Demonstration of average absolute errors for models applied to construct Figure 5.

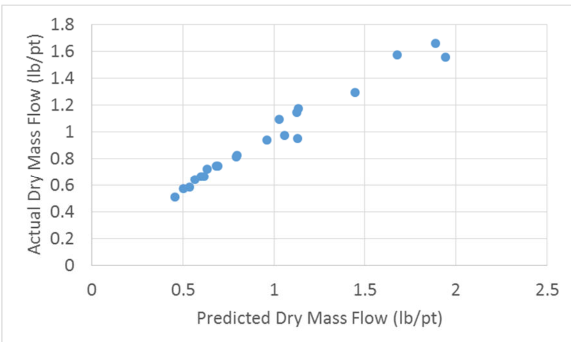
Chart	y-intercept	1st Regressor	2nd Regressor	Avg. Abs. Error, %
a	Zero	Sum	None	8.62
b	Non-zero	Average	None	6.71
c	Zero	Sum	Moisture	7.53
d	Non-zero	Average	Moisture	5.11

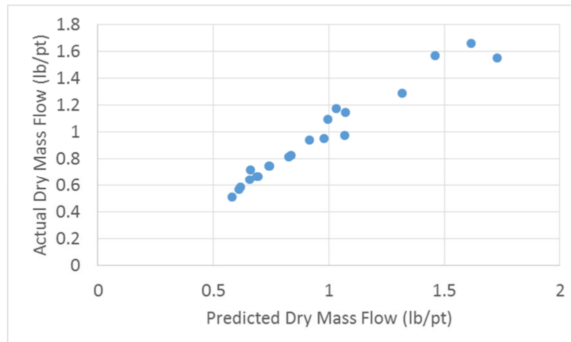
In Figure 6, the charts shown show actual (measured) dry mass flow as a function of predicted dry mass flow, both as units of lb/pt. Models used to develop Figures 6a, 6b, 6c, and 6d are the same as those described to develop Figures 5a, 5b, 5c, and 5d, respectively, except that the models for Figure 6 predict dry yield and those for Figure 5 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 sonar 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)





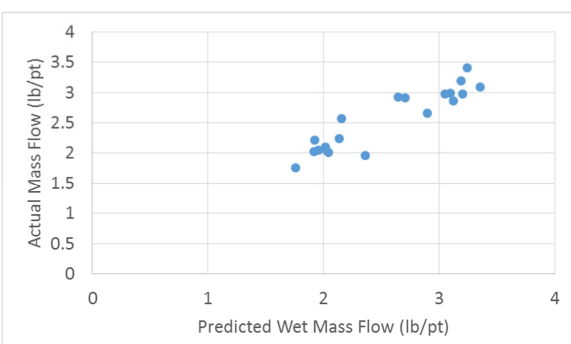
(c) (d)

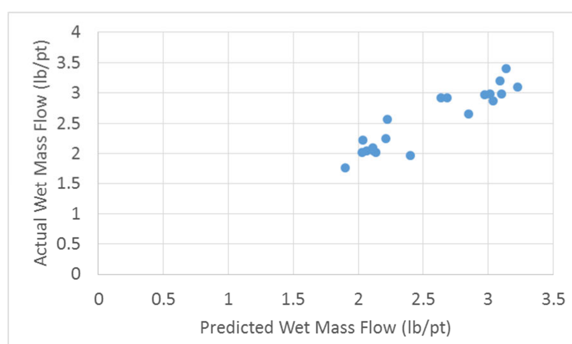
Figure 6. Demonstration of the relationship between dry mass flow prediction (lb/pt) and actual, or measured, dry mass flow (lb/pt) with regards to regressors used for evaluation. Models used for construction of Figures 6a, 6b, 6c, and 6d are outlined in Table 14.

Table 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 7 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 15 displays average absolute errors for the two methods of error determination. Figure 7a uses the sum of sensor readings for analysis and is forced through the origin. Figure 7b uses the average of sensor readings for analysis and is not forced through the origin. Table 15 shows the average absolute errors of the two charts.





(a) (b)

Figure 7. Relationship between predicted wet mass flow (lb/pt) and actual wet mass flow (lb/pt). Both use only one regressor.

Table 15. 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

Acknowledgments

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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.