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Development and Testing of a Forage and Hay Yield Monitor for Use on Mowers

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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 to 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.*

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

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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 without 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 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 of the 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 be able to specifically tell where the hay that went into each bale came from 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 boost farmer's profits tremendously.

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 hay 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 height 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 calculate 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 look at it from the top. 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 91.44 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 the 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 5.08x5.08 cm. (2x2 in.) angle iron approximately 5.08 cm. (2 in.) long mounted to the boom. One model 3521_0 infrared sensor (Phidgets Inc., Calgary, Alberta, Canada) was mounted to each of these pieces of angle iron. These 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 101.6 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 approximately 5.08 cm. (2 in.) wide by 10.16 cm. (4 in.) long by 2.54 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 travelled 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 25.4 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) 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 measured off to be 30 ft long. The first plots that were 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 1, negative grass height values in the point data were replaced with values of zero. In the second method, table 2, negative grass height values in the point data were replaced with blank values. For each dataset in tables 1 and 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 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]
All grasses[4]	8 IR	Wt = f[Ht^4,MC]	A	18.03
	4 IR	Wt = f[Ht^4,MC]	A	17.67
	2 IR	Wt = f[Ht^4,MC]	A	17.57
Oats	8 IR	Wt = f[Exp(Ht),MC]	A	7.24
	4 IR	MF = f[Ht^2,MC]	A	5.99
	2 IR	MF = f[Exp(Ht),MC]	A	7.61
H. pearl millet	8 IR	Wt = f[Ht^4,MC]	A	13.76
	4 IR	Wt = f[Ht^4,MC]	A	13.98
	2 IR	Wt = f[Ht^4,MC]	A	14.98
Bermudagrass	8 IR	MF = f[Exp(Ht),MC]	A	9.19
	4 IR	MF = f[Ht^2,MC]	A	9.15
	2 IR	MF = f[Ht^2,MC]	A	9.15
Bermudagrass	8 Son	MF = f[Ht^(0.25),MC]	A	8.32
	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. 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, %
All grasses	8 IR	Wt = f[Ht^4,MC]	A	18.59
	4 IR	Wt = f[Ht^4,MC]	A	18.16
	2 IR	Wt = f[Ht^4,MC]	A	17.87
Oats	8 IR	MF = f[Ht^(0.25),MC]	A	6.43
	4 IR	MF = f[Ht,MC]	A	5.62
	2 IR	MF = f[exp(Ht),MC]	A	7.57
H. pearl millet	8 IR	MF = f[Ht^4,MC]	A	12.54
	4 IR	MF = f[Ht^4,MC]	A	12.41
	2 IR	MF = f[Ht^2,MC]	A	14.34
Bermudagrass	8 IR	MF = f[Exp(Ht),MC]	A	9.19
	4 IR	MF = f[Ht^(0.5),MC]	A	9.09
	2 IR	MF = f[Ht,MC]	A	9.15
Bermudagrass	8 Son	MF = f[Ht^(0.5),MC]	A	10.26
	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 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 3, there were no statistical differences between using blanks or zeros, suggesting that both methods produce equally acceptable results.

Table 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 4) For data where negative values were replaced with blanks, there were also no statistical differences between yield prediction models (table 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 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 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 6, it is shown that for the dry prediction models, there were also no statistical differences between 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 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 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 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 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 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 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 10). For the following analyses in this manuscript, models applied will be in the form of multiple linear regressions.

Table 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 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 11 and 12). In tables 11 and 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 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 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.

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