Development of a real-time algorithm for automation of the grain yield monitor calibration

by

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"I can do all things through Christ which strengtheneth me."

Philippians 4:13 (KJV)

ABSTRACT

This study sought to develop an understanding of the accuracy of the impact based yield monitor and characterize field performance. The study evaluated yield monitor performance on the mass flow signal, individual load, field level, and season level. An automated system utilizing pressure pads located in the combine grain tank combined with an algorithm was developed and implemented to calibrate the impact based yield monitor in harvesting of corn. The developed algorithm defined specific bounds for the calibration period and estimated partial tank load weight, replacing the operator entered load weights from the prescribed manual calibration process. The automatic calibration system was integrated with the impact based yield monitor system, entirely removing operator interaction in the yield monitor calibration process. The complete yield monitor with integrated automatic calibration was field tested during the 2015 corn harvest season and compared versus a manual calibration. The automated system outperformed the manual calibration in long term studies, successfully compensating the yield monitor calibration for changing crop conditions.

CHAPTER 1: IMPACT BASED YIELD MONITOR PERFORMANCE

Abstract

Since the initial introduction of the grain yield monitor, there have been evaluations of its performance. Most evaluations have focused on lab scale tests of the sensor performance and its ability to be calibrated in field trials. This study focused on the full spectrum of performance of the impact based grain yield monitor with observations and conclusions drawn on the mass flow signal, load to load variation, field accuracy, and full season performance. The load variance expectation of the impact based yield monitor was characterized and the yield difference requirements for statistical significance were developed to aid in evaluation of yield monitor based evaluations of agronomic strip trials. Expected field means for manufacturer recommended calibrations produced field mean errors of ±5% with full season evaluation with a single calibration producing less than 1% error.

Introduction and Prior Art

The performance of grain production systems are most commonly benchmarked against the resulting yield. Benchmarking can be achieved through physically weighing harvested grain, this however reduces the spatial resolution as grain is aggregated to a transport vehicle and in some cases benchmarking may be delayed until grain is marketed. The yield monitor's primary purpose on introduction was to serve as the source of information in the implementation of site-specific cropping practices, and as of 2005, there was over a 44% adoption rate of yield monitors in the Corn Belt (Schimmelpfennig & Ebel, 2011). The widespread adoption of yield monitoring technology enabled producers to estimate harvested grain mass that otherwise could only be achieved through weighing grain. The accuracy of the yield monitor has been under investigation since its introduction and is typically compared against the traditional benchmark methods of large aggregated weights by producers.

A variety of technologies are available for commercial yield monitoring with the impact based yield monitor being the most common in North America. The impact based yield monitor is a system comprised of an impact plate mounted to a force transducer located at the discharge of the clean grain elevator and a controller or display that interprets information from the force transducer to estimate a grain mass flow rate. The conversion of the force transducer output to mass flow is based on producer completed calibration processes that is required to ensure yield monitor accuracy.

The accuracy of the impact based yield monitor has been evaluated under a variety of conditions and formats. Determining the accuracy of the impact based yield monitor defines the scope of which the resulting data can be used for agronomic and cropping practice decisions. In recent years, calibrated yield monitors have been utilized for a range of agronomic purposes, business decisions, and government yield reporting (USDA, 2016). Agronomic usage is better defined as hybrid test strips, split planter hybrid trials, and specific chemical application evaluation.

Test stand evaluations were completed by Burks (2003), evaluating mass flow variability and accumulated load weights, impact of varying flow rates (Burks, et al., 2004), field terrain (Fulton, et al., 2009), and crop property effects (Reinke, et al., 2011). These studies focused on the impact based yield monitor's ability to be calibrated to estimate mass flow and to compensate for other mechanical influences with the evaluation metric being average flow rate or accumulated mass. This helps define load weight accuracy in controlled environments, but does not characterize the performance of the yield monitor in normal field conditions that include moisture content variation and field dynamics.

Field test studies analyzing individual load errors, Grisso (2002) reported field evaluations of load errors of 4% on a load basis and higher errors in loads less than 1,800 kg. Missotten (1996) additionally reported larger load errors for small test plots. Krill (1996) reported load weight errors of less than 5% for corn and as high as 15% for soybeans for calibrated yield monitors. These studies observed smaller samples sizes of loads and do not observe complete field and season level yield monitor performance with performance in these areas being primarily cited from manufacturer claims.

Characterizing the impact based yield monitor performance across the full application spectrum will define the level of confidence yield data must be given when decision processes are driven by the yield monitor reported results. This defines the objectives of this research to characterize the performance of impact based yield monitoring systems on several levels of evaluation for harvesting corn. The objectives of the research:

- Determine instantaneous mass flow variability
- Determine load to load variability of the impact based yield monitor
- Evaluate field level performance of the grain yield monitor
- Evaluate field to field performance of a calibrated yield monitor
- Investigate yield data sample size effects on precision

Materials and Methods

Impact based yield monitor system theory of operation

As previously described the impact based yield measurement system consists of a plate instrumented with a load cell located at the top of the clean grain elevator and is referred to commonly as the mass flow sensor. The clean grain elevator moves grain that has successfully passed through the threshing and cleaning systems from an accumulation point to a grain storage tank located in the upper portion of the harvester. The clean grain elevator consists of a metal chain equipped with rectangular paddles that operates in a metal tube to convey the grain primarily in the vertical direction (Figure 1). The grain ascends the elevator riding on the paddles (35 of Figure 1), with centrifugal acceleration causing the grain to exit the elevator as the chain makes a 180° turn to return to the bottom of the harvester. The paddles are typically produced from recycled tires with some manufacturers opting to use a hard plastic paddle to improve component consistency. The top of the elevator is designed to discharge the grain from the paddles so the grain can be expelled further into the grain tank by a fountain auger (45 of Figure 1). The impact plate is located perpendicular to the direction of grain discharge, placed directly in the path of grain exiting the top of the elevator. The resulting force imparted on the impact plate by the grain is measured by the yield monitor system and a mathematical relationship of force to mass flow is used to estimate the grain mass flow rate. The mathematical relationship is developed from the calibration process and is designed to reduce the non-linear relationship of the measured force to measured mass (Myers, 1996).

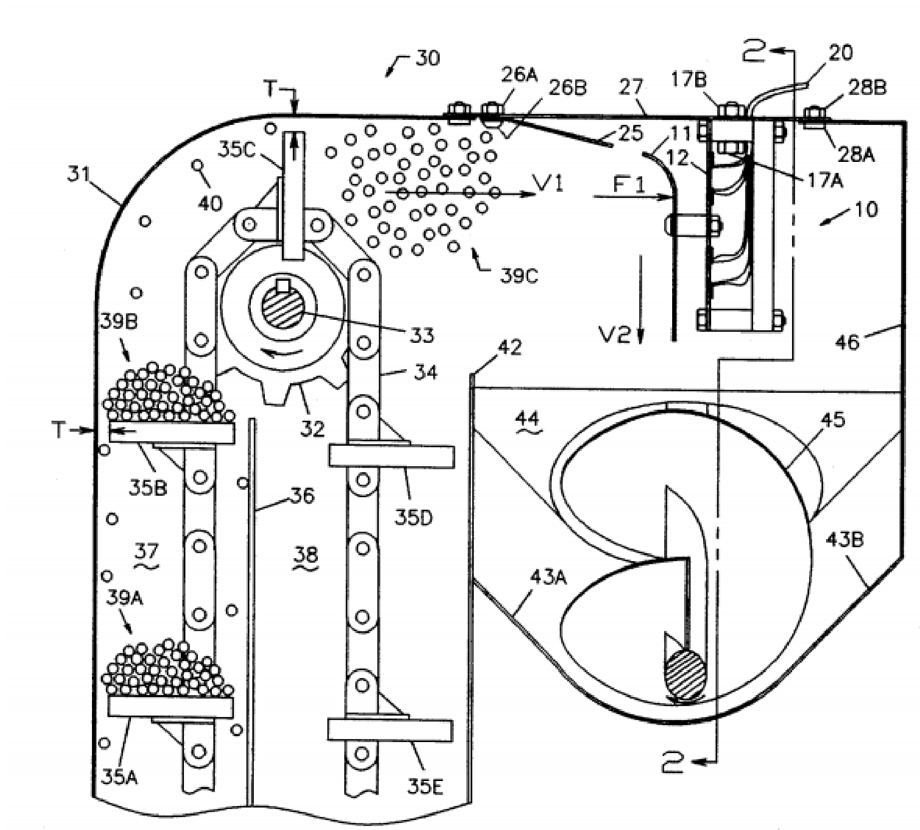

Figure 1: Impact based mass flow sensor mounted at the top of the clean grain elevator (Myers, 1996)

The sensor system relies on the physics of grain discharging from the elevator to transfer the momentum of the grain to the impact plate (11 of Figure 1). The resulting force and duration imparted by the grain onto the impact plate is equal to the product of the mass and change in velocity of the grain from before and after impacting the force sensor (Equation(1); (Zhou & Liu, 2014). The change in velocity is only considered in the normal direction of the force sensor. This equation is considering a single particle only and is based on impulse momentum. A more generalized observation considers the force measurement in time, the mass m(t) at the time of the measurement, Δt is the length of a sample period, v_1 the mean velocity of the particles, and c is the coefficient of restitution of the grain particles (Equation(2); (Zhou & Liu, 2014). The particle velocity is a function of the elevator speed and grain particle position on the paddle with respect to the rotational point as the paddle rotates around the top of the elevator (Reinke, et al., 2011).

$$F \cdot \Delta t = m \cdot (v_1 - v_2) = m \cdot (1 - c) \cdot v_1 \tag{1}$$

$$F(t) = \frac{m(t)}{\Delta t}(1 - c) \cdot v_1 \tag{2}$$

Observing the process, two primary factors affect the impact plate based system: the initial available energy of the grain as it leaves the elevator paddle and momentum transfer to the impact plate. The first factor is related to the mass of the grain and its exit velocity with the exit velocity being affected by several factors. The discharge velocity of the grain is influenced by the initial location of the grain particle on the paddle in reference to the pivot location and the frictional coefficient. The friction and initial position influences the generated tangential velocity of the grain as it is expelled from the paddle as a higher coefficient of friction slows the transition of the grain particle to the outer tip of the paddle, decreasing its final release position on the paddle and reducing the velocity. This creates a gradient of particle velocities based on the radial location of the grain particles on the paddles (Strubbe, et al., 1996; Reinke, et al., 2011). The grain pattern once expelled from the elevator varies with the paddle shape and paddle tip clearance with the shape of the discharge pattern affected by the volume of grain and paddle size (Strubbe, et al., 1996). The shape of the paddles concentrate the grain flow towards the outer rotational radius of the paddle which are typically worn at the corners. The wear is best described by the permanent reduction in size of the paddle as the corners abrade from use and the permanent deformation of the paddle as the corners curl away from the direction of travel. The paddle tip clearance which is defined as the clearance from the outer tip of a paddle to the top of the elevator housing represented by T of Figure 1, influences the release point of the grain. As the tolerance gap increases, the grain slips off of the paddle earlier as the paddle travels around the first 90° of the elevator top and travels closer to the top of the elevator relying on the deflector shown at 25 of Figure 1 to direct the grain towards the force sensor. This reduces the velocity of the grain and modifies the impact angle of the grain to the force sensor. Additional wear to the top of the elevator and the deflector can modify the grain trajectory and interaction with the force sensor over time.

Momentum transfer is affected by grain density and coefficient of restitution (Reinke, et al., 2011). The crop properties are an unknown factor to the force sensor when calibrated during normal harvest, requiring re-calibration to compensate for large changes. Previously demonstrated in a mathematical model applied to test stand data from the University of Kentucky Yield Monitor Test Stand, the surface frictional properties of grain increase with moisture content and momentum transfer decreases with the increasing moisture content (Reinke, et al., 2011). This analysis used a regression approach to estimate the crop properties from simplified models, but indicates the type of change in force sensor response based on a modification of the crop properties. The study also indicated that if the crop properties could be estimated, a model may potentially be used to accurately estimate the grain mass flow across a wide range of crop variation. This emphasizes the need for calibrations when crop properties change to maintain accuracy and is typically recommended by yield monitor manufacturers to re-calibrate for large changes in moisture content and individual calibrations for each crop (i.e.: corn, soybeans, wheat).

The yield monitor is calibrated to correct the mathematical relationship of force to mass flow accounting for the specific mechanical and crop specific variation of the harvester. The calibration process is completed by relating the accumulated measured force by the impact plate and the mass of grain harvested for the same time period. A single calibration point is created by initiating a calibration through a user interface to the yield monitoring system with an empty grain tank. The operator then harvests between 1,400 and 3,600 kg of grain at a consistent harvest speed. The consistent harvest speed attempts to produce a consistent mass flow rate. Once an acceptable mass of grain has been collected, the operator stops harvesting and completes the calibration through the user interface. The grain is then offloaded onto a cart equipped with calibrated scales and the resulting weight is entered back into the yield monitor which updates the relationship between measured force by the impact plate to grain mass. This process is ideally replicated at four or more different harvest speeds to produce a multipoint calibration that represents the operational flow range of the harvester for the specific crop.

Test fixture for instantaneous mass flow evaluation

A test fixture was used to estimate the variability of the 1 Hz yield monitor mass flow data in ideal controlled conditions. The cause of the variability is not of interest with the emphasis of the work on understanding the expected variability under constant mass flow conditions. The purpose was to observe the expected variation from a single yield point on a yield map. This required a constant mass flow to be introduced to the clean grain system of a harvester. The mass flow or load weight accuracy of the yield monitor was not investigated in this test based on the results of previous studies and was specifically focused on the variation in mass flow rate under constant conditions (Risius, 2014; Burks, et al., 2003).

Five tests were completed with three different harvesters (Table 1). The flow ranges targeted were based on machine expected capacities for dry corn for the class size of the harvester. Dry corn was sourced from the local grain elevator for all testing purposes with a different batch of grain used for each data set. Paddle tip clearance was verified to be within manufacturer specification for all tests and all harvesters were configured with manufacturer installed yield monitors. The yield monitors were calibrated per the manufacturer's specification for each test.

Table 1: Test stand produced data sets for 15% dry corn

Data Set	Machine ID	Replicates	Flow Rate (kg/s)	Notes
A	1	4	5	Class VII
A	1	4	10	Class VII
A	1	4	15	Class VII
A	1	4	20	Class VII
A	1	4	25	Class VII
B	1	4	8	Class VII
B	1	4	15	Class VII
B	1	4	25	Class VII
B	1	4	35	Class VII
B	1	4	45	Class VII
C	1	6	5	Class VII
C	1	6	10	Class VII
C	1	6	15	Class VII
C	1	5	25	Class VII
C	1	6	30	Class VII
D	2	3	25	Class VIII
D	2	3	30	Class VIII
D	2	3	35	Class VIII
D	2	2	50	Class VIII
E	3	3	25	Class IX
E	3	3	30	Class IX
E	3	3	35	Class IX
E	3	3	45	Class IX

The test stand was constructed in 2013 to support yield sensor evaluation and development at the Iowa State Research Farm (Risius, 2014). The yield test system was designed to convey grain into the clean grain pan of a combine harvester using a belt conveyor feeding grain from an instrumented gravity wagon (Figure 2). Feed rate from the gravity wagon is controlled via four electrically driven, linear actuated gates equipped with closed loop feedback control (Figure 3). The gravity wagon was instrumented with a commercial Avery Weigh-Tronix scale system and calibrated versus a certified scale. The yield test stand is capable of supplying up to 10,000 kg to the harvester in a given test at flow rates of 0 to 55 kg/s. A National Instruments CRIO 9038 was used to control the gravity wagon gate system and to record data at 1 Hz.

Figure 2: Yield system test stand feeding grain into harvester clean grain system

Figure 3: Yield system test stand metering gate with positional feedback gate control

The induced yield monitor mass flow and corresponding gravity wagon weight was recorded at 1 Hz. There was an approximate 10 second delay from when grain exits the gravity wagon until it reaches the harvester's mass flow sensor located at the top of the clean grain elevator. Tracking the gravity wagon's weight throughout a test run allowed for verification of consistent mass flow introduced into the harvester clean grain system. The consistency in flow rate removes any effects from the transfer delay from the feeding system to the impact based mass flow sensor error analysis. Assessing the mass flow sensor performance under ideal flow conditions, the targeted region for analysis was determined to be 35 seconds after mass flow was established with the analysis occurring on the next 60 seconds of mass flow data (Figure 4). Actual test length varied by flow rate with the length driven by the target mass of approximately 3600 kg in the grain tank at the conclusion of each test.

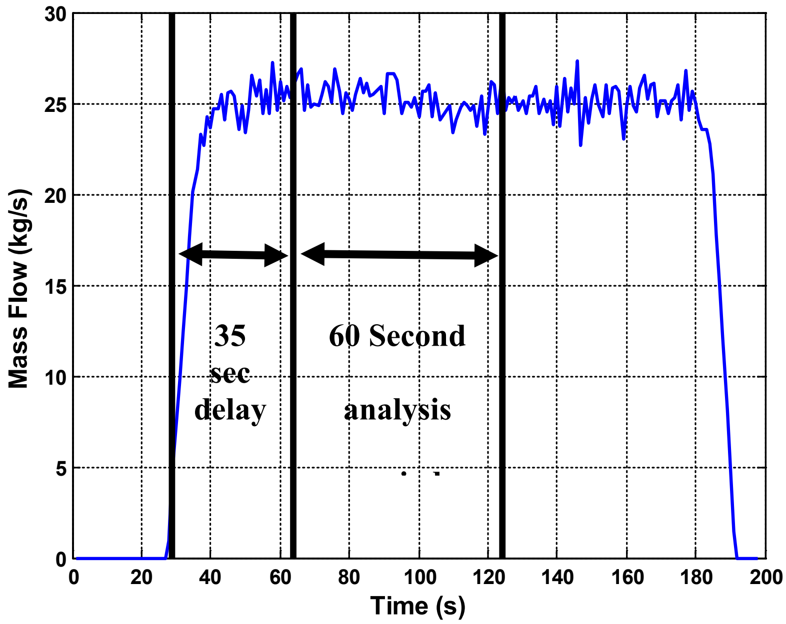

Figure 4: Time series mass flow estimates produced by calibrated yield monitor

Methodology for dynamic in-field yield monitor error analysis

The natural operating state of a yield monitor can only be achieved through field testing. The exposure to natural field variation that induces flow rate changes, crop characteristics, and field dynamics cannot be achieved in a test stand. The largest variation associated with field testing are caused by crop characteristics. Testing with freshly harvested grain that has not been damaged or degraded from handling can only be completed through in-field harvest. Field testing additionally allows the performance of the yield monitor to be quantified from a similar perspective of the producer. Three specific metrics were used to focus on evaluating the season long and field level performance during corn harvest of a calibrated yield monitor: (1) the expected load to load variability under consistent crop conditions, (2) mean field error, and (3) the effects of load size on load variability (Table 2).

Table 2: Data set description for specific evaluations

Evaluation	Season	Data Sets	Machines	Reps	Definition
Field Calibration	2010 - 2015	38	22	1376	Load to load variability and mean error
Season Calibration	2015	22	1	651	Mean field error
Load Size	2014-2015	24	13	804	Effects of load size on variability

Data for this study was collected beginning in the fall of 2010 and was completed in the fall of 2015 on various harvesters equipped with impact based grain yield monitors. The yield monitors were calibrated using in-field scale carts and were evaluated on a load basis utilizing the same grain cart that was used to complete the calibration. The data set was limited to normal corn harvest moisture content with all data less than 25% moisture content.

The yield monitor for each data set in the field calibration analysis was calibrated in the field that the data set was collected. This method evaluated the field mean and load to load variability, providing an ideal scenario for yield monitor performance as the yield monitor is calibrated under the same conditions that it was evaluated. The analysis was focused on yield monitor error and does not investigate the cross data set differences of moisture content and test weight. These factors are excluded from the analysis because the yield monitor was calibrated in the specific conditions to appropriately compensate for the crop conditions.

The season calibration analysis was completed by calibrating the yield monitor at the start of the season in the first harvested field. The analysis was completed on all data collected post calibration completion. This approach provided observations of the yield monitor drift once calibrated and was evaluated with considerations for moisture change. Average flow rates ranged between 8 and 30 kg/s with a mean of 18 kg/s for the loads included in the data set with moisture content ranging from 13% to 25% with a mean of 18%. The yield monitor was calibrated on September 22nd, 2015, at 22% MC with a multipoint calibration completed at approximately 7, 10, 14, 20, and 24 kg/s with the final data set harvested October 19th, 2015. The flow rates of the calibrations were confirmed post-harvest to appropriately represent the operational flow range (Figure 5).

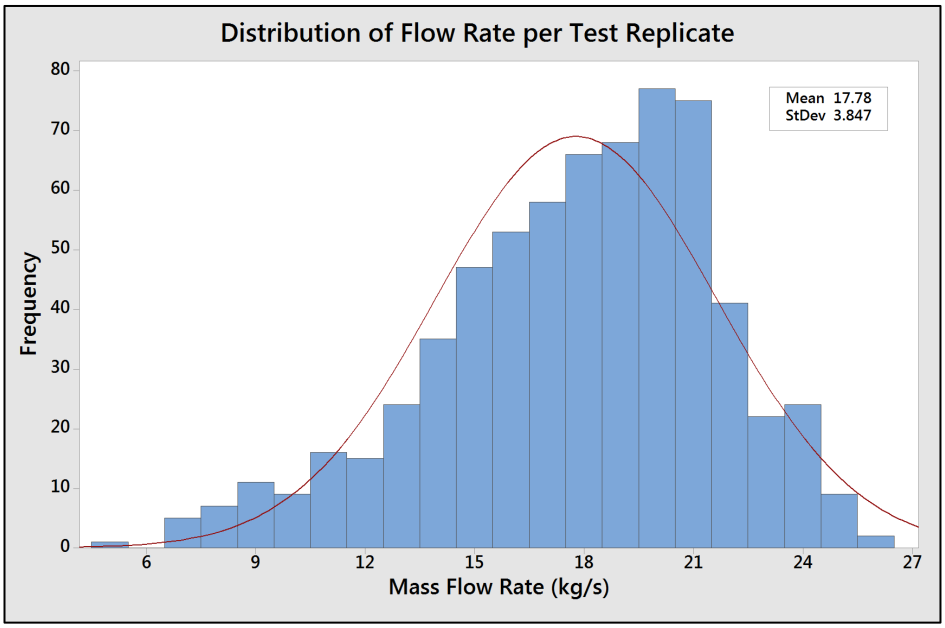

Figure 5: Mean mass flow rate for individual test replicates for the season long single multipoint calibration study.

The final analysis on the field collected data was a comparison of the load size to measured variability. General assumptions were that increasing load size will decrease the load to load variability error because the effect of random error associated with the impact based yield monitor would be reduced. The process for evaluating the variation across multiple data sets required that they be adjusted for calibration bias. Each data set was individually processed to subtract the data set mean error from all load weight error in the data set to produce a data set mean error of zero. The variability within a data set was not changed through this process and makes all loads comparable across data sets. Load weights ranged from 2 to 8 Mg and the maximum load size was limited by harvester storage capacity. Load weights were binned by 1 Mg increments and evaluations completed on the distribution of error.

Results and Discussion

Mass flow sensor variability

The analysis of the mass flow sensor data focused on the variability during consistent flow conditions. The standard deviation for each test replicate was calculated as a percentage of the mean mass flow for the same time period to evaluate the percentage of variation by flow rate. The mass flow rate was found not to be statistically significant to the normalized variation with no distinct trends in relation to mass flow. Data set B covered the largest flow range with an increase in normalized variation trending to approximately 35 kg/s, but was reduced at the highest flow rates (Figure 6).

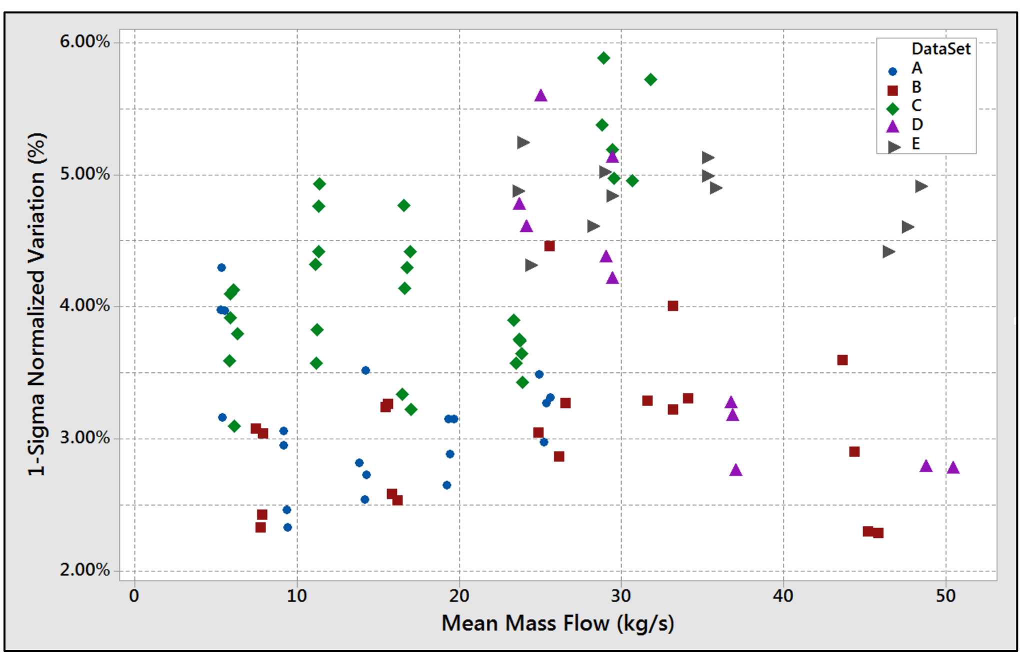

Figure 6: Standard deviation of 60 seconds of mass flow normalized by the mean mass flow vs the mean mass flow rate.

Further evaluation by flow rate indicates that flow rate was statistically significant to the normalized variation of data set D (Table 3). The variation is separated by flow rates for data set D with the two higher flow rates being statistically different from the low flow rates. All other data sets produced no statistical differences across the range of flow rates.

Table 3: Comparison of statistical differences by specific flow rate range and data set for normalized variation

Data Set	Flow Rate (kg/s)	Samples	Mean	Tukey Grouping								
	5	4	3.85%		B	C	D	E	F	G	H	
	10	4	2.70%									I
A	15	4	2.90%							G	H	I
	20	4	2.96%							G	H	I
	25	4	3.26%						F	G	H	I
	8	4	2.72%								H	I
	15	4	2.91%							G	H	I
B	25	4	3.42%					E	F	G	H	I
	35	4	3.46%				D	E	F	G	H	I
	45	4	2.77%							G	H	I
	5	6	3.77%			C	D	E	F	G		
	10	6	4.31%		B	C	D	E				
C	15	6	4.03%		B	C	D	E	F			
	25	6	3.68%				D	E	F	G	H	I
	30	6	5.35%	A								
	25	3	4.99%	A	B							
D	30	3	4.57%	A	B	C	D	E				
	35	3	3.06%						F	G	H	I
	50	2	2.78%						F	G	H	I
	25	3	4.81%	A	B	C						
E	30	3	4.83%	A	B	C						
	35	3	5.01%	A	B							
	45	3	4.65%	A	B	C	D					

The mean normalized variation is statistically different by data set and is even different among the same machine in the case of comparison of data sets A and B to data set C (Table 4). This indicates that the produced normalized variation is calibration dependent when comparing data sets A, B, and C. It could also be stated that variation is machine dependent based on the results of comparing machine 1 and 3 (Data sets A, B, and C to data set E), but because of calibration differences of Machine 1, it cannot be proven with this data set.

Table 4: Statistical difference by data set for normalized variation

Data Set	Samples	Mean	Tukey Grouping		
A	20	3.1%	A		
B	20	3.1%	A		
C	30	4.2%		B	C
D	11	3.9%		B	
E	12	4.8%			C

The mean variation produced in the study is 3.1% and is similar to the 4% (2003) and 3.4% (2004) variation reported by Burks. The produced variability is calibration dependent but cannot be defined as machine dependent in this study due to the variation produced from machine 1 in three separate calibrations of A, B, and C.

Field level yield monitor calibration

A calibrated yield monitor is expected to produce a normal distribution of error on a load basis with ideally a mean error of zero and any deviation from zero being considered a bias in the calibration. The analysis was completed in two parts by first evaluating the mean error of individual yield monitors, and the second evaluating the load to load variability of a calibrated yield monitor.

Field level calibrations ideally compensate for the specific crop conditions and operational flow rates that induce error bias. Evaluating individual calibrations can help draw conclusions about expected accuracy when a specific calibration is completed. A total of 38 individual calibrations were completed in this study with resulting field means ranging from -7% to 4.4%, total mean of -0.5%, and standard deviation of 2.1% for field means (Figure 7). Previous studies reported expected yield monitor mean absolute error of 0 to 4% (Missotten, et al., 1996; Grisso, et al., 2002). The variation in mean accuracy of the calibration indicates that regardless of the calibration there is an expected range for mean error of the yield monitor. Specific field calibrations reduce bias error, but do not guarantee the removal of field level bias. Mean error by machine (Table 5) and specific calibration (Table 6) were found to be statistically significant to mean yield monitor error through one-way ANOVA's. Due to proving the calibrations are distinct however, it cannot be determined if mean error is distinct by machine.

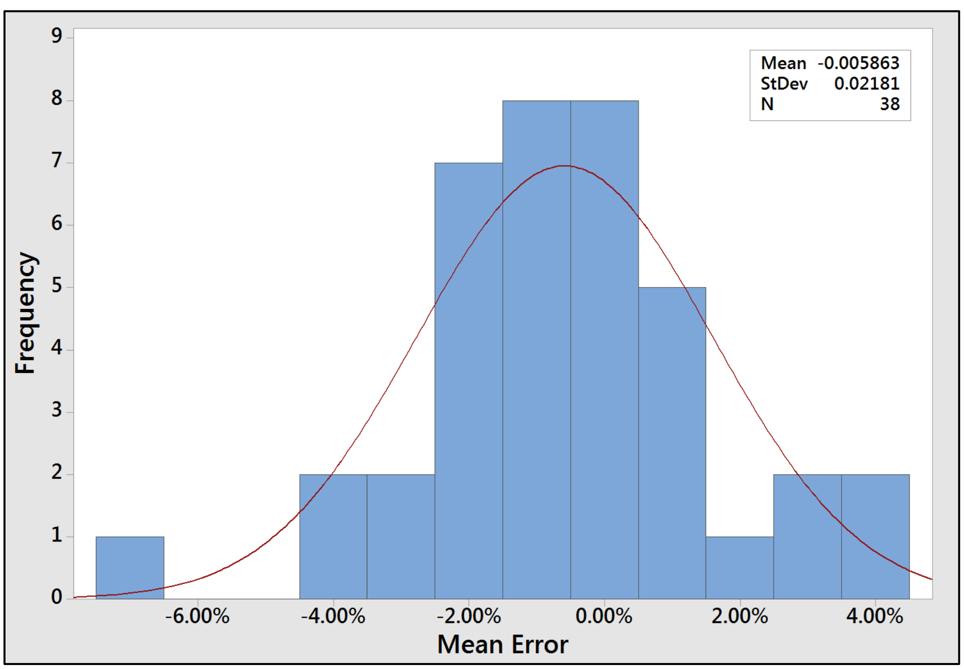

Figure 7: Distribution of field mean errors for individual field calibration data sets.

Table 5: One-way ANOVA of yield monitor error by machine

Source	DF	SS	MS	F-Value	P-Value
Machine	21	0.3036	0.01446	11.58	0
Error	1354	1.6897	0.00125		
Total	1375	1.9933			

Table 6: One-way ANOVA of yield monitor error by data set

Source	DF	SS	MS	F-Value	P-Value
Data Set	37	0.5594	0.01512	14.11	0
Error	1338	1.4339	0.00107		
Total	1375	1.9933			

Considering that individual loads are part of a larger distribution of error with a mean and standard deviation, the calibration is made up of four loads that are drawn from the distribution when the calibration is created. This is considering the effects of random error associated with the impact based mass flow sensor. Testing the hypothesis that a larger standard deviation indicates the probability of a larger bias, a regression analysis of mean error predicted by standard deviation was found to have no statistical significance on mean field error or absolute mean field error. This indicates that mean error at the field level is independent of the mass flow sensor variability.

Observing the error as a continuous density function (Figure 8), nearly 70% of the calibrated yield monitors resided within ±2.5% mean error. Considering each yield monitor was subject to its own calibration, this is a reasonable performance. Less than 5% of yield monitors resided outside of ±5% accuracy. This performance generally agrees with many manufacturer claims of accuracy, but is also evaluated under ideal conditions with the evaluation occurring under the same conditions as the calibration.

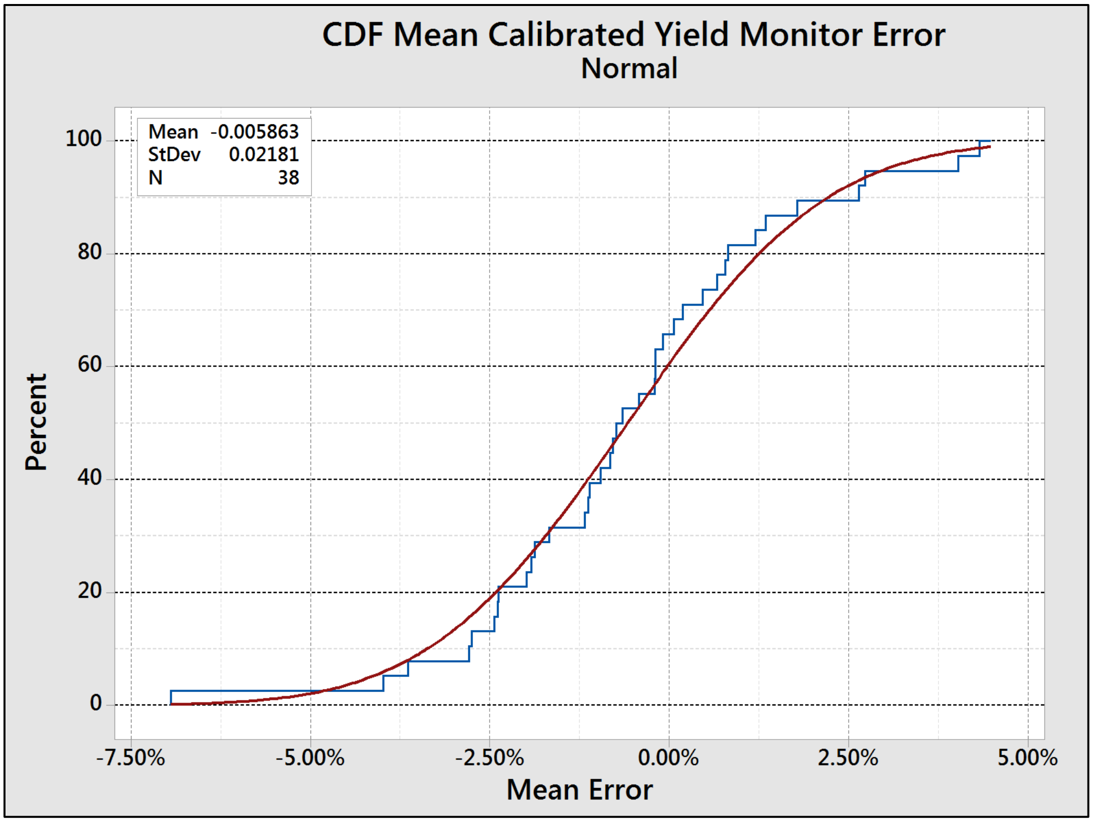

Figure 8: Continuous density function for calibrated yield monitor error.

Individual load errors have been described in the range of 2 to 4% (Doerge, 1996), less than 5% (Krill, 1996), and greater than 10% for smaller loads (< 1,800 kg). An investigation into the load to load variability of a yield monitor is of interest for the use of the estimated yield from two individual loads comparing specific agronomic treatment applications. Knowing that load to load variability exists, characterizing the variability can be used to create evaluation guidelines for individual load weights produced by a yield monitor. Variability of the yield monitor is best described by the standard deviation of load error distribution. The aggregated standard deviations are normally distributed with a mean of 3.3% and standard deviation of 1.2% (Figure 9). This describes the average expected variation within the 38 data sets and 1,376 loads collected within this study.

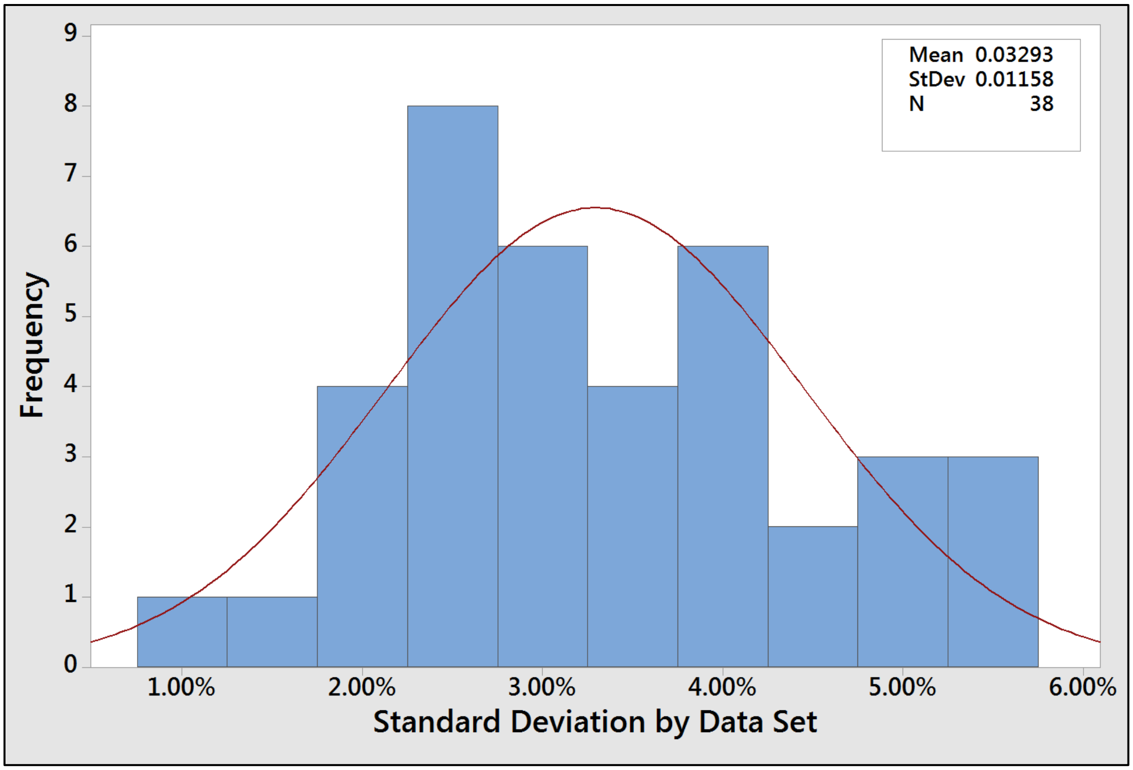

Figure 9: Distribution of standard deviation of yield monitor error for individual data sets.

The resulting distribution of calibration standard deviations, was used to develop recommendations for comparing individual loads. Assuming that error was normally distributed for a single yield monitor and mean error of the yield monitor was considered negligible as comparison of two samples harvested by the same machine would be subject to the same bias a general recommendation was developed. Observing a single load, consider that the load is a sample from the population with a mean of $\bar{x}_1$ and standard deviation σ_1. Where the load error comes from within the distribution is unknown, $\bar{x}_1 \pm 2 \cdot \sigma_1$ (95%), and the actual standard deviation of the specific yield monitor calibration is generally unknown to producers as this type of analysis is not completed by producers. Application of a prediction interval to the distribution of standard deviations produced in this study was used with the upper prediction interval tail to estimate the maximum expected standard deviation of a yield monitor not in this study.

Application of a Chi squared distribution properties to the predicted standard deviation for a single load produced an estimated yield difference requirement to determine if samples are statistically different. A range of confidence levels when applied to the highest yielding sample based on the Chi squared distribution and utilizing the maximum level of the standard deviation prediction interval for the specified confidence level, produces a required yield difference to determine statistical difference between two independent yield samples (Table 7). For example, to determine statistical difference between two samples at the 95% confidence level with the highest yielding sample at 12.5 Mg/ha (200 bu/ac) would require a difference of 1.95 Mg/ha (31 bu/ac).

Table 7: Required Yield Difference between Yield Samples to Determine from Statistically Different Populations

Confidence Level	Std. Dev. Upper Tail	Required Yield Difference
50%	4.0%	3.9%
68%	4.4%	6.2%
90%	5.2%	12.1%
95%	5.6%	15.5%
99%	6.4%	23.3%

The required differences appear large when considering higher yield crops. A reduction in the required yield difference can be achieved by increasing the number of sample loads. This is achieved by increasing the number of treatment replicates to reduce the effects of the yield monitor load to load variability by central limit theorem with the assumption that yield replicates from a treatment are normally distributed. A minimum of three replicates per treatment would allow for the application of a student's t-test between two specific treatments. Additional studies have recommended multiple replications for on farm agronomic studies to raise confidence in the use of yield monitor technologies in evaluating smaller yield differences (Nelson, et al., 2015).

Field to field accuracy from full season corn harvest

The season long study began with the calibration of the yield monitor with a multipoint calibration and was not re-calibrated for the remainder of the season. The total harvest observed 3,900 Mg (186,000 bu) with six specific field sites visited. The overall season error for the yield monitor based on total grain mass was 0.6% versus the scale cart. Daily performance of the yield monitor varied early in the season as moisture conditions widely varied and more consistent daily performance was recognized later in the season when operating in lower and more stable moisture conditions (Table 8). Field A on 9/25/2015 observed a large increase in error due to a rain event while harvesting. This caused a change in moisture content of the grain and additionally applied a large amount of surface moisture to the grain that had adverse effects on the impact based mass flow sensor. Field B produced statistically different mean error for the two dates associated with the field. Inspection of the flow ranges indicated that 9/28/2015 operated with a mean of 16 kg/s, 9/29/2015 operated with a mean flow rate of 10 kg/s. This is at the lower end of the manual calibration points and was reflected in a 5% shift in error for the day. The reduction in flow rates was due to down corn from high winds produced overnight between the two harvest days causing the operators to reduce harvest speed to accommodate for the crop conditions.

Table 8: Daily performance of calibrated yield monitor

Date	Field	Mean Error	Std. Dev. Error	Mean MC%	Loads	Grain Harvested (MT)
9/22/2015	A	2.5%	2.8%	21.1%	14	43.2
9/23/2015	A	5.4%	3.5%	19.5%	13	68.7
9/24/2015	A	6.1%	6.1%	21.3%	35	186.0
9/25/2015	A	17.6%	7.2%	25.1%	32	178.6
9/28/2015	A	9.3%	6.7%	24.9%	9	54.3
9/28/2015	B	-0.7%	1.7%	20.5%	53	325.0
9/29/2015	B	-5.9%	5.1%	19.5%	24	122.3
10/1/2015	A	2.9%	3.1%	22.3%	59	356.6
10/2/2015	A	2.9%	6.0%	22.6%	89	491.4
10/5/2015	C	-3.7%	1.7%	17.2%	23	134.6
10/5/2015	D	-4.8%	3.2%	18.5%	19	106.7
10/6/2015	D	-1.6%	1.5%	18.7%	70	447.7
10/7/2015	D	-3.2%	2.7%	18.3%	18	115.4
10/8/2015	D	-3.3%	6.9%	17.5%	19	113.8
10/9/2015	D	-3.8%	1.8%	17.1%	37	225.8
10/12/2015	E	-2.4%	1.8%	19.1%	27	171.1
10/13/2015	E	-1.7%	1.7%	18.9%	48	299.0
10/16/2015	E	-3.9%	5.9%	18.9%	9	55.6
10/16/2015	F	-4.7%	1.4%	16.8%	4	19.8
10/17/2015	F	-3.2%	1.5%	18.7%	65	265.8
10/19/2015	F	-2.4%	1.7%	15.6%	34	186.4

Considering the results of the field B data set error when analyzed by flow rate, an evaluation of load errors versus the mean mass flow rate for individual loads as reported by the yield monitor was conducted (Figure 10). Load weight error was determined dependent on mass flow rate, emphasis on the low flow rates considering a large increase in error for loads with flow rates less than 10 kg/s. Recall that low flow calibration points were produced at approximately 7 and 10 kg/s to provide calibration coverage in the lower flow rate ranges. This behavior of accuracy at the fringes of the calibration ranges can be expected and has been observed by Burks (2003).

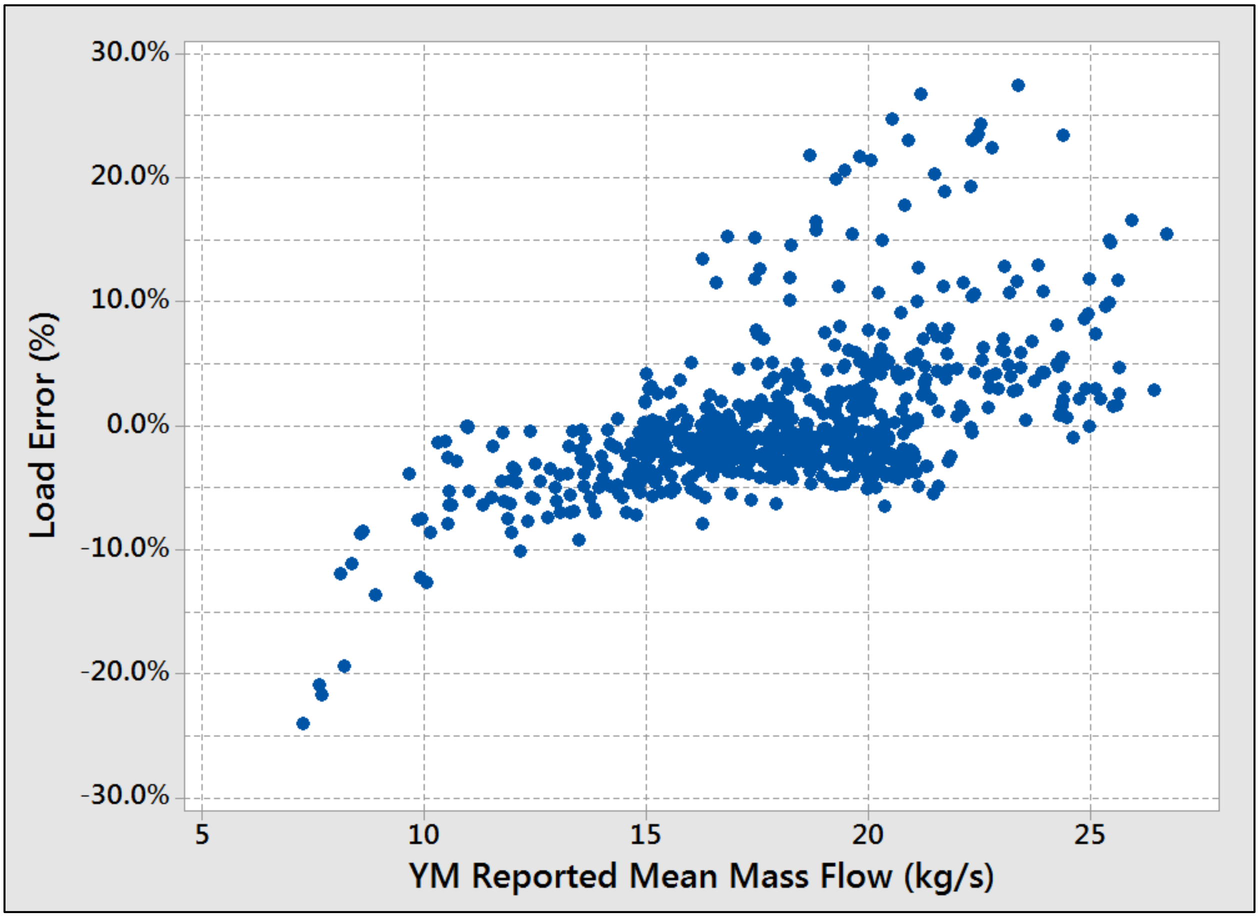

Figure 10: Load weight error versus average mass flow as reported by the yield monitor for the load period for seasonal evaluation.

Observations were made in relation to the calibration point flow rates and the accuracy of the specific flow ranges. The application of the calibration was unknown for a multipoint calibration, but focusing on specific regions, there was a distinct shift in mean error for a range based on flow rate and was already proven that flow rate influenced error for this study. This hypothesis observed if the error was possibly related to the calibration point flow rates. No conclusions could be drawn if the error by flow range was influenced by the calibration points specifically because of the unknown application method of the calibration, but it was distinctly observable that the flow rate ranges produced statistically different mean error (Figure 11).

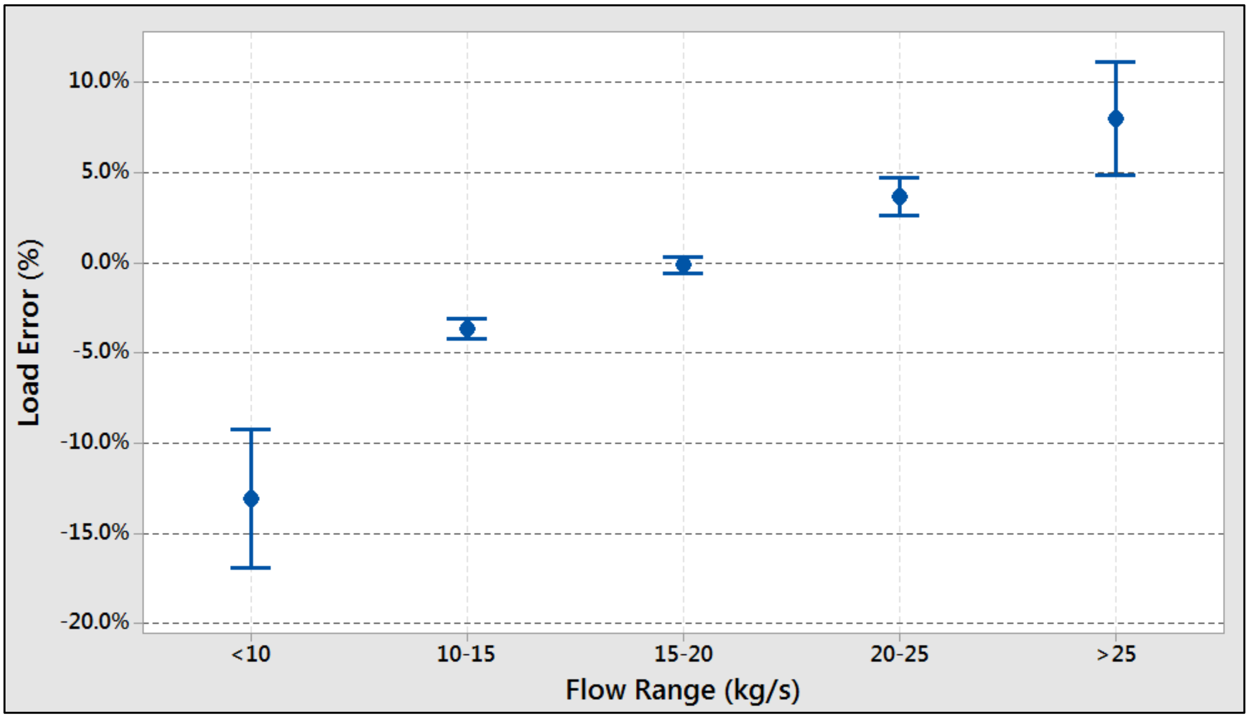

Figure 11: 95% Confidence interval for error by load mean flow rate binned by flow ranges.

Observing field mean errors for the season calibration harvester, Figure 12, there was a large difference from field A to the remainder of the harvest. When considering the overall field mean error was 0.4%, field A pulled the overall average high for the remainder of the season and produced a statistically different mean than the remaining fields. The final five fields produced an average of -2.5% error with little variation and the mean moisture content dropped below 20% where field A ranged from 19.5 to 25% moisture content. The overall performance of the yield monitor for the season was good considering the calibration was completed in field A and no adjustment to the calibration was made throughout the season.

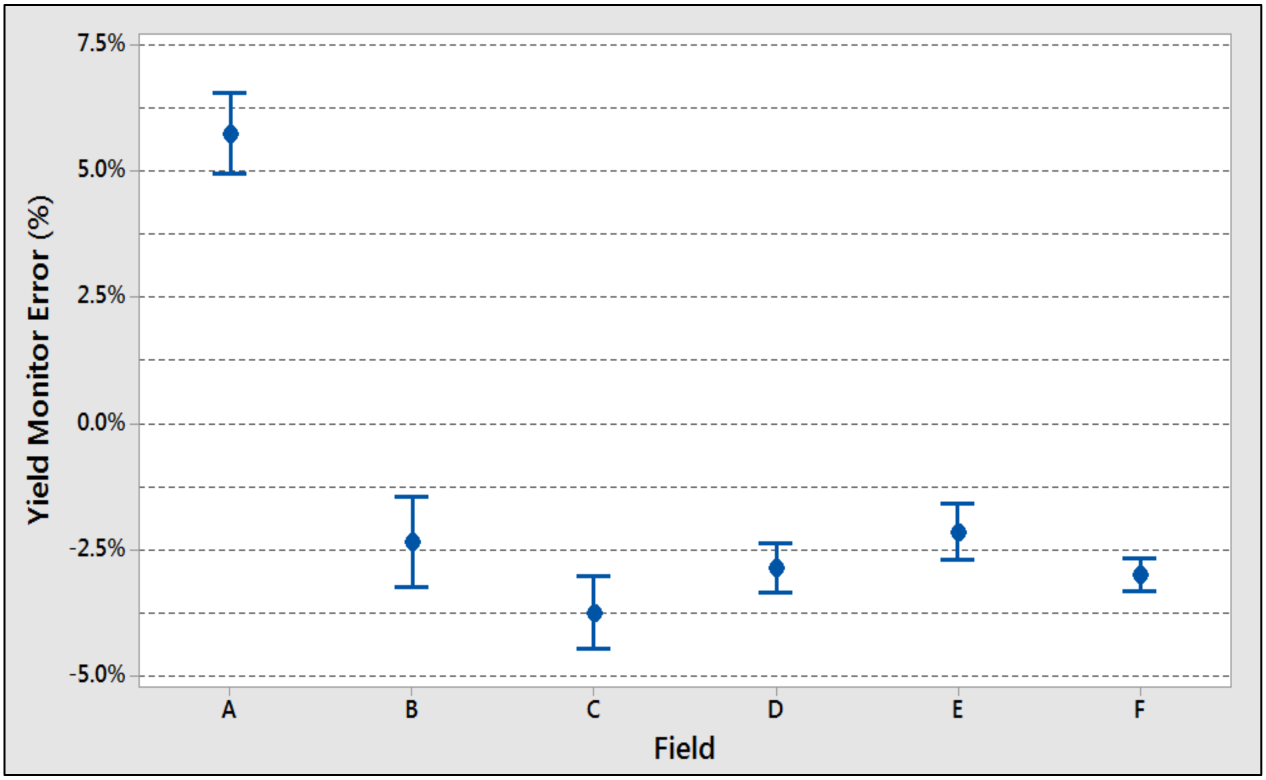

Figure 12: Confidence intervals (95%) on a field basis.

Considering the large shift in field error from field A to field B, the relationship between load weight error and moisture content were observed (Figure 13). This was an expected variation due to the changes in crop properties induced by moisture content. Also note that the error greater than 10% observed in the evaluation of error by mass flow rate (Figure 10), was associated with high moisture content observed in Figure 13. Below 20% moisture content there appears to be no significant variation or trend in error and that yield monitor performance was not influenced by moisture content in these ranges.

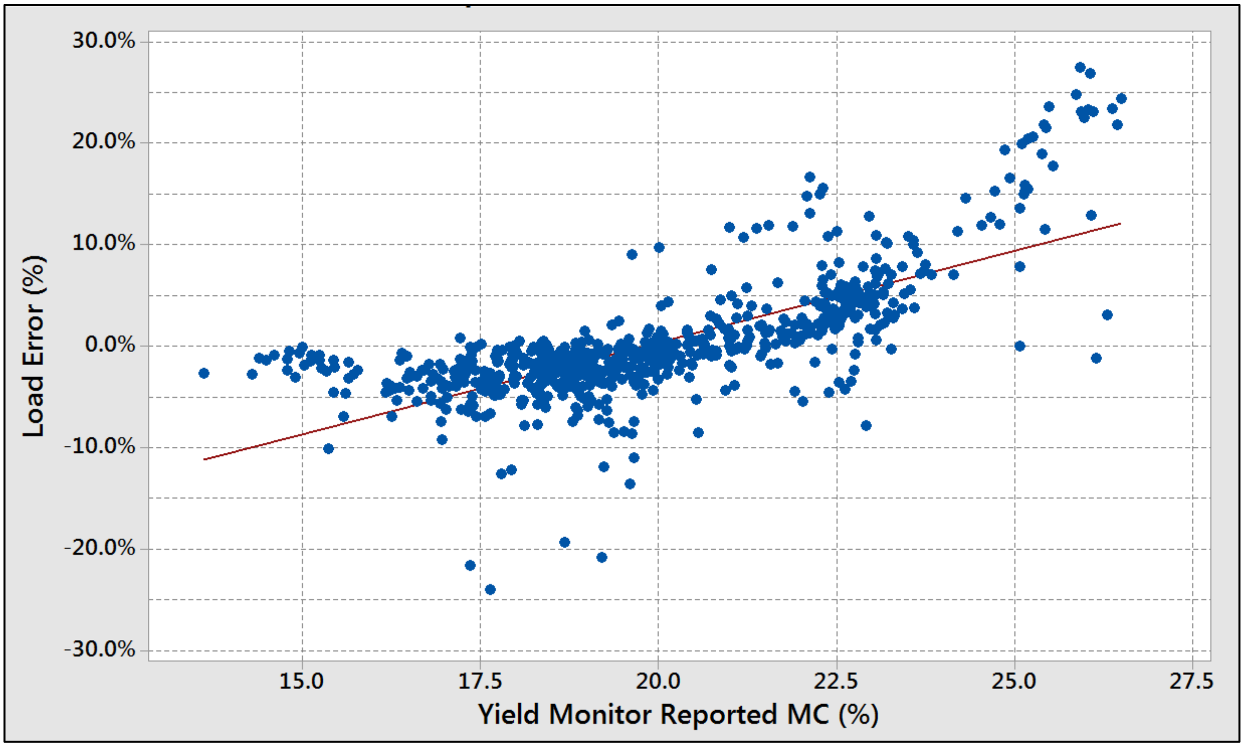

Figure 13: Load weight error versus yield monitor reported grain moisture for seasonal evaluation.

Binning the loads by moisture content ranges, loads with greater than 22.5% moisture produced a mean error greater than 7.5% (Figure 14). The mean error is less than 3.8% for loads with moisture content less than 22.5%. All ranges except for 15-17.5% and 17.5% to 20% were observed to be statistically different with the mean error ranging from -0.5 to -3.75% for loads with less than 20% moisture content. The level of difference is much smaller below 20% moisture content, but the ranges are still statistically different from each other. This supports existing literature on the influence of crop properties on the performance of the impact based yield monitor (Reinke, et al., 2011).

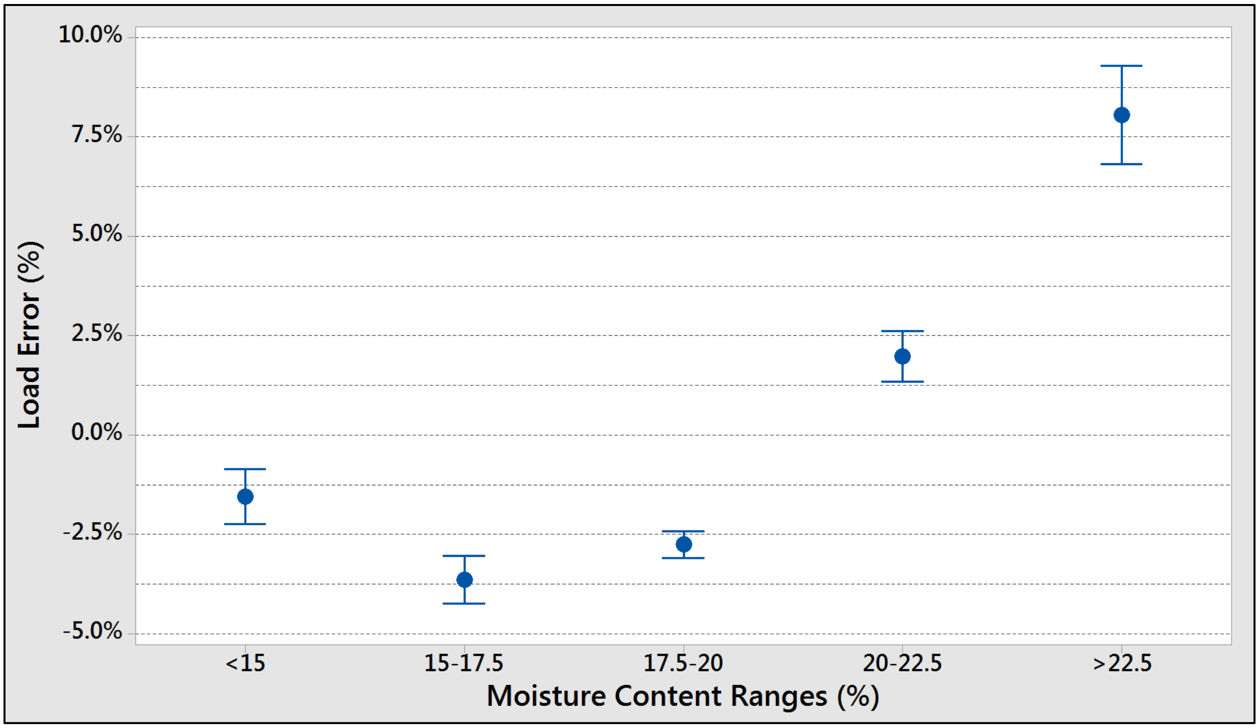

Figure 14: 95% Confidence interval for error binned by average yield monitor reported moisture content for the loads.

The season performance of the yield monitor for a one time calibration performed within expectations for an impact based yield monitor. The influence of mass flow rate on performance was larger than expected due to the range of flow rates encompassed by the calibration points. The effects of grain moisture agree with previous studies on the influence of crop properties and their interaction with the impact based mass flow sensor. This study encompassed a data sets of several magnitudes larger than previously reported in any yield monitor study and provides the most complete analysis of full season performance of a yield monitor.

Load size effects on load variation

The general hypothesis was that larger load weights reduce the variability of yield monitor reported load weights. The assumption was based on longer sustained flow rates reduce the transitional flow rates from entering and exiting crop that contribute to yield monitor error. Additionally longer sustained flow reduces random error associated with the yield monitor via central limit theorem.

Evaluating the variance by load size, a test for equal variances was completed to compare variances for load ranges (Table 9). Variances were found to be unequal between the 1-2 Mg versus 2-3 Mg and the 2-3 versus 5-6 Mg load size ranges. Standard deviations ranged from 2.6% to 3.6% with no statistically significant decrease in variance for the larger load sizes.

Table 9: Resulting p-values for equal variance test for load weight error by load size ranges (P <0.05 reject H_o of equal means)

		Load Size Range (Mg)								
		1 - 2	2 - 3	3 - 4	4 – 5	5 - 6	6 - 7	7 - 8	Std. Dev. Error	Load Count
Load Size Range (Mg)	1 - 2	-	0.01	0.70	0.31	0.18	0.41	0.53	3.1%	176
	2 - 3	-	-	0.01	0.73	0.00	0.41	0.78	2.6%	356
	3 - 4	-	-	-	0.23	0.34	0.29	0.44	3.2%	102
	4 - 5	-	-	-	-	0.07	0.78	0.96	2.7%	41
	5 - 6	-	-	-	-	-	0.08	0.21	3.6%	52
	6 - 7	-	-	-	-	-	-	0.88	2.8%	59
	7 - 8	-	-	-	-	-	-	-	2.7%	17

No reduction in variance was found for the data set observed by increasing load size. Previous studies indicated a reduction in the maximum errors for increased load size or harvested area from 5% to 3% harvesting wheat (Missotten, et al., 1996). Observing maximum errors, there is a decrease in the maximum errors produced from the smallest load sizes to the largest (Figure 15). However the reduction in a few maximum error points does not provide any statistical evidence that variation is reduced by increasing load size.

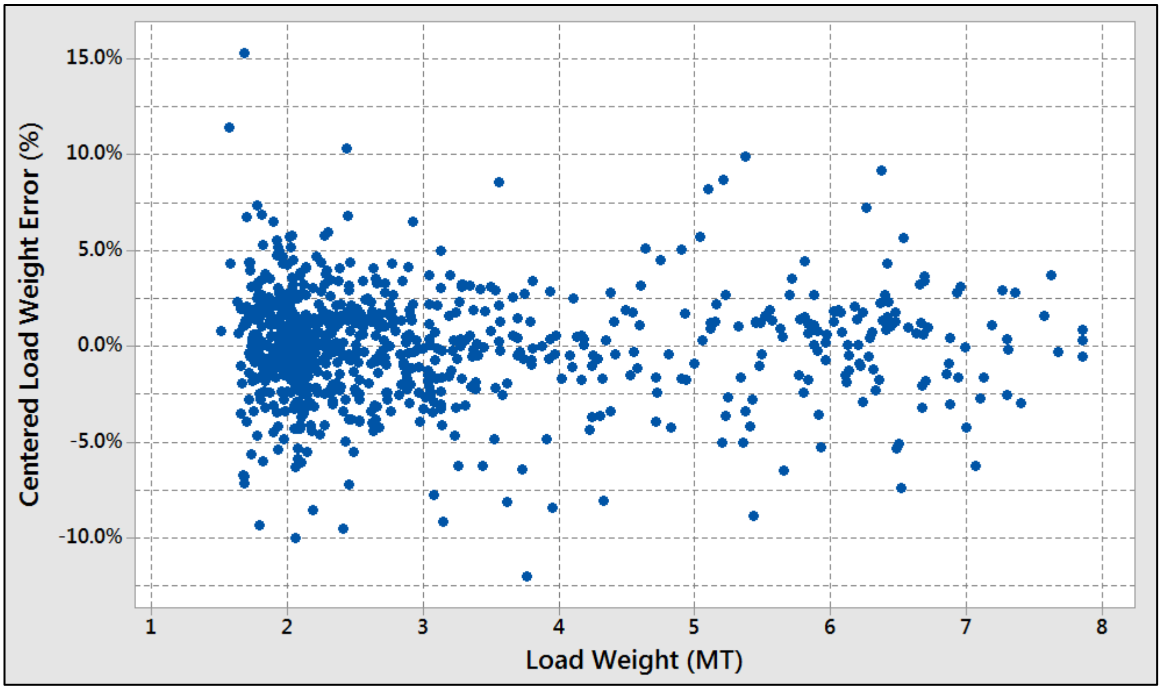

Figure 15: Individual load weight error with data set mean bias removed versus load weight size.

Conclusions

Variability in the accuracy of the impact based mass flow sensor was characterized on a real time and full load basis. The impact based flow sensor produced 3.8% mean standard deviation on a 1 Hz basis between data sets and 3.3% mean standard deviation for load weights by data set. The daily standard deviation of load weight error for full season evaluation was 3.5% in comparison to the individual field calibrations. The similarities in the variation indicate that an appropriate characterization for the impact based yield monitor was completed in this study.

Yield monitor mean error on a field level for accurately calibrated yield monitors can be expected to vary between ±5% error and ±2.5% error for 70% of calibrations based on results of this study. Recommendations for agronomic sized test plots were developed to define required yield differences for statistical confidence levels and it is recommended to use replicates if attempting to discern between smaller yield differences.

The full season long evaluation of the calibration confirmed that crop variation affects the impact based yield monitor accuracy. Performance did stabilize for grain moisture less than 20% in this study. The accuracy of the calibration was mass flow rate dependent, but no conclusions can be drawn about the quality of the calibration as its actual application to convert force measurement at the impact plate to mass flow is unknown. Operating in flow ranges at the fringe of the calibration ranges can be expected to reduce load weight accuracy, but a characterized level of variation can be expected within the defined calibration flow ranges.

CHAPTER 2: AUTOMATIC CALIBRATION SYSTEM FIELD PERFORMANCE

Abstract

The previously developed automatic calibration algorithm was successfully integrated with an impact based yield monitor in this research. The integrated system successfully calibrated the yield monitor and invoked central limit theorem with the resulting yield monitor accuracy reflecting the accuracy of the partial tank weight estimates. The automatic calibration yield monitor produced accuracies that were consistently better than a one-time multipoint manual calibration on full season performance analysis by producing lower mean error for over 75% of fields harvested. The season long calibrations exceeded the accuracy targets of ±3% for 50% of data sets for the S690 automatic calibration yield monitor, but failed for the S670. The S670 was determined to have a bias in the automatic calibration algorithm and updates for future field deployment were quantified.

Introduction

The operator calibrated impact based yield monitor performance was characterized in corn to expect field mean errors of ±2.5% for 70% of calibrations and ±5% overall for field level calibrated yield monitors. This produces a best case scenario for impact based yield monitor performance in corn as calibrations are specific for field conditions. Seasonal performance observed field mean errors ranging from 7.5% to -2.5% for a yield monitor with a one-time multipoint calibration. This range was increased from the field level calibration results and larger for seasonal calibrations that encompass larger crop moisture ranges or for harvesters that receive a single point calibration.

The automatic calibration algorithm developed in Chapter II was integrated into an impact based yield monitor for the 2015 field season. Additional support systems were integrated with the yield monitor and automatic calibration algorithm to support storage and management of the increased calibration points. Testing and evaluation was completed in corn with the focus of the research based on the following objectives:

- Determine the correlation of the automatic calibration yield monitor accuracy with the accuracy of the algorithm generated partial tank weights.
- Quantify performance of the automatic calibration algorithm integrated with the impact based yield monitor across field and seasonal performance.
- Determine sources of variation in the calibration algorithm based on estimation equation parameters

USDA crop yield reporting from a yield monitor requires the yield monitor to be calibrated and verified to within 3% accuracy in the field it is calibrated (USDA, 2016). The implementation of an automatic calibration system, the yield monitor calibration is continually updated as calibration points are created. Extending the USDA requirement, the target performance of the automatic calibration yield monitor was ±3% on a field level for a minimum of 50% of a seasonal harvest to provide a higher level of compliance with the USDA requirement. Additionally, full season mean error on total mass harvested should not exceed ±2.5% and field mean errors should remain bounded at ±5%. These were the specific target performance levels of the automatic calibration algorithm for the 2015 field season.

Materials and Methods

Implementation of automatic calibration algorithm with impact based yield monitor

The previous chapter described the development of the automatic calibration algorithm that produces a partial tank weight to calibrate the yield monitor. The algorithm was integrated with the current production impact based yield monitor embedded controller. The embedded hardware controlled CAN bus communication to provide needed signals to the algorithm and managed the storage of any calibration or buffered values that required long term memory through a power cycle of the controller (Figure 16). The automatic calibration algorithm was executed at 1 Hz in consistency with the development process.

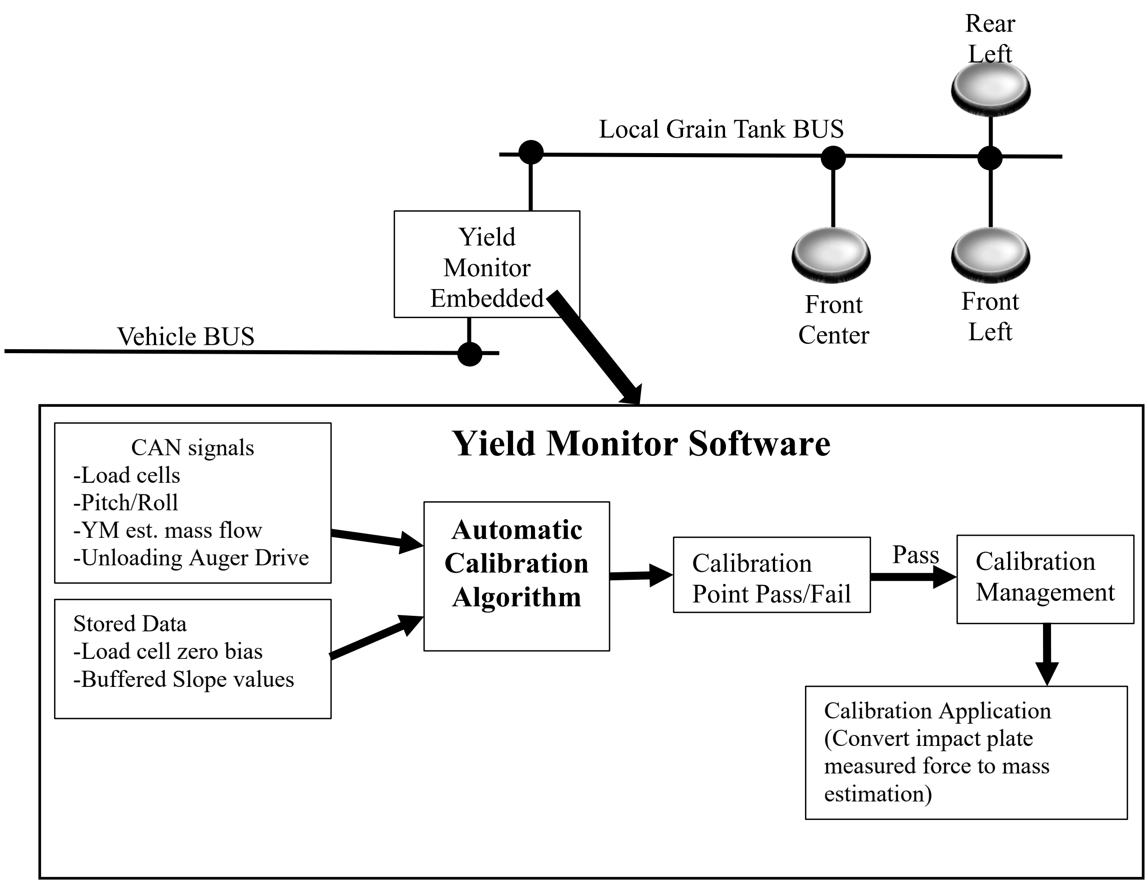

Figure 16: System diagram of the automatic calibration algorithm integrated with the production impact based yield monitor.

Integration required added communication between the calibration algorithm and the yield monitor software. A calibration status was provided from the automatic calibration algorithm with four states to indicate the current process to the yield monitor. This was required to indicate to the yield monitor when a calibration is occurring and when it was completed (Table 10).

Table 10: Calibration states used in process with the yield monitor and automatic calibration algorithm.

State	Calibration State Description
0	Not in a calibration mode, the grain tank is filled past the calibration ranges and needs emptied.
1	The grain tank has been emptied and the algorithm is ready to calibrate.
2	Calibration is active, a load cell has exceeded the required start threshold.
3	Calibration is complete, the automatic calibration algorithm estimates a mass flow rate and calculates a partial tank weight that is passed to the yield monitor software.

The calibration process began with an empty grain tank and progressed through the states as criteria was met based on the level of the load cell responses (Figure 17). State 1, determined by the load cell responses being lower than a predetermined threshold that define an empty grain tank, was completed when the front left or rear left load cells reached the start threshold. This transitioned the calibration state to 2 and remained in this state until the front center load cell response reached the defined stop threshold. During state 2, the automatic calibration algorithm buffered load cell, pitch, roll, and yield monitor reported mass flow data. Simultaneously, the impact based yield monitor operated in calibration mode buffering force sensor data required for creating the relationship of grain mass to measured force. At the transition from state 2 to state 3, the buffered data was processed by the automatic calibration algorithm described in Chapter 2 and a resulting partial tank weight estimated. Rejection criteria for the calibration load was also assessed at this time to determine if a partial tank weight was potentially inaccurate and was rejected if specific criteria was not met. Upon passing, the partial tank weight was transferred to the calibration management system and was applied to the yield monitor calibration

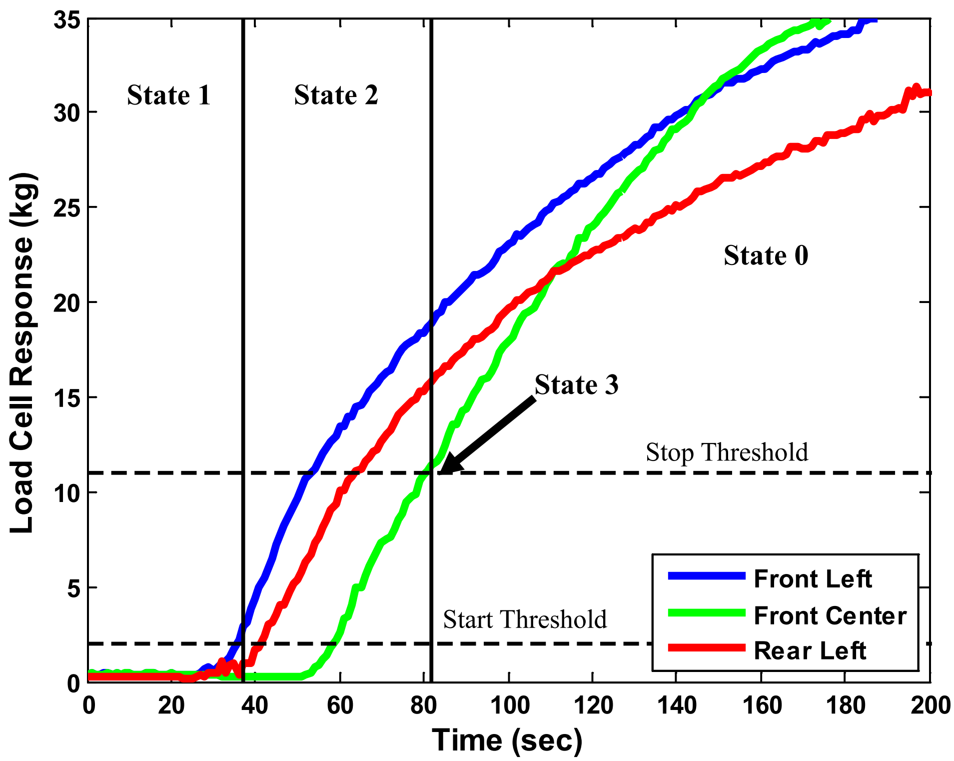

Figure 17: Calibration process described as load cells respond with state definition

Description of calibration management system

Multi-point manual calibrations generally consist of four calibration points completed at different flow rates to best characterize the operational grain mass flow range for the specific harvester and crop conditions. Manual calibrations are completed with a ground truth that has a low expected error and variability. The automatic calibration algorithm increased the ground truth load weight variability with their replacement by the partial tank weight estimations. The expectation as characterized in Chapter 2, was that the partial tank weight on a field level would a mean error with a standard deviation of approximately 5%. This required multiple calibration points per designated flow range and relied on central limit theorem to produce a yield monitor calibration that is representative of the automatic calibration algorithm mean error.

Combatting the increased variability and the potential of a new calibration point for each fill of the grain tank, a proprietary calibration management system was developed and implemented by the yield monitor manufacturer. The description of the system remains in general terms due to the proprietary nature of the system, but an understanding of its generic operation is further described to understand its potential impact on the merging of the automatic calibration algorithm and the yield monitor.

The primary goal of the system was to provide a calibration point buffering system to accurately calibrate the yield monitor through averaging multiple calibration points while maintaining an accurate calibration across a wide range of flow rates. Five flow rate ranges were determined based on the potential capacity of a harvester for a given crop with the capability to store up to a total of 50 calibration points with individual limits set for each flow range. The management system operated the flow ranges as first-in-first-out (FIFO) buffers. A feature was added that detected shifts in the calibration and removed calibration points from the buffers that were determined to be inaccurate to the current relationship of measured force at the impact plate to grain mass flow rate. The process of removing calibration loads from a flow range buffer of the calibration management system is referred to as a flushing event. This example occurred entering a new field and the flushing operation can be observed for flow ranges 3 and 4 at load three where a large number of the loads were flushed from the flow range buffers. The flow range buffers can be observed refilling with calibration points post the flushing event.

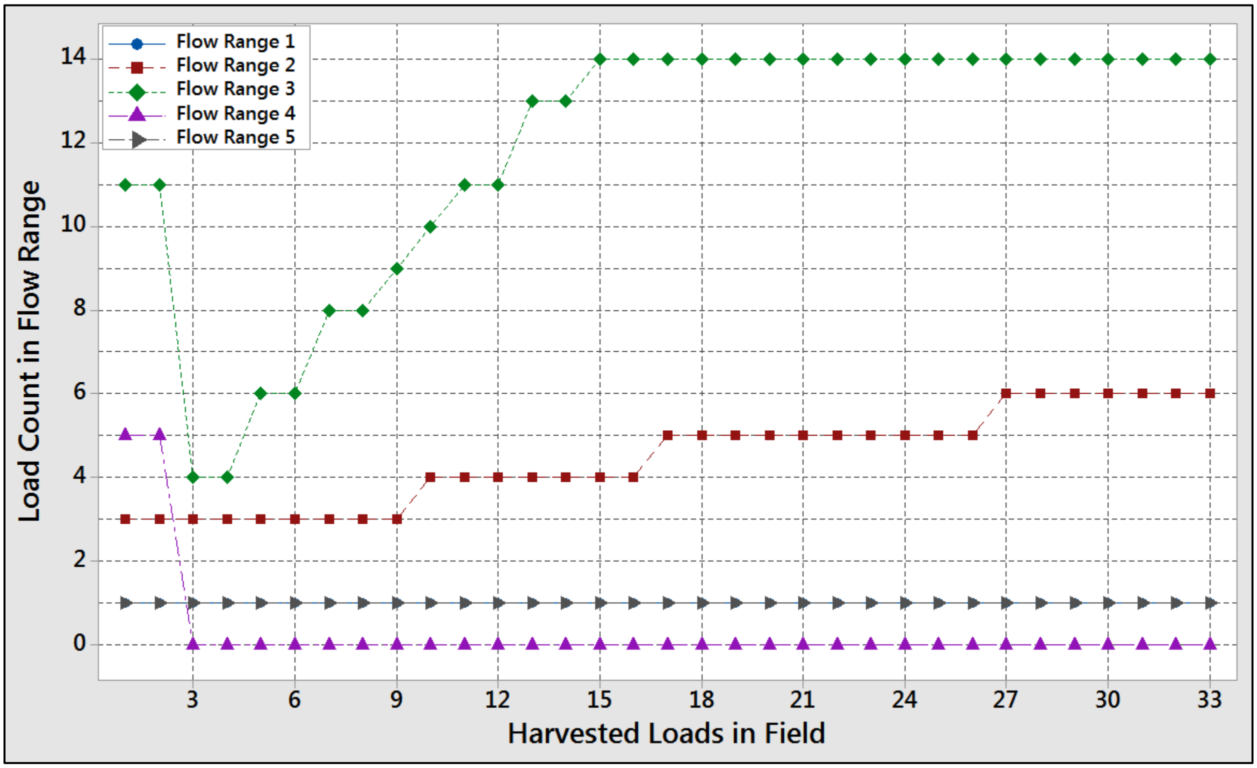

Figure 18: Example of calibration management operation for single field harvesting

This was typical operation of the calibration management system when a change in the relationship of measured force by the impact sensor to the mass flow rate was detected. Once a specific flow range was filled to its capacity with calibration points, the range acted as a FIFO as observed for most loads after load 15 for flow range 3 (Figure 18). Investigation into the performance of the calibration management is out of scope due to its proprietary nature, but was considered in the evaluation to understand shifts in performance in long term data sets.

Methodology for dynamic in-field yield monitor error analysis

Testing the developed automatic calibration yield monitor began in 2015 following the algorithm development from the 2013 and 2014 field data sets discussed in Chapter 2. Data was collected for S690 and S670 grain tank configurations for the 2015 field season by Iowa State University and the project sponsor collaborating field teams. Focus of the data collection and verification work occurred for both the S690 and S670 automatic calibration yield monitors in corn harvest. Over 5,040 Mg (198,000 bushels) of corn were harvested for the S690 configuration on seven different harvesters and 2,700 Mg (106,000 bushels) of corn were harvested for the S670 configuration on four harvesters (Table 11).

Table 11: 2015 summarized harvest totals for S690 and S670 grain tank configurations

Machine ID	Automatic Calibration Algorithm	Load Count	Grain Harvested (Mg (bushels))	Manual Calibration Frequency	Mass Flow Rate (kg/s)	
					Mean	Std. Dev.
S690-B	S690	721	4,070.6 (160,252)	Season	19.9	3.9
S690-F	S690	52	188.3 (7,414)	Field	18.8	4.8
S690-G	S690	56	112.8 (4,440)	Field	14.2	3.4
S690-H	S690	56	117. (4,607)	Field	14.3	3.7
S690-I	S690	14	154.8 (6,095)	Field	26.6	4.8
S690-J	S690	17	177.9 (7,004)	Field	30.0	4.4
S690-K	S690	33	164.9 (6,491)	Field	18.2	2.7
S670-A	S670	347	1,857.1 (73,110)	Season	16.9	4.3
S670-B	S670	103	386. (15,196)	Field	22.0	5.6
S670-G	S670	84	390.8 (15,386)	Field	18.2	3.1
S670-H	S670	30	113.3 (4,460)	Field	18.2	3.1

Larger volumes of data were produced from S690-B and S670-A as these machines were located at Iowa State University and also produced more season long evaluations of the automatic calibration algorithm. Machine naming is matched with Chapter 2 to provide context from season to season. Data from harvesters S690-B, S670-A, and S670-B pre-2015 were used for model training for their respective automatic calibration algorithm. Described in Chapter 2, the same process for field data collection and production of a calibrated 1 Hz mass flow signal by the yield monitor manufacturer were employed for the 2015 harvest season.

The machines were equipped to operate both the automatic calibration algorithm and an operator produced manual calibration, producing parallel mass estimates from each calibration method. A minimum of a four point calibration was completed on all harvesters with the frequency of calibrations listed in Table 11. Season calibration indicates the harvester was manually calibrated once for the corn harvest season with a one-time multi-point calibration. Field calibration indicates the harvester was calibrated with a multi-point calibration for the respective data set.

The automatic calibration yield monitor operated continuously and no modifications were made throughout the season to the algorithm or the calibration management buffers. This induced some variability in the results of the automatic calibration yield monitor for field level manual calibration comparisons as the calibration buffers in many cases were comprised of multiple days of calibration points. This occasionally resulted in the automatic calibration being adjusted during collection of a data set as flushing events occurred to update the automatic calibration yield monitor for the specific crop conditions. The actual adjustment of the calibration cannot be quantified as the direct application is proprietary to the yield monitor manufacturer. The change in number of calibration points can be observed through diagnostics to indicate a shift occurred and the resulting shift in produced yield monitor error, but conclusions about the calibration accuracy changes can only be generalized.

The distributions of mean mass flow rate of data replicates were similar for the S690 and S670 field testing with means of 18.5 and 19.4 kg/s for the S670 and S690 grain tank configurations respectively (Figure 19). The S670 distribution was slightly larger with a 0.5 kg/s larger standard deviation, but overall produced similar distributions of flow rate. The expectation was that the S690 grain tank machines would produce higher flow rates due to the larger throughput capability.

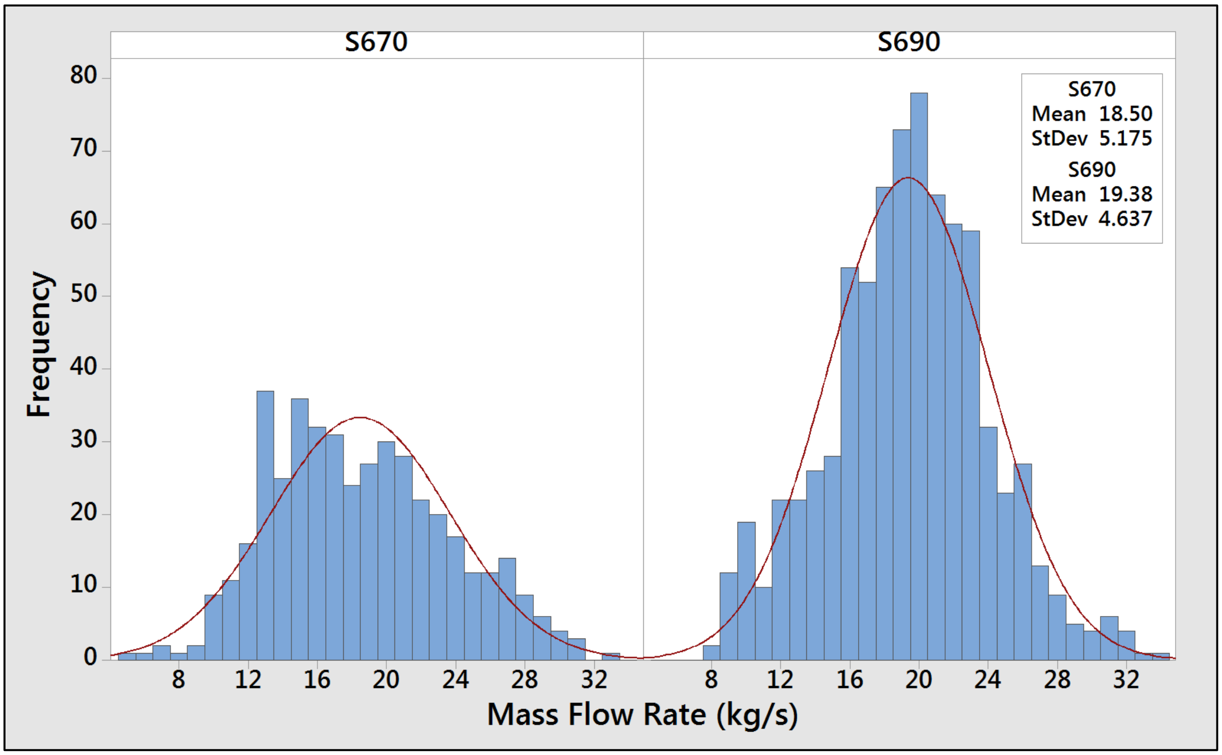

Figure 19: Mean mass flow rate from calibrated mass flow for individual loads collected during the 2015 harvest season in corn.

The S690 configured harvesters were exposed to a higher range of moisture versus the S670, observing a mean of 14.6% yield monitor reported moisture for the S670 and 19.7% for the S690 automatic calibration yield monitors. Several of the S690 harvesters began data collection earlier in the harvest season, gaining exposure to higher moisture corn. This provided a strong evaluation data set for the S690 with exposure to a wider range of crop variation that may not have been well represented in the data sets used to develop the automatic calibration algorithm.

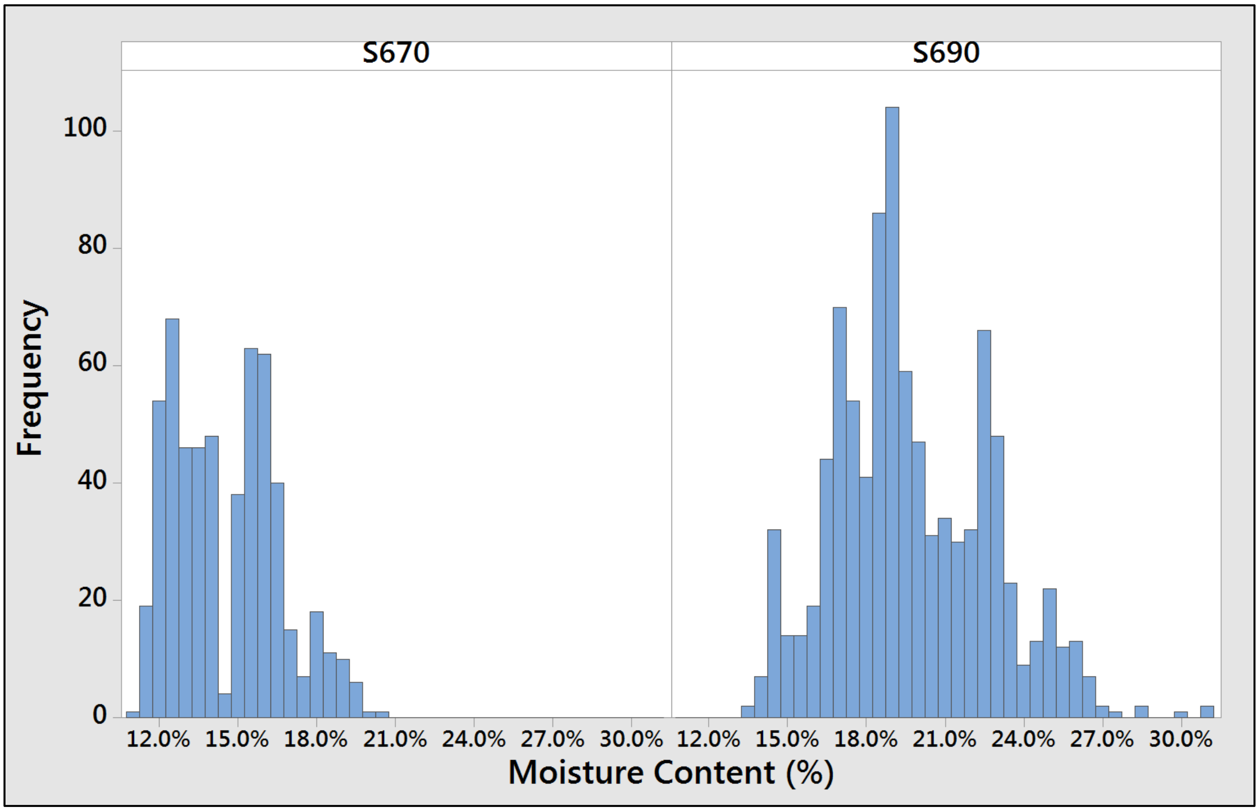

Figure 20: Yield monitor reported mean moisture content for individual loads collected during the 2015 harvest season in corn.

Dynamics experienced during the calibration period of the automatic calibration algorithm present potential influence on the accuracy of the partial tank weights. Assessment of the produced partial tank weight by the automatic calibration algorithm and complete yield monitor in correlation with the dynamic effects of pitch and roll are out of scope for this research. There are potential effects of pitch and roll on the performance of the impact based mass flow sensor that are not quantified in relation to their effects and the potentially induced errors cannot be decoupled from the automatic calibration algorithm based on the data available in this study. The automatic calibration yield monitor was exposed to a range of pitch and roll during the calibration process at ±4° of roll and ±2.5° of pitch (Figure 21). Both grain tank configurations were exposed to similar variations in pitch and roll.

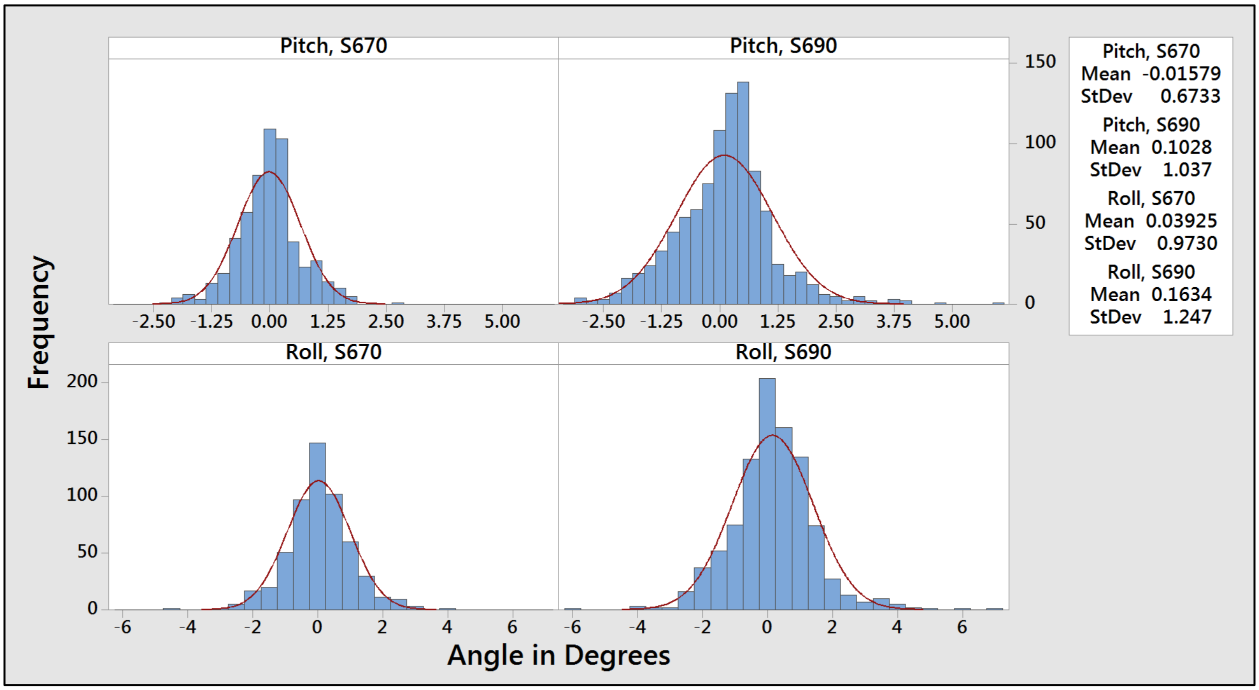

Figure 21: Average pitch and roll experienced during automatic calibration period for individual calibration loads.

Rejection of partial tank weights

Part of the integration process of the automatic calibration algorithm into the yield monitor was the implementation of a decision support system to reject a partial tank weight if there was a potential large error in partial tank weight estimation. Specific pass or fail criteria was defined in Table 12 with three forms of requirements to accept a partial tank weight to the yield monitor calibration. A poor estimation value by the calibration algorithm of the mean mass flow rate resulted in a failed calibration and was bounded by the requirement of estimating a positive flow rate and a maximum allowable flow rate of 60 kg/s. The maximum flow rate bound was based on a maximum potential flow rate capacity of the largest class of harvester. Pile formation was expected to start on the left side of the grain tank and continue to the right, in the case that the front center load cell exceeded the calibration start threshold before the front left and front right load cells, the calibration was failed. This was assumed that the grain pile was forming uncharacteristically and accurate estimations about mass flow rate cannot be made. The last algorithm specific failure case was a bounding of the calibration to 400 seconds. This was specified based on flow rates theoretically being greater than 3 kg/s as average partial tank weights are 1,200 kg. Additionally the embedded hardware was bounded by memory capacity limiting calibration buffer sizes to support robust algorithm operation.

Table 12: Specific exit criteria to fail adding automatic calibration algorithm generated partial tank weights to the yield monitor calibration

Category	Description	Physical Bounds
Algorithm Failure Criteria	Mass flow estimation out of range	0-60 kg/s
	Front center load cell responds before front or rear left load cells	NA
	Calibration time exceeds 400 seconds	400 seconds
Machine Dynamics	Mean Pitch	±3°
	Mean Roll	±2°
	Pitch Standard Deviation	1.6°
	Roll Standard Deviation	1.6°
Mass Flow Variability	Standard deviation as a fraction of the mean mass flow reported by the yield monitor	0.7
Manual override	Engagement of the unloading auger during a calibration.	NA

The mean pitch, mean roll, standard deviation of pitch and roll are calculated over the calibration period of the automatic calibration algorithm. The bounds were determined based on reducing the variability in partial tank weight estimates that are added to the yield monitor calibration. The determination of the bounds was out of scope for this research and serve as specification to acceptable calibration points.

Engagement of the unloading auger caused an exit of the calibration process and no partial tank weight was estimated. Engagement of the unloading auger removes grain from the grain tank and interferes with the characteristic pile formation in the grain tank. This interruption in the calibration process cannot be accounted for and resulted in immediate failure of the calibration load.

Results and Discussion

Automatic calibration algorithm performance for 2015 field season

Manually calibrating the yield monitor, ground truth for the calibration was produced by a grain cart. The accuracy of the grain cart weight was generally treated as absolute. Chapter 1 characterized the accuracy of the impact based yield monitor when calibrated on a field level. The yield monitors were calibrated and evaluated with the same grain carts removing potential bias from the evaluation. Despite the ideal calibration, the yield monitors produced a range of field level mean error. This implied that the resulting yield monitor produced error was a function of the applied calibration and the inherent variability of the impact based mass flow sensor. The implementation of the automatic calibration algorithm introduced a new potential error source within the yield monitor calibration as the calibration weights now had level of variability and potential bias in comparison to a grain cart. Grain carts additionally have variability, but appear to have less than half the variability of the automatic calibration generated partial tank weights.

Observations were made on the accuracy of the automatic calibration algorithm to estimate the mean mass flow rate of the calibration period. Application of the regression algorithm developed in Chapter 2 to the 2015 harvest data produced a range of errors within ±5% for a harvester's specific mean error except S690-F (Figure 22). S690-F mean error of the mass flow estimates was approximately -10% and was beyond the expected bounds of mean mass flow error. Initial observations, only S690-B was part of the training data set for the calibration algorithm in Chapter 2, this indicates that the algorithm is transferable across harvesters with the same grain tank configuration.

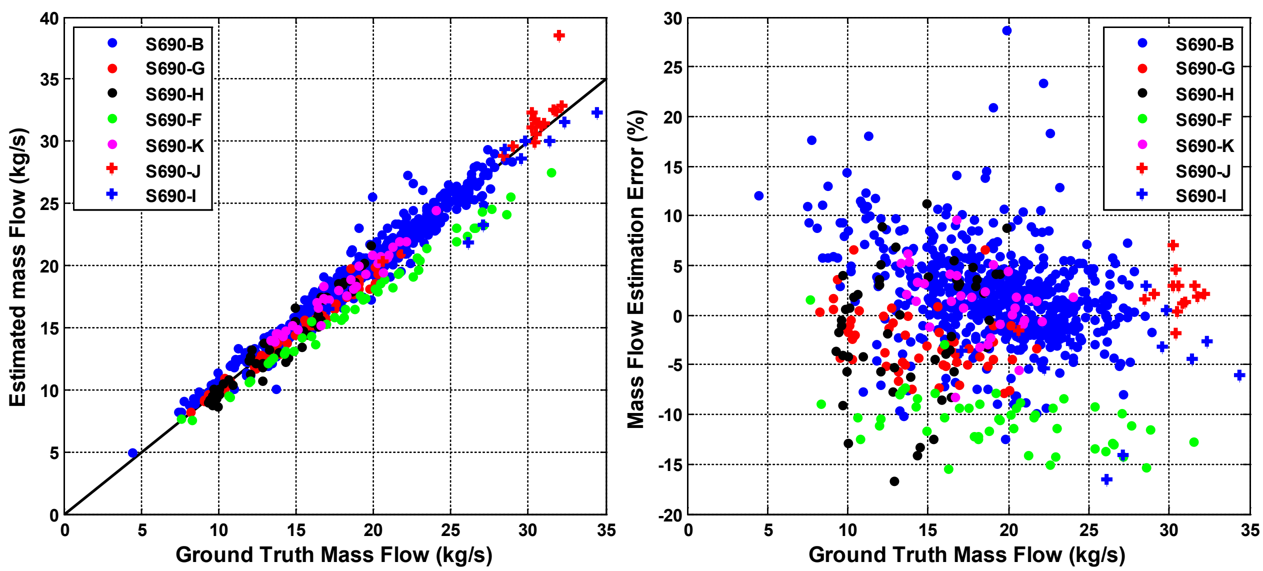

Figure 22: Field performance of the automatic calibration algorithm to estimate mass flow rate for the calibration period. Fall 2015 corn harvest for the S690 grain harvest.

Performance of the S670 automatic calibration algorithm in corn exhibited a general positive mean error for all machines (Figure 23). S670-A appeared to produce distinctly different results from the other three tested S670 harvesters. S670-A was the largest contributor to the calibration algorithm training model and appears to have biased performance of the mean mass flow rate estimations. The automatic calibration algorithm successfully estimated mean mass flow rates for harvesters outside of the development data set, observing harvesters S670-F and S670-G.

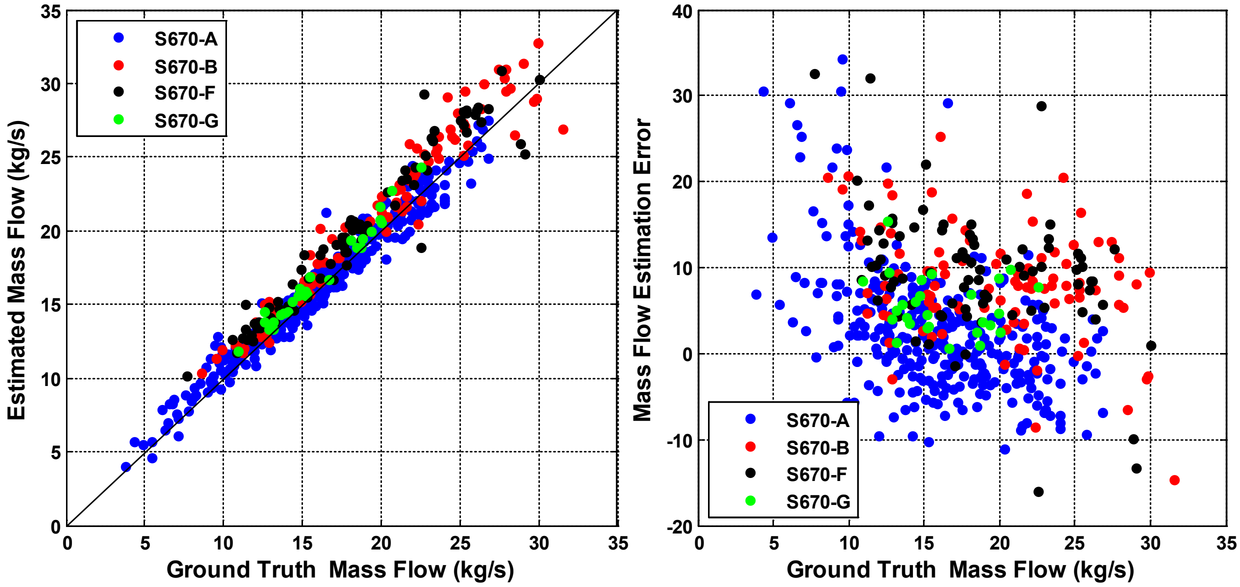

Figure 23: Field performance of the automatic calibration algorithm to estimate mean mass flow rate for the calibration period. Fall 2015 corn harvest for the S670 grain harvest.

The season mean produced partial tank weight error resulted with all S690's except for S690-F and S690-I were within ±3% (Table 13). S690-I was a single data set with limited samples reducing its significance in assessing a larger span of performance. Large standard deviations were observed for S690 harvesters F, I, and J. S690-I and S690-J were both based on single data sets and were exposed to variable flow rates during calibrations contributing to a wider range of error with S690-J maintaining an acceptable mean error. The S670 configurations produced consistent standard deviations of error with S670-A producing the best results based on mean partial tank weight error. This is expected with the largest portion of the S670 algorithm training data produced by S670-A.

Table 13: Automatic calibration algorithm partial tank weight produced error by machine for the 2015 harvest season in corn.

Machine ID	Automatic Calibration Algorithm	Partial Tank Weight Error		Calibration Loads
		Mean	Std. Dev.	
S690-B	S690	2.2%	4.3%	564
S690-F	S690	-6.2%	8.9%	59
S690-G	S690	-2.8%	2.8%	49
S690-H	S690	0.4%	5.1%	42
S690-I	S690	-6.1%	9.1%	9
S690-J	S690	0.8%	10.6%	14
S690-K	S690	1.3%	3.7%	32
S670-A	S670	1.3%	5.2%	268
S670-B	S670	7.8%	5.9%	79
S670-F	S670	7.8%	6.6%	66
S670-G	S670	1.8%	2.9%	20

Error by data set was tared by the mean error for the data set and grouped by flow rate bins to observe the effects of mass flow rate on the accuracy of the algorithm removing data set bias (Figure 24). As observed in Chapter 2 in the development of the algorithm, the field performance exhibited non-linearity in estimating the mass flow rate with higher errors at lower flow rates. This was true for both the S670 and S690 grain tank configurations for the 2015 field season, indicating that there is a fundamental change in the grain pile formation process or in the force distribution within a grain pile caused by flow rate.

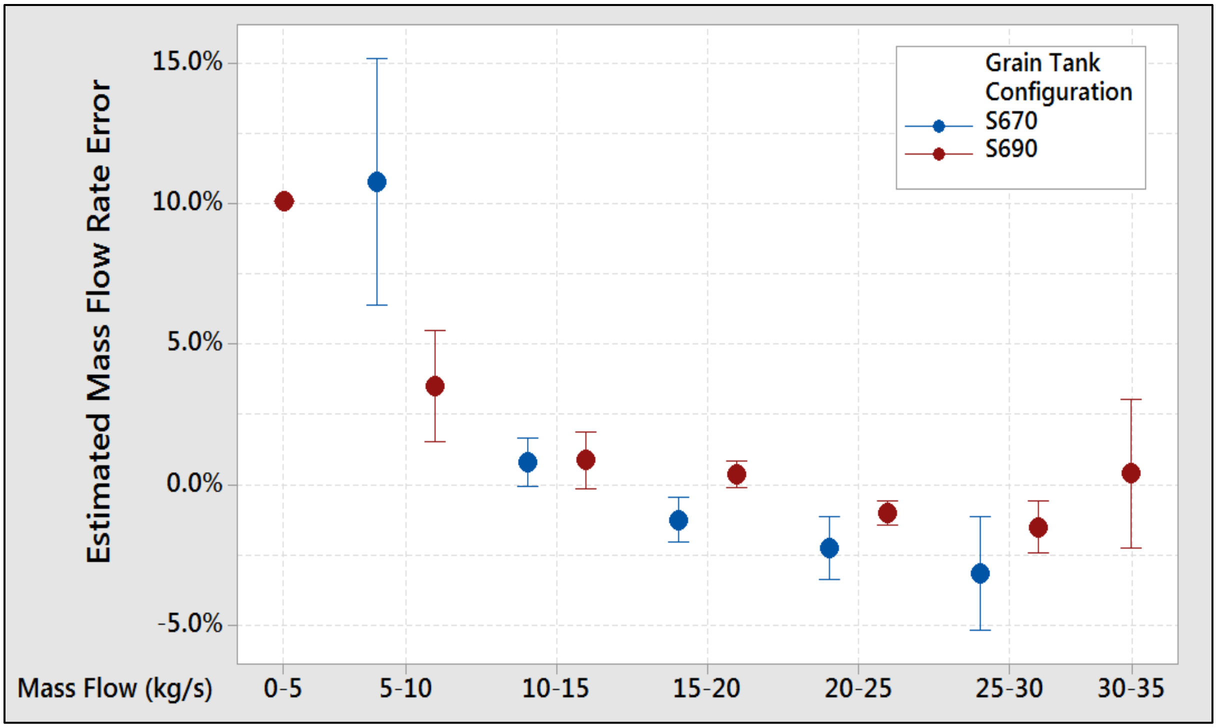

Figure 24: Performance of the automatic calibration algorithm to linearize mass flow rate for both grain tank configurations.

The accuracy of the partial tank weight system was evaluated across flow ranges for data set level produced mean error. The hypothesis was that the data set mean error of the complete automatic calibration yield monitor and the automatic calibration partial tank weights were statistically equal on a 95% confidence level. This hypothesis was used in the development of the automatic calibration algorithm to estimate the field performance and determine if performance of the algorithm was acceptable. The calibration management system adds an additional layer of complexity between the partial tank weight estimates and the resulting yield monitor output. The unknown yield monitor application process and calibration point retention of the calibration management system when a calibration flush occurs created additional concern about the resulting automatic calibration yield monitor to track the performance of the calibration algorithm. This assessment focused on determining the differential in error produced by the partial tank weights and the yield monitor to determine if there was a statistical difference.

The hypothesis of equal means was tested by applying a t-test with 95% confidence level to each data set comparing the produced distribution of error of the partial tank weight estimations of the calibration algorithm and the resulting yield monitor produced load weight error. Data sets with less than 20 loads were excluded from the analysis to ensure that the calibration management system had opportunity to appropriately adjust the calibration with no restrictions based on the flushing of calibration loads from the calibration buffer. The null hypothesis of equal means was rejected for 28% of data sets in the evaluation. This resulted in a 72% acceptance rate of equal means and was acceptable considering the potential error variation produced by the yield monitor that was characterized in Chapter 1. Under ideal circumstances with individual data set calibrations, the yield monitor still produced mean errors in the ±5% error range for data set level yield monitor calibrations. Observing the differential between mean error of the partial tank weight estimates and the yield monitor load weights on a data set basis indicated a similar level of variation reported in Chapter 1 (Figure 25). Over 80% of data sets observed a differential error between the partial tank weights and the yield monitor load weights of ±2.5% and correlated with previous results.

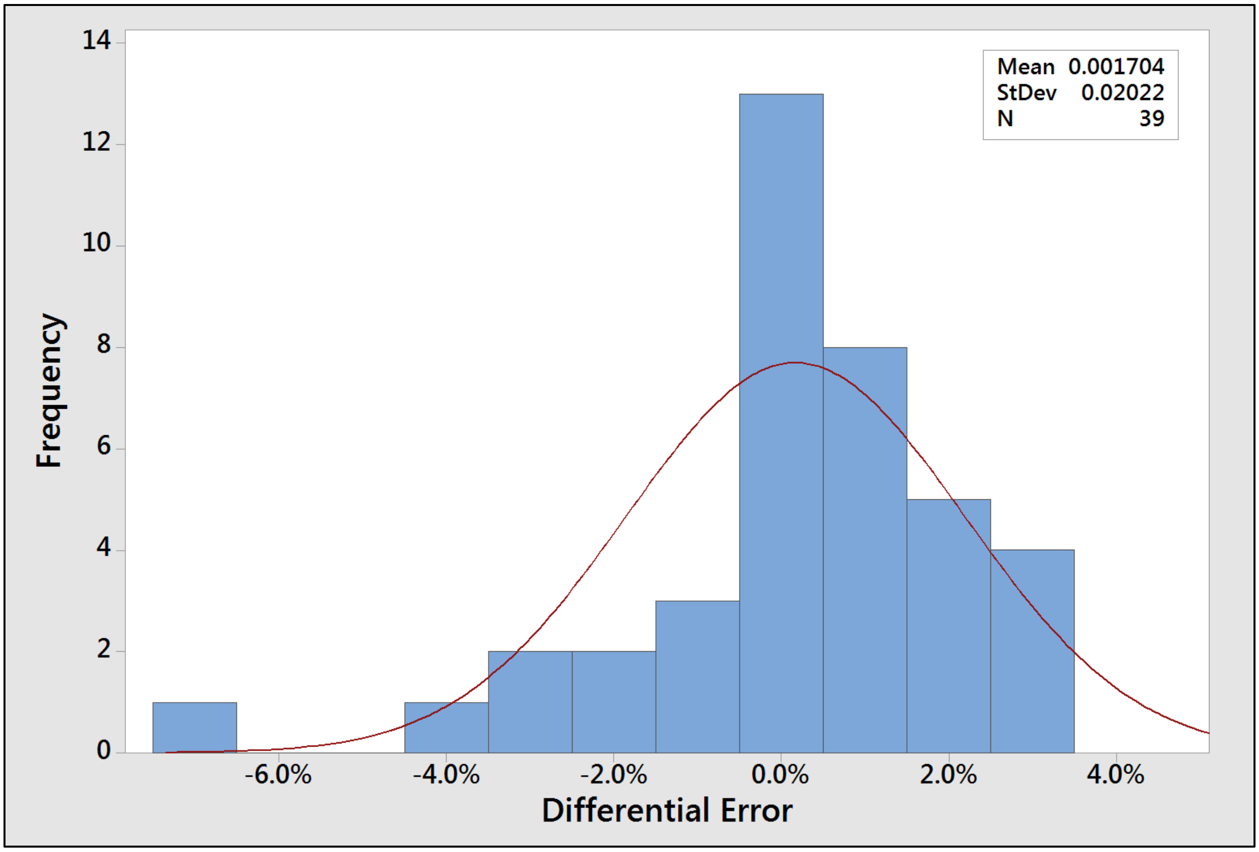

Figure 25: Distribution of the differential automatic calibration mean mass flow rate error and the mean automatic calibration yield monitor load weight error by data set

This evaluation concluded that the calibration management system was effectively invoking central limit theorem to produce a yield monitor calibration that was representative of the partial tank weights produced by the automatic calibration algorithm. The range of differential errors between partial tank weights and the automatic calibration yield monitor was in agreement previous evaluations of ideally calibrated yield monitors (Figure 7 vs Figure 25).

Performance of field level manual calibrations versus automatic calibration

Evaluation of the yield monitor as calibrated manually and by the automatic calibration algorithm was completed in parallel for the 2015 test season. Field testing was completed with

11 machines with two machines receiving a seasonal level manual calibration of the yield monitor for corn. The remaining machines received data set level calibrations and are considered best case scenario for yield monitor performance. This evaluation focuses on the performance of the yield monitors calibrated by the automatic calibration algorithm in comparison to the manually calibrated. Evaluations were completed on the data set mean error of load weights produced by both calibration methods.

Field level multi-point manual calibrations produce a best case scenario for manually calibrated yield monitors as determined in Chapter 1. Expected field mean errors range from ±5% to ±2.5% for 70% of calibrations. The automatic calibration system was not expected to achieve the same level of accuracy and was hypothesized based on the resulting data set mean error produced by the partial tank weight estimations when the verification data sets were evaluated from the development of the automatic calibration algorithm at the end of Chapter 2.

The mean error by data set of the manual calibrated and automatic calibration yield monitors was compared testing the null hypothesis of equal mean errors using a t-test at the 95% confidence level. The manual calibration yield monitor produced statistically equal or more accurate mean error than the automatic calibration yield monitor (Table 14). This was an expected result as the manual calibration was specific for field conditions and was calibrated using the grain cart or scale system that served as the ground truth.

Table 14: Field level calibration comparison and performance of manual and automatic calibration algorithm (shaded indicates equal means, 95% CI).

Machine ID	Site ID	Total Loads	Mean Error		Mean Mass Flow (kg/s)	Std. Dev Mass Flow (kg/s)	Mean Moisture Content
			Auto	Manual			
S690-F	102	8	-9.90%	-5.90%	15.9	3.8	15.0%
S690-F	103	24	-8.70%	-9.60%	20.2	4.6	16.7%
S690-F	104	20	-10.20%	-10.00%	20.6	6.4	16.3%
S690-G	19	28	-6.60%	4.00%	15.2	3.7	19.1%
S690-G	20	28	-2.20%	1.30%	14.1	3.5	41.9%
S690-H	21	28	2.60%	0.20%	14.3	3.6	17.0%
S690-H	22	28	-4.10%	0.50%	13.9	3.3	16.9%
S690-I	73	14	-0.90%	-1.10%	28.6	3.8	26.0%
S690-J	74	17	1.00%	-0.70%	30.6	1.0	24.8%
S690-K	106	33	-0.40%	-1.70%	18.0	2.9	14.4%
S670-B	68	29	8.80%	-0.20%	17.3	4.6	18.8%
S670-B	83	22	10.90%	-0.10%	21.3	4.0	14.0%
S670-B	88	56	3.40%	-0.40%	21.0	5.3	13.6%
S670-F	93	28	9.70%	2.60%	17.1	3.8	17.8%
S670-F	95	52	6.40%	1.20%	22.6	5.5	15.4%
S670-G	71	30	5.10%	-0.80%	17.4	2.8	15.9%

Considering the USDA crop reporting requirements of ±3% on a field level for the field the calibration was completed (USDA, 2016), combined with the desire to meet the requirement for 50% of fields, the automatic calibration yield monitor exhibited a 50% success rate for the S690 algorithm and no success for the S670 algorithm. Comparing to the manual calibration, there was only a 10% increase in success rate among the S690 harvesters, but a 100% success rate for the S670 harvesters.

A win/loss comparison was made between the manual calibration and automatic calibration yield monitors by the differential of the absolute mean data set error of the respective calibration methods. The results provides an indication of the winning calibration, positive result indicates the automatic calibration was better, and the magnitude of the win. The S690 automatic calibration won 30% of comparisons and lost 30% others by less than 1% error magnitude (Figure 26). Maximum losses for the S690 occurred with 4% differential error to the manual calibration. The S670 automatically calibrated yield monitor lost all comparisons to the manual calibration with a minimum loss of 3% and a maximum loss of 11% (Figure 27). The spread of differential error of the S670 is double that produced by the S690 calibration comparisons.

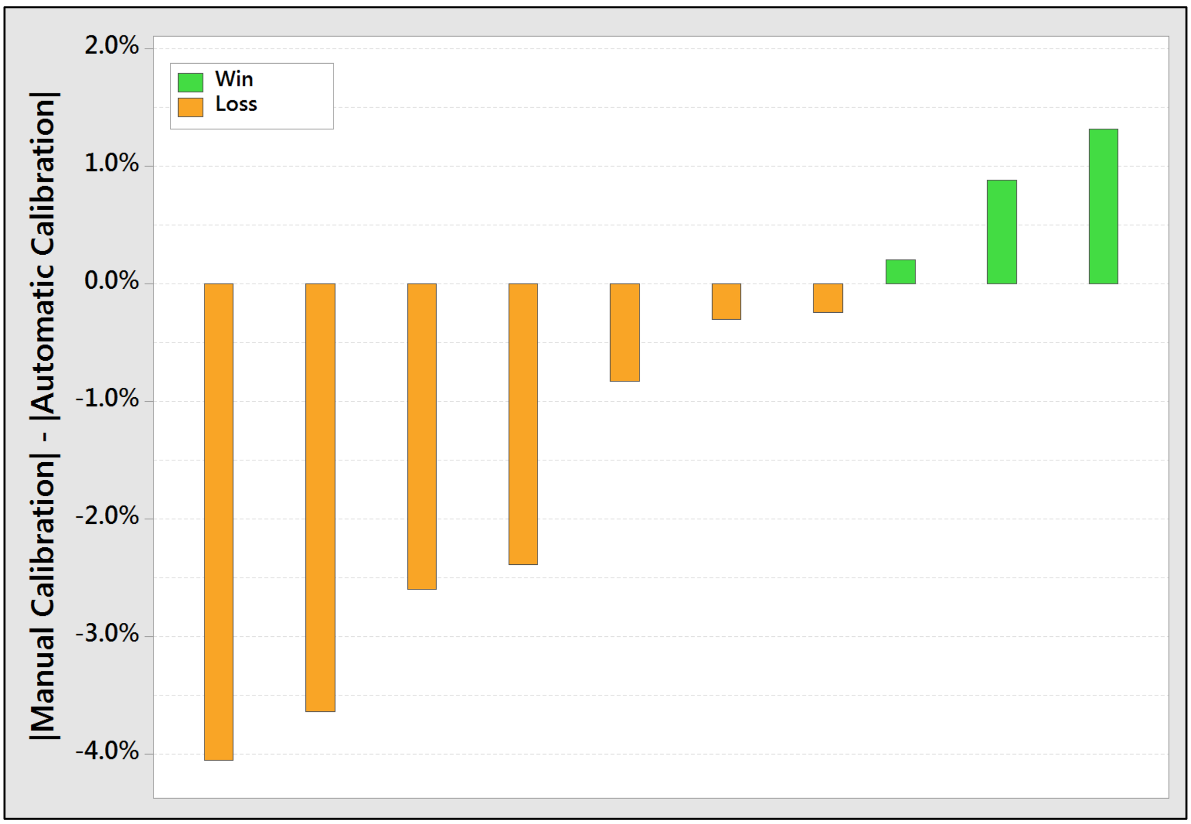

Figure 26: Win/Loss of S690 automatic calibration algorithm versus the manual calibration yield monitor data set mean error.

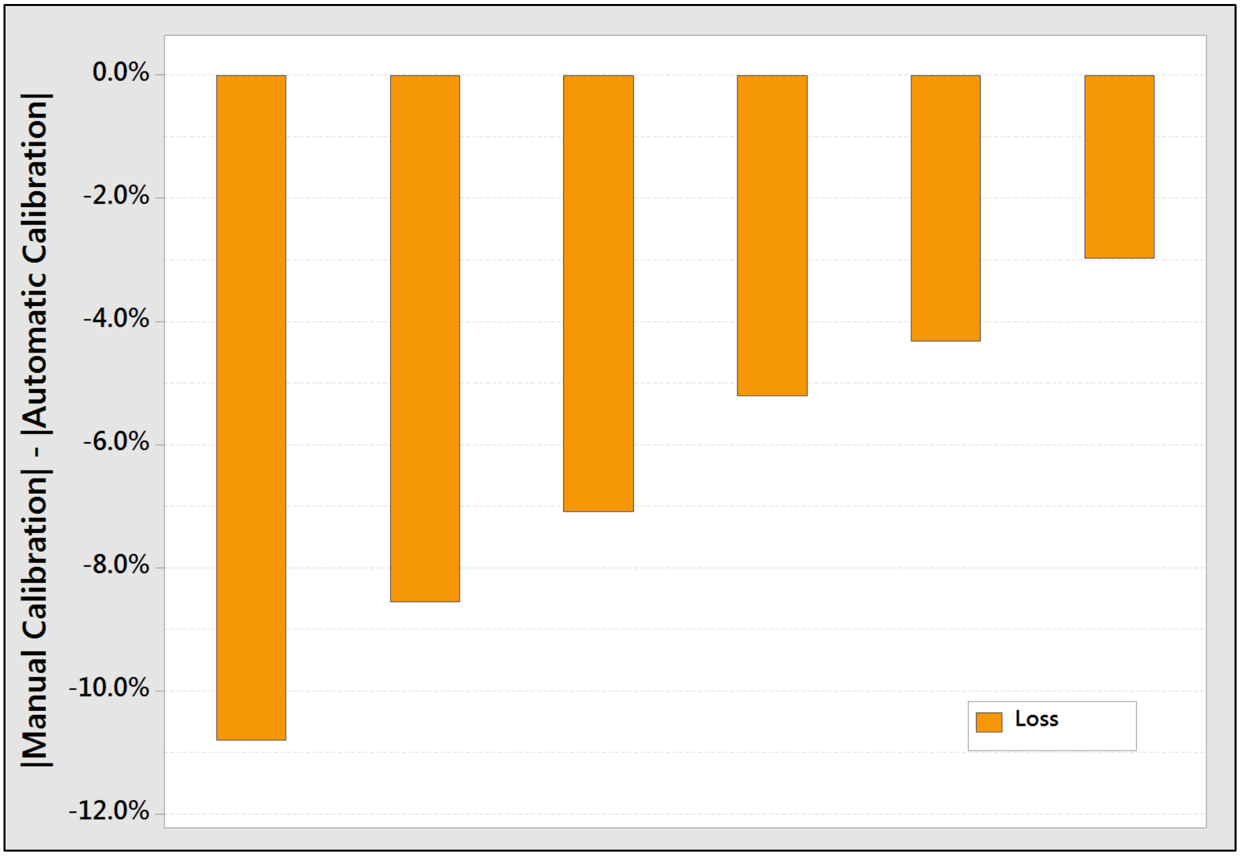

Figure 27: Win/Loss of S670 automatic calibration algorithm versus the manual calibration yield monitor data set mean error.

The resulting comparison to the data set level manual calibration of the S690 automatic calibration algorithm was better than expected and indicates the transferability of the algorithm to machines outside of the training data set. The 30% win rate of the automatically calibrated yield monitor for the S690 and at worst case scenario lost by 4% to an ideally applied manual calibration is considered excellent given the range of crop moistures and conditions covered. The S670 appeared affected by a calibration bias as all automatic calibration error was positive in the range of 3.4% to 10.9% with the manual calibration ranging from -0.8% to 2.6% (Table 14).

Comparing the overall performance of the manual and automatic calibration systems for summarized data set mean error, the manual calibrations for both the S690 and S670 grain tank configurations produced more accurate means (Table 15). A t-test applied at the 95% confidence level resulted in the S690 configuration having no statistical difference in the distributions of data set mean error for the manual and automatic calibration yield monitors with the S670 automatic calibration algorithm failing the test of equal means to manual calibration. Application of a test of equal variances at the 95% confidence level revealed that the automatic calibration and manual calibration yield monitors produced equal variance for both automatic calibration algorithms.

Table 15: Summary statistics of data set mean error for S670 and S690 yield monitors

Model	Data Sets	Auto Calibration		Manual Calibration	
		Mean	Std. Dev.	Mean	Std. Dev.
S690	10	-4.0%	4.7%	-2.3%	4.7%
S670	6	7.4%	2.9%	0.4%	1.3%

If the overall bias error of the S670 calibration algorithm from Table 15 was eliminated from the mean error of each data set, removing the calibration algorithm bias, the S670 produced wins for 33% of the comparisons and a differential error of a max win by 0.3% and a max loss by 3.6%. Accordingly the S690 produced wins 40% of comparisons with the error ranges increasing to a maximum win of 5% and a maximum loss of 6%. By this assessment it appeared that the S690 bias was limited and from observations of individual data sets, the bias error was driven primarily by the results of S690-F data sets.

Full season performance of S690-B and S670-A

The manual calibration performance of S690-B was discussed in Chapter 1 as the full season evaluation of a manual calibration. S690-B was manually calibrated on September 22nd, 2015, at 22% MC with a multipoint calibration completed at approximately 7, 10, 14, 20, and 24 kg/s with the final data set harvested October 19^{th}, 2015. A manual calibration that is completed early in the harvest season and unchanged for the remainder of the season would be considered the most common operation of a grain yield monitor. In many cases the calibration is completed with less calibration points than used in this study. The automatic calibration system began the season operating with the calibration from the previous harvest season in the calibration management system. This would be considered normal operation of the automatic calibration yield monitor at beginning of a harvest season as the calibration from the previous season would not be cleared from the yield monitor by the operator.

The automatic calibration yield monitor resulted in large errors at that start of the season as the calibration load buffer contained calibration points from the previous season. Approximately 15 loads into the season, the calibration management system flushed a large volume of calibration points from the flow ranges of 2, 3, and 4 of the calibration FIFO (Figure 28). The resulting error was corrected from an average of 18% to 2% error. The initial flush was a result of the calibration management system recognizing a difference in the existing relationship of force at the impact sensor to the grain mass flow rate. This type of flushing event was repeated regularly throughout the season, most notably in conjunction with grain moisture content changes.

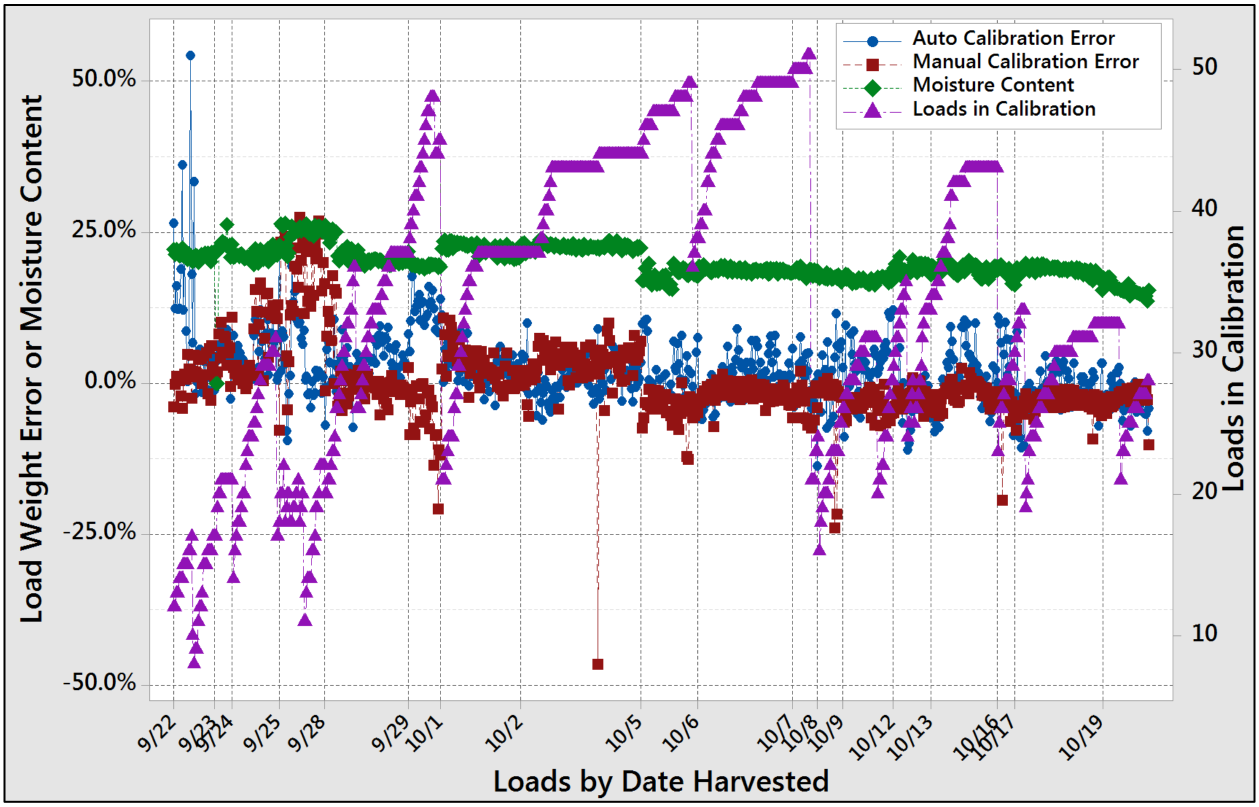

Figure 28: Load weight errors produced by the yield monitor for the automatic calibration and manual calibration by harvest date for S690-B.

S670-A was calibrated October 14th, 2015 at 14% MC with a multipoint calibration at 10, 14, 18, and 24 kg/s with the final data set collected on October 30th 2015. The automatic calibration algorithm started from the manufacturer's defaulted calibration and the system was operated for approximately 20 loads before the manual calibration was completed. The pre-manual calibration yield monitor can be observed by the large errors on 10/12 and 10/13 (Figure 29). The automatic calibration began from the default calibration with no calibration loads in the calibration management system. S670-A observed limited moisture changes throughout the season and the increase in moisture content can be observed in the final field of the season started on October 24th.

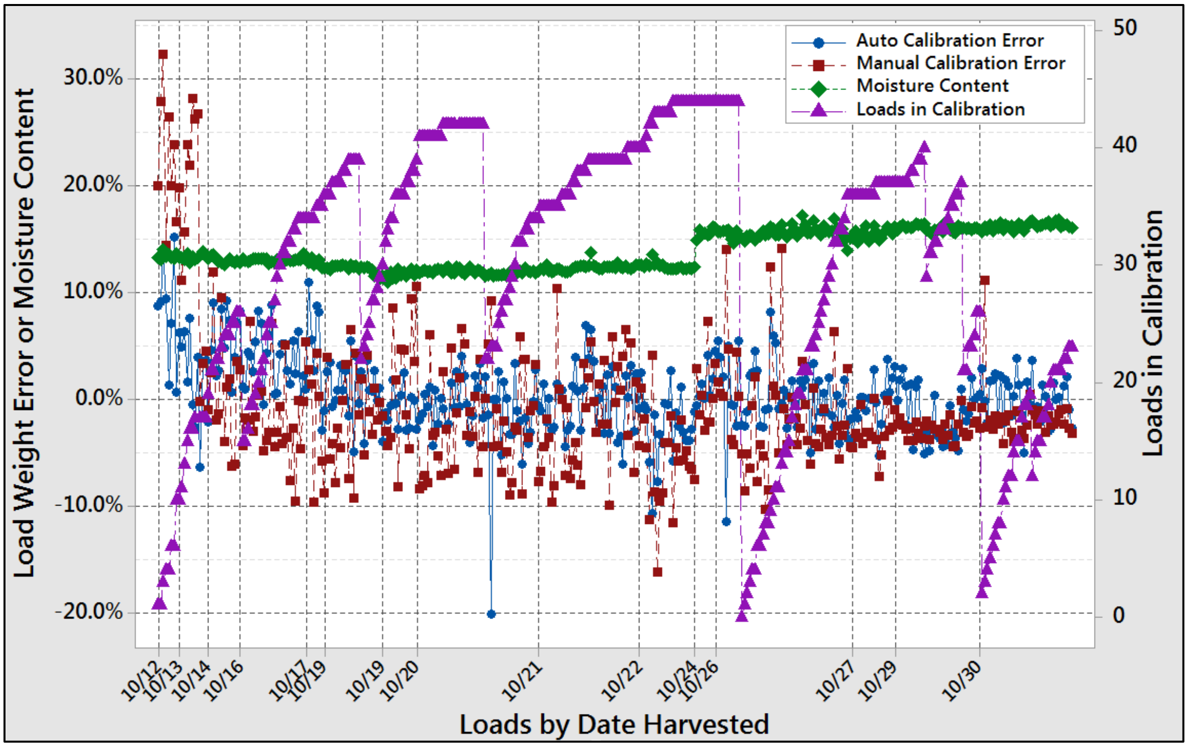

Figure 29: Load weight errors produced by the yield monitor for the automatic calibration and manual calibration by harvest date for S670-A.

S690-B error for the complete season based on total mass harvested resulted in 2.2% error and 0.6% for the automatic calibration algorithm and manual calibration respectively. Utilizing a t-test at the 95% confidence level, the automatic calibration yield monitor was compared to the manual calibration yield monitor with better accuracy defined as the yield monitor that produced the smallest absolute mean error for a given data set when the null hypothesis of equal means is rejected. Observing data sets that produced statistically different means, the automatic calibration yield monitor produced higher accuracy results for 52% of data sets, 29% of data sets exhibited no statistical difference, and the manual calibration produced better accuracy for 19% of the data sets (Table 16). The automatic calibration yield monitor produced better accuracy for 73% of data sets where data set means were determined to be unequal by the t-test.

Table 16: Performance comparison of the automatic calibration and manual calibration yield monitors for S690-B (shaded indicates equal means, 95% CI)

Date	Field	Total Loads	Mean Error		Mass Flow (kg/s)		Mean Moisture Content
			Auto	Manual	Mean	Std. Dev.	
9/22/2015	A	31	10.4%	1.5%	17.1	4.1	21.2%
9/23/2015	A	13	5.7%	5.4%	18.2	3.3	19.5%
9/24/2015	A	35	5.8%	6.1%	22.3	3.0	21.3%
9/25/2015	A	33	3.5%	17.7%	19.5	1.9	25.1%
9/28/2015	A	9	2.4%	9.3%	17.1	3.2	24.9%
9/28/2015	B	53	3.8%	-0.7%	15.5	2.0	20.5%
9/29/2015	B	24	12.4%	-5.9%	9.1	1.2	19.5%
10/1/2015	A	59	2.8%	2.9%	18.9	1.8	22.3%
10/2/2015	A	89	0.8%	2.9%	20.5	3.7	22.6%
10/5/2015	C	23	1.4%	-3.7%	17.1	3.1	17.2%
10/5/2015	D	19	2.2%	-4.8%	14.7	2.9	18.5%
10/6/2015	D	70	1.0%	-1.6%	17.3	2.1	18.7%
10/7/2015	D	18	-0.4%	-3.2%	16.1	2.7	18.3%
10/8/2015	D	19	1.3%	-3.3%	16.1	3.9	17.5%
10/9/2015	D	37	3.1%	-3.8%	15.7	2.9	17.1%
10/12/2015	E	28	-2.6%	-2.4%	17.7	3.0	19.1%
10/13/2015	E	49	0.9%	-1.7%	16.9	2.7	18.9%
10/16/2015	E	9	5.8%	-3.9%	13.2	2.4	18.9%
10/16/2015	F	4	-1.7%	-4.7%	15.2	3.2	16.8%
10/17/2015	F	65	-1.2%	-3.2%	19.7	2.2	18.7%
10/19/2015	F	34	-2.6%	-2.4%	19.8	1.9	15.6%

Field B produced a large positive error on 9/29/2015, corresponding with a negative shift in the manual calibration. This was caused by operating at lower flow rate conditions due to down corn that forced the operator to reduced harvest speeds. The decrease in flow rate correlates with the expected increase in yield monitor error based on the results presented in Figure 24 where flow rates below 10 kg/s produced significantly higher partial tank weight errors.

The results were observed on a data set basis as a win or loss comparison by subtracting the absolute error of the automatic calibration from the absolute mean error of the manual calibration yield monitor resulted in 63% win rate for the automatic calibration yield monitor (Figure 30). The automatic calibration yield monitor lost by a maximum of 8.9% and won by a maximum of 14.2%. The worst loss was produced from the first data set with the automatic calibration yield monitor requiring a number of loads to appropriately update the calibration through the management system. The largest win was produced during a rain event on 9/25 where the automatic calibration yield monitor compensated for the grain properties change and the manual calibration unable to compensate for the adverse effects produced by the excess surface moisture.

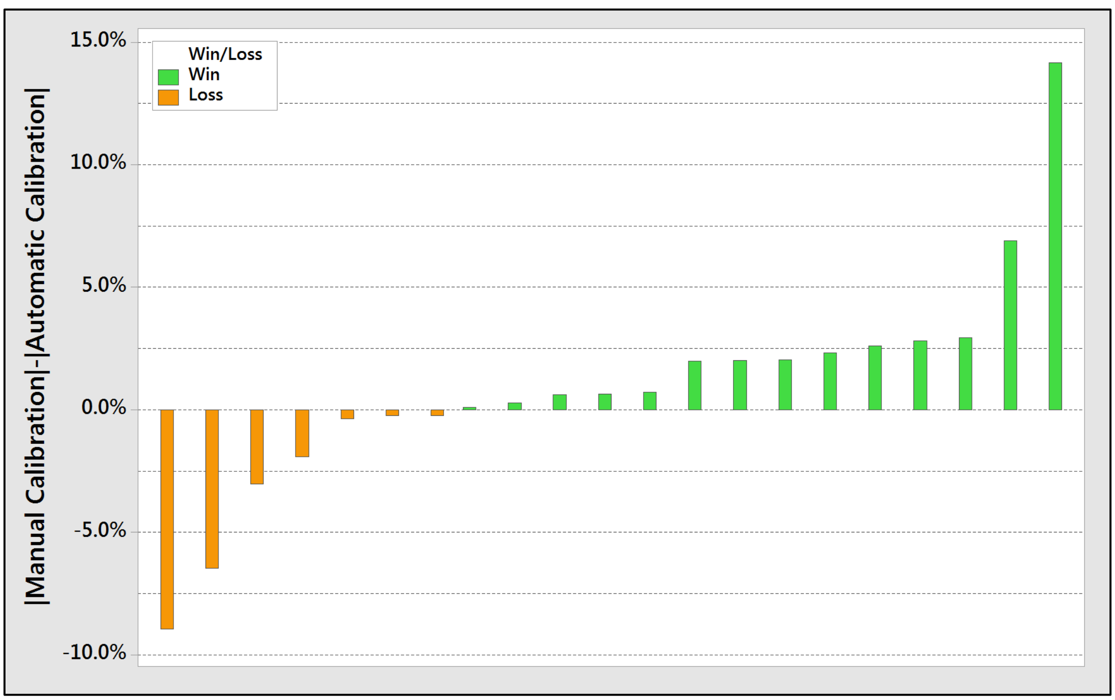

Figure 30: Win/Loss of the automatic calibration yield monitor versus the manual calibration yield monitor on a data set level for S690-B.

Aggregating data sets and observing errors on the field level, the automatic calibration algorithm won 83% by a minimum magnitude of 1.3% (Figure 31). Field means are a common level of comparison in production agriculture for accuracy and yield. The superior performance of the automatic calibration yield monitor produced a single loss, occurring in field B that was largely driven by the single day of low grain mass flow harvesting (Table 17). This comparison to the most common level of manual yield monitor calibration proves that the automatic calibration system functions in a desired manner by improving the accuracy of the yield monitor and requiring no interaction from the operator.

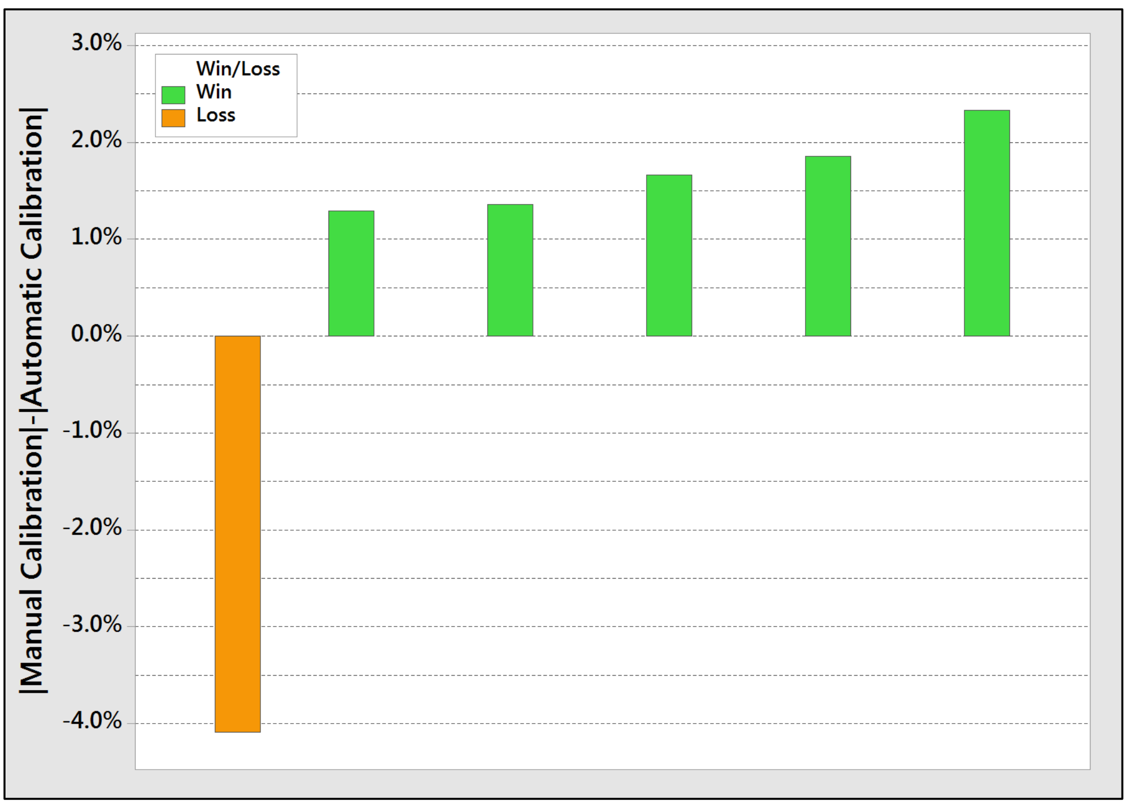

Figure 31: Win/Loss of the automatic calibration yield monitor versus the manual calibration yield monitor on a field level for S690-B.

Additionally, a t-test was applied to test for equal field mean error comparing the automatic and manual calibration yield monitors at the 95% confidence level. All fields were determined to have unequal means for S690-B. Field level performance, 33% fields failed to maintain ±3% accuracy as defined for bounds of the automatic calibration yield monitor for USDA crop yield reporting requirements, but met the stated passing criteria requiring a 50% success rate. However the manual calibration failed at a 50% rate for the same set of fields.

Table 17: Field level performance of the automatic and manual calibration yield monitors for S690-B.

Field	Loads	Automatic Calibration		Manual Calibration		Differential
		Mean	Std. Dev	Mean	Std. Dev	Absolute Error
A	269	3.6%	6.4%	5.3%	7.2%	1.7%
B	77	6.4%	5.0%	-2.3%	4.0%	-4.1%
C	23	1.4%	4.8%	-3.7%	1.7%	2.3%
D	163	1.5%	4.4%	-2.9%	3.2%	1.4%
E	86	0.3%	5.1%	-2.1%	2.5%	1.9%
F	103	-1.7%	3.3%	-3.0%	1.7%	1.3%

Evaluating the S670-A following the same process as S690-B, based on total mass harvested, S670-A automatic calibration yield monitor produced 0.3% error. The manual calibrated yield monitor for corn harvested after completion of the manual calibration of S670-A produced -2.0% error and -1.1% error for the full season.

A t-test for comparing equal mean error produced by the manual and automatic calibration yield monitors was completed on a data set basis at the 95% confidence level. The automatic calibration and manual calibration percentages are derived from data sets with unequal means and the data set with smallest absolute error is determined as the more accurate calibration. When considering equal means, the yield monitors produced equal error for 27% of data sets, automatic calibration was more accurate for 53% of data sets, and the manual calibration 20% of data sets. The first two days of harvesting 10/12 and 10/13, the manual calibration was not yet complete and was potentially not a fair comparison, but is realistic to regular harvesting conditions as a manual calibration may not be completed for several days into a season. Some producers rely on a secondary service such as a seed dealer to provide a weigh wagon to support a calibration which may not be available on the first days harvesting, leaving a producer with potentially several days of inaccurate yield data. Comparing this to the S690-B results, the automatic calibration converged within 15 loads due to flushing old calibrations and converged for S670-A within 7 loads. Despite a potential convergence time, the operator was not reliant on a ground truth source to calibrate the yield monitor and emphasizes the advantages of the automated system.

Table 18: Performance comparison of the automatic calibration and manual calibration yield monitors for the S670-A (shaded indicates equal means, 95% CI), (*) by manual calibration indicates calibration was not yet complete)

Date	Field	Total Loads	Mean Error		Mass Flow (kg/s)		Mean Moisture Content
			Auto	Manual	Mean	Std. Dev.	
10/12/2015	G	7	9.3%	*23.6%	6.9	1.6	13.4%
10/13/2015	G	13	2.1%	*15.2%	8.6	2.2	13.4%
10/14/2015	G	12	5.7%	1.2%	14.2	3.5	13.1%
10/16/2015	G	25	3.6%	-1.5%	12.4	3.0	13.1%
10/17/2015	H	5	7.2%	-0.1%	14.9	4.1	13.0%
10/19/2015	H	24	0.7%	-1.9%	16.5	3.5	12.3%
10/19/2015	I	13	3.9%	1.5%	12.2	4.1	11.8%
10/20/2015	I	46	-1.0%	-2.0%	14.9	3.8	12.0%
10/21/2015	I	38	0.0%	-1.4%	14.1	3.0	12.4%
10/22/2015	I	21	-2.5%	-5.7%	17.1	4.1	12.5%
10/24/2015	J	8	1.6%	1.0%	12.1	2.0	15.7%
10/26/2015	J	52	0.2%	-1.4%	15.9	4.9	15.7%
10/27/2015	J	16	0.1%	-2.9%	15.6	2.5	15.6%
10/29/2015	J	32	-1.4%	-2.7%	16.1	3.5	16.1%
10/30/2015	J	35	0.1%	-1.6%	17.0	3.9	16.3%

Comparing performance as win/loss as previously completed for S690-B, the automatic calibration produced wins for 73% of data sets (Figure 32). The large magnitude wins resulted from pre-manual calibration completion. The worst loss occurred at a field change with a five load data set. The large magnitude wins continue to emphasize the benefits of the calibration system reducing operator concern with organizing early season calibrations to ensure accurate yield data.

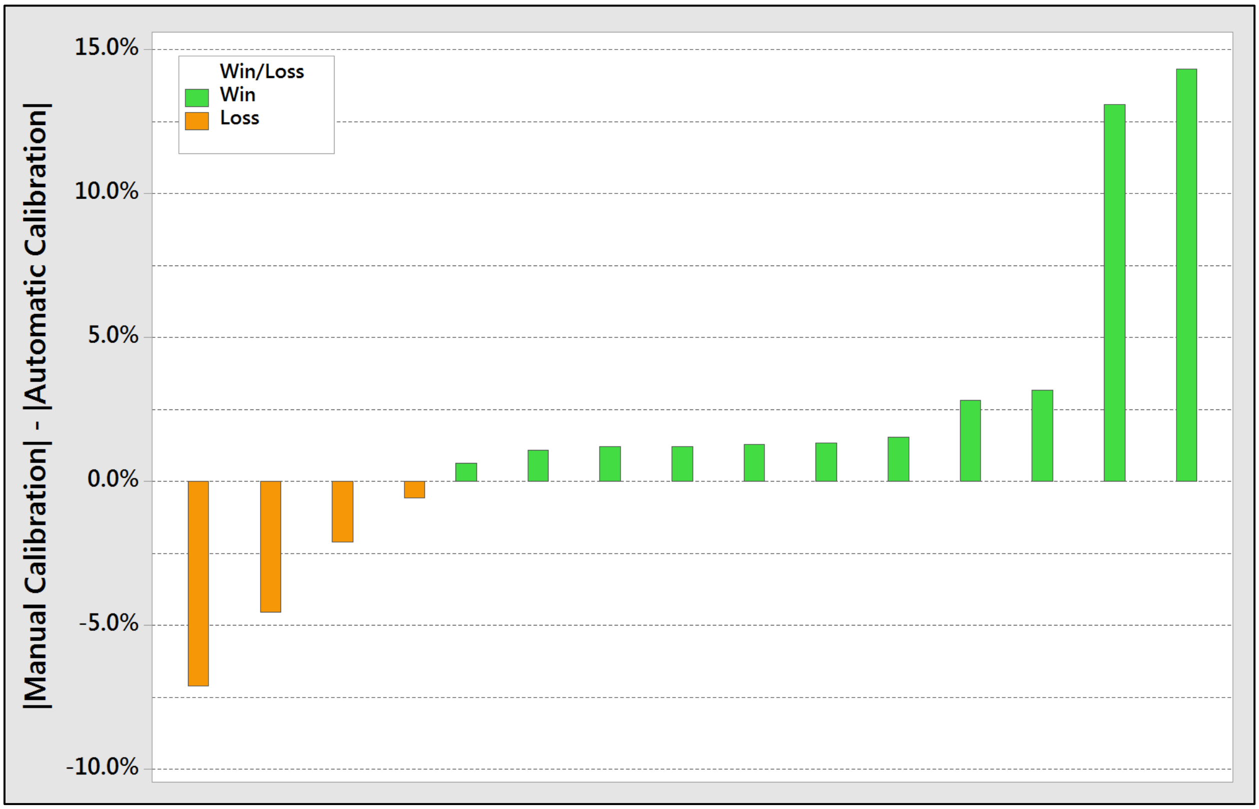

Figure 32: Win/Loss of the automatic calibration yield monitor versus the manual calibration yield monitor on a data set level for S670-A.

Comparing wins and losses on a field level, the automatic calibration yield monitor won 75% of comparisons, with the only loss occurring by less than 0.25% error (Figure 33). The absolute differential error was small for the three data sets with the only manual calibration win from data set H with both yield monitor calibrations within ±2% error (Table 19). The automatic calibration produced acceptable results for the USDA crop reporting for 75% of data sets similarly to the manual calibration. The performance of the automatic calibration yield monitor exceeded success requirements for the USDA crop reporting.

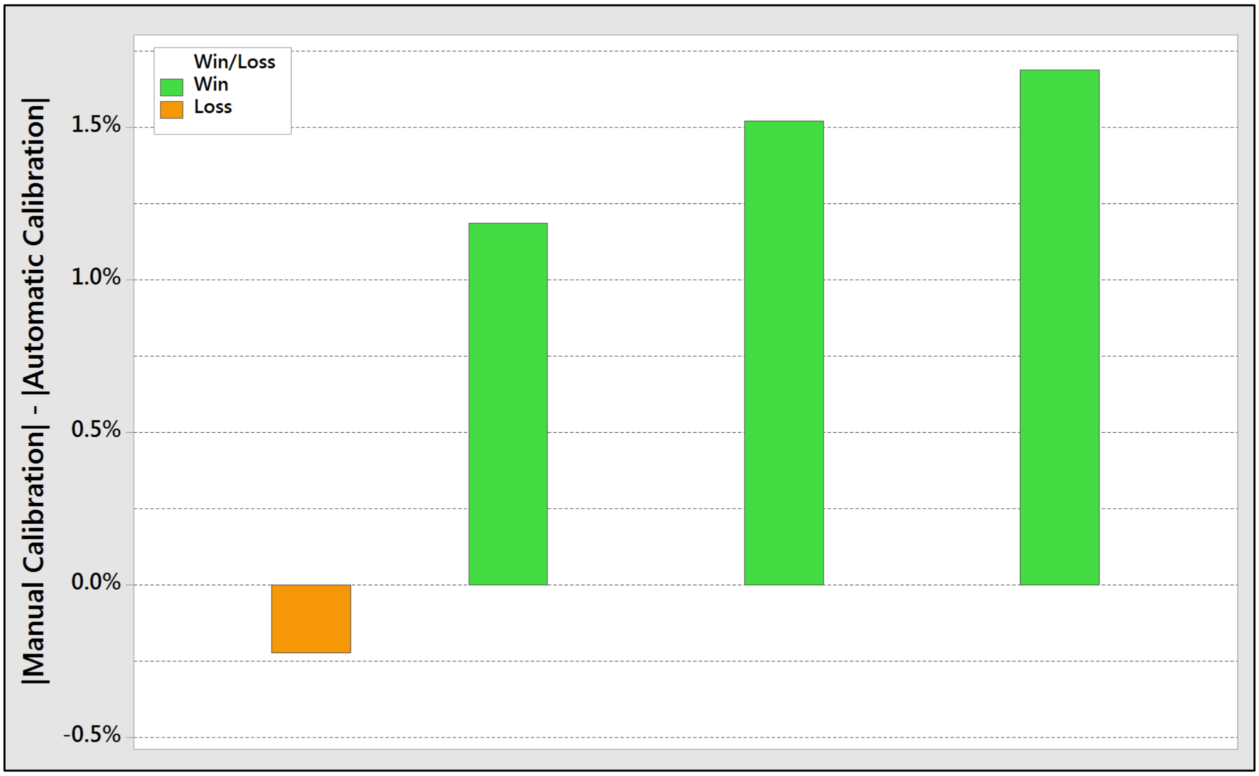

Figure 33: Win/Loss of the automatic calibration yield monitor versus the manual calibration yield monitor on a field level for S670-A.

Table 19: Field level performance of the automatic and manual calibration yield monitors for S670-A.

Field	Loads	Automatic Calibration Error		Manual Calibration Error		Differential Absolute Error
		Mean	Std. Dev	Mean	Std. Dev	
G	57	4.4%	3.9%	5.9%	11.4%	1.5%
H	29	1.8%	3.7%	-1.6%	4.6%	-0.2%
I	118	-0.9%	3.4%	-2.1%	5.3%	1.2%
J	143	-0.1%	2.8%	-1.8%	3.6%	1.7%

Performance investigation of S690 configuration of automatic calibration algorithm

Field performance of S690-F produced an average of nearly -10% and appeared as statistically different to the remainder of S690 field level calibration results. Investigating the cause of the large negative offset, the accuracy of the automatic calibration algorithm to estimate mean mass flow rates is observed to identify if the yield monitor performance was representative of the algorithm produced error. The resulting S690-F estimated mean mass flow rates for the calibration period correlated with the field produced results (Figure 34). I

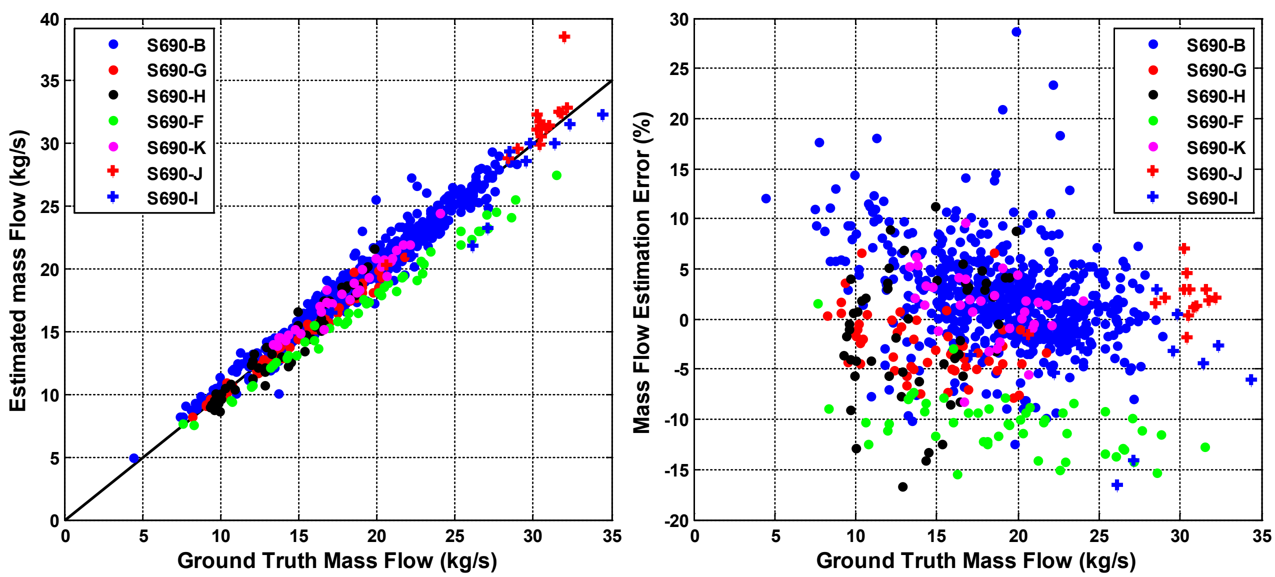

Figure 34: Field performance of the automatic calibration algorithm to estimate mass flow rate for fall 2015 corn harvest for the S690 grain harvest.

Investigating further, an analysis of specific regression parameters was completed on the S690-F data sets and compared to S690-B data set produced parameters chosen specifically from a data set with similar moisture content. The chosen S690-B data set was collected on 10/19/2015. The yield monitor system reported a mean moisture content of 15 to 17% moisture content for the data sets harvested on 11/16/2015 – 11/18/2015 of S690-F. Observing the ratio of the load cell rate of change for the full calibration to the mean mass flow rate of the calibration period was produced and observed (Figure 35).

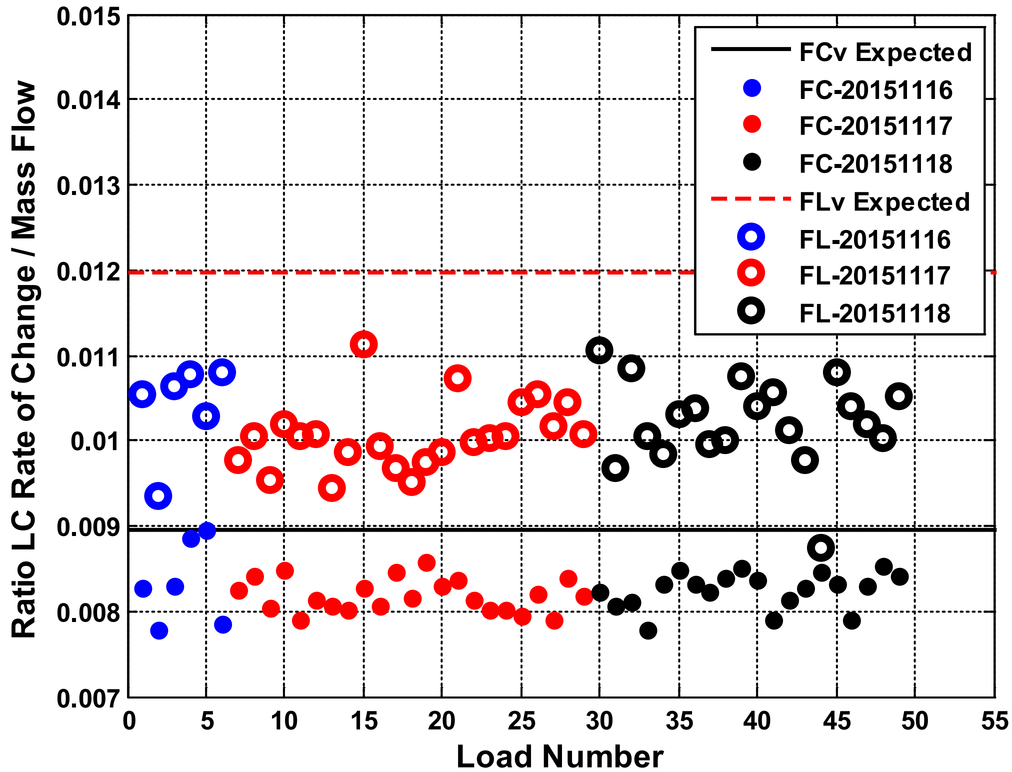

Figure 35: Ratio of load cell rate of change (kg/s) to mass flow rate (kg/s) for the front center and front left load cells by date harvested for S690-F.

The expected ratio for the front center load cell was 8% lower than expected and the front left load cell ratio was 15% lower than expected. The expectation was derived from the example S690-B data set. This corresponds with the low mass flow rate estimations by the calibration algorithm with the front center load cell response being the most influential parameter in the estimation algorithm. Some variation in load cell rates of change from data set to data set can be expected, but the magnitude of difference was outside an acceptable range.

Determining the potential source of the bias, the load cell signals were assessed to observe if there was a visible difference in the fundamental load cell response. The comparison was completed with the aforementioned data sets from S690-B and S690-F. The observation process was completed by plotting load cell responses with the zero bias offset applied by the accumulated mass in the grain tank. The grain tank mass was estimated by integrating the ground truth mass flow provided by yield monitor manufacturer. Plotting by accumulated mass allowed for observation of all load cell responses regardless of flow rate as on the same x-axis. Observing as a time response, the load cells would have to be binned by flow rate to make any useful comparisons.

The front center load cell zero bias for S690-F was larger than required (Figure 36). The incorrect bias caused the load cell response to be less than zero when there was no grain on the load cell. The process for creating the load cell zero bias or tare value is completed only when the grain tank is emptied with the separator of the harvester disengaged and the grain tank is completely emptied. During the last load cell zeroing event, a larger than necessary offset was created for the front center load cell. The source of this large tare value was unknown and could have been caused by several options that are out of scope for this research. However, the effects of an incorrect bias are evaluated. It was found that the front center and front left load cells had larger than necessary load cell bias values that resulted in negative load cell values when tared during an empty grain tank. The effects of the offset caused an increase in the length of the calibration by approximately 13% if constant mass flow was assumed. Extending the calibration length reduced the load cell rate of change parameter specifically for the front center load cell. Additional effects in the embedded implementation, the load cell values are tared and stored as unsigned integers, flooring any values less than zero to zero. This compounded the issue for the front center and front left load cells as the time period of the calibration was extended and the load cell response was still limited to the tared response only greater than zero.

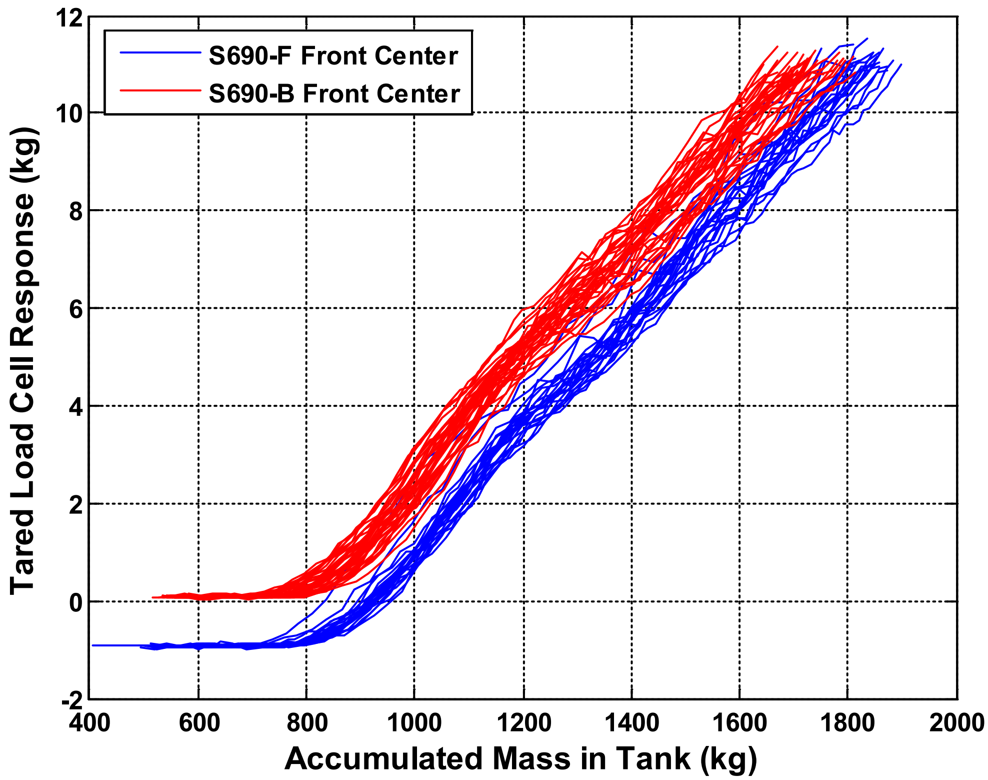

Figure 36: Front Center load cell responses by accumulated grain mass for single data sets for separate machines operating in approximately 17% MC corn for the specified calibration period for the automatic calibration algorithm.

When a correction was applied to the load cell zero bias for S690-F, the ratio of load cell rate of change to mass flow correlated with the results from S690-B for the front center load cell rate of change (Figure 37). This correction affected both the front left and front center load cell responses, but did not match the front left load cell response of S690-F and S690-B. There was a larger variation in the load cell rate of change observed for the front left load cell in Chapter 2 and the response was determined to be more dependent on grain properties.

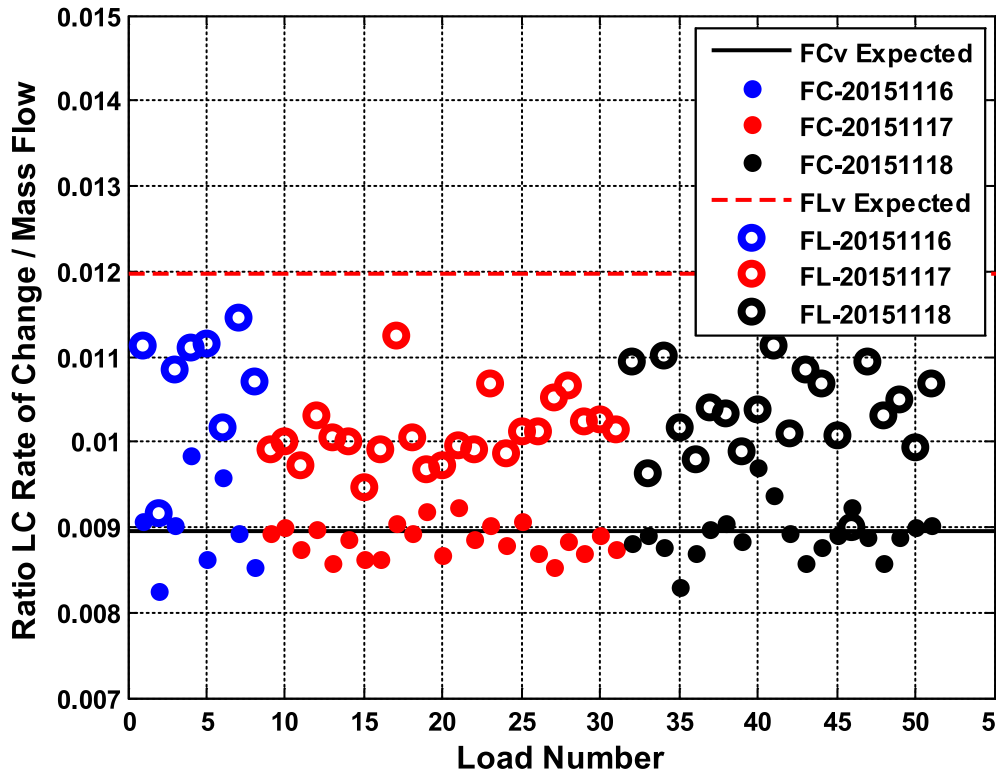

Figure 37: Ratio of load cell rate of change (kg/s) to mass flow rate (kg/s) for the front center and front left load cells for S690-F with expected results based on S690-B.

The discovered issue with the S690-F load cell zero bias led to an assessment of the effects of the load cell zero bias on the relationship of load cell rate of change to mass flow for all S690 harvesters. Observed in all S690 data, the load cell zero bias had a significant impact on the ratio of load cell rate of change to mass flow rate for the front center load cell (Figure 38). It was determined that the regression needed improvements minimize the effects of inaccurate load cell bias values. An ANOVA was completed relating the ratio of load cell rate of change to mass flow rate and the zero bias of the load cells. Results of the ANOVA indicated the zero bias of the front center and front left load cells was statistically significant to ratio of the load cell rate of change to mass flow for all three load cells. This enforced the importance of accurate zero bias on a machine or data set basis.

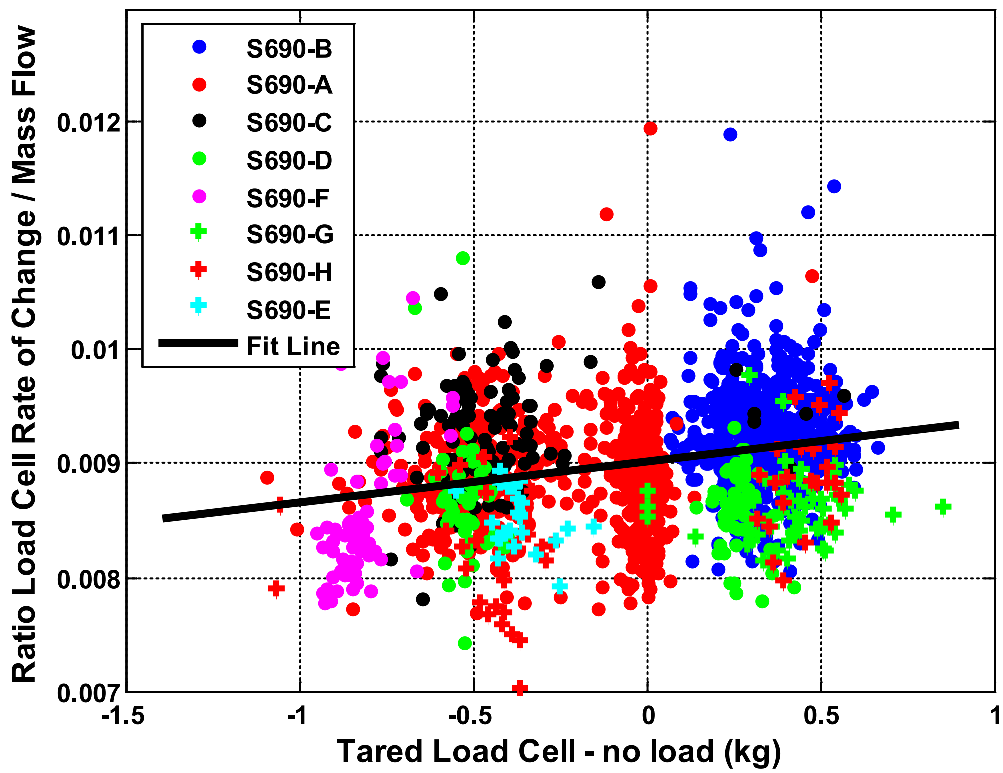

Figure 38: Influence of the Front Center load cell tared value on the calculated front center load cell rate of change ratio to the mass flow rate for S690 harvesters.

The auto calibration algorithm was updated to adjust the load cell zero bias for each S690 data set. The 2015 data sets were reprocessed with same mass flow regression estimation to determine if there was a performance improvement for the correction. A large decrease in partial tank weight error was observed for S690-F with slight changes for the other S690 harvesters (Table 20). The overall mean error was increased, but the standard deviation of mass flow estimations was reduced by correction of the load cell bias. A refactoring of the regression algorithm was recommended with active load cell bias correction. Further analysis is out of scope for this study but is considered for continuous improvement to the automatic calibration algorithm.

Table 20: Partial tank weight performance adjustments post application of load cell zero bias correction

Machine	Mean		Standard Deviation	
	Fall 2015	Zero Bias Corrected	Fall 2015	Zero Bias Corrected
S690-B	1.7%	3.0%	5.2%	4.6%
S690-F	-10.3%	-3.2%	2.7%	3.8%
S690-G	-2.5%	-1.4%	3.0%	3.0%
S690-H	-1.3%	1.9%	5.8%	4.4%
S690-I	-5.9%	-4.7%	2.9%	6.8%
S690-J	1.6%	3.9%	9.1%	7.5%
S690-K	1.4%	2.7%	3.5%	3.5%
Overall	0.6%	2.2%	5.3%	4.8%

Automatic calibration algorithm improvements

Following the 2015 harvest season the regression equation development process was evaluated and specific improvements were identified. The S670 field testing results indicated that the calibration was heavily biased to S670-A. Methods to reduce specific machine bias in the regression equation process were implemented and are feature option part of the Matlab LinearModel.fit regression object. A weighting function was invoked that allowed for application of specific weighting for individual replicates when training the regression algorithm. Even weighting was then applied on a machine basis, giving equal contribution to the regression process for all harvesters.

There were additional concerns related to the randomized selection of data replicates and if the randomization selection process of specific data replicates to the algorithm training set would produce select the same parameters for the mean mass flow estimations. A simple set of repeated tests creating training data sets through the randomized selection process described in Chapter 2 and completing the regression training that produced mass flow estimation equation. The selected parameters revealed specific parameters were continually selected, but some parameters were selected depending on the training data set. The regression process was updated to complete the randomization and regression training process 25 times. The resulting unique combination of parameters selected most often was selected as the specific regression equation. For example, the unique combination of front center and front left load cell rate of change were selected as the best regression model 14 of 25 times, this combination of parameters would be selected as the regression equation. The resulting 14 slightly different sets of equations were evaluated on the residuals and the final regression equation selected based on minimizing mean error and standard deviation on grain tank model and machine level. The final calibration selection required a level of observational decisions based on resulting error to select the most robust regression equation.

This process was completed for the S690 and S670 corn calibration algorithms and the resulting error of the produced partial tank weights assessed to determining the level of improvement. Data from the S670-A harvester was excluded from the S670 training data set. The decision to remove the S670-A data from the training set was based on the bias the machine was invoking onto the calibration and the resulting produced partial tank weights confirmed the machine as statistically different. Updates improved the mean error of the majority of S670 harvesters with little to no change to the S690 harvesters (Table 21). S670-A's exclusion from the regression resulted in a -5.4% mean error of the partial tank weights, but the improvements to

S670-B, F, and G were required. Note that the correction for incorrect bias was not implemented in the observed update.

Table 21: Partial tank weight error and resulting standard deviation on a machine level for updated automatic calibration algorithm

Calibration Algorithm	Machine	2015 PTW Error		FY2016 PTW Error	
		Error	Std. Dev	Error	Std. Dev.
S690	S690-B	1.9%	5.2%	1.8%	5.2%
S690	S690-F	-10.6%	2.7%	-10.7%	2.7%
S690	S690-G	-3.1%	3.0%	-3.1%	3.0%
S690	S690-H	-1.1%	5.8%	-1.1%	5.8%
S690	S690-I	-1.3%	2.9%	-1.3%	2.8%
S690	S690-J	2.2%	9.1%	2.1%	9.1%
S690	S690-K	1.0%	3.5%	1.0%	3.5%
S670	S670-A	0.2%	6.0%	-5.4%	6.1%
S670	S670-B	7.0%	6.3%	-0.9%	5.8%
S670	S670-F	7.4%	6.7%	-0.9%	7.6%
S670	S670-G	5.6%	3.3%	-1.4%	3.0%

Conclusions

Field deployment of the automatic calibration algorithm combined with a calibration management system observed that the completed system successfully invoked central limit theorem to the generated partial tank weights. The resulting yield monitor calibration reflected the accuracy of the partial tank weights within the expected bounds of accuracy for an impact based yield monitor.

Field testing revealed that the automatic calibration algorithm successfully calibrated the impact based yield monitor. Automatic versus manually calibrated yield monitors for data set level calibrations, produced automatic calibration wins for 30% of S690 data sets and 0% for the S670 calibration. However when the automatic calibration yield monitor was compared to a seasonal calibration, the automatic calibration yield monitor produced more accurate mean field error for 75% and 83% of fields for the S670 and S690 calibration algorithms respectively. The automatic calibration algorithm improved the yield monitor calibration and removed otherwise required operator interaction for manual calibrations.

The USDA reporting accuracy goal was achieved for both season long calibrations and the S690 data set level calibration tests, but failed for the S670 data set level calibrations. Improvements implemented in the regression process improved partial tank weight error means to an acceptable for the S670 and removed the bias created by S670-A. The application of the automatic calibration algorithm to harvesters outside of the training data was proved through the results of the 2015 field season.

CHAPTER 3: CONCLUSIONS

Serving as the primary source for site-specific farming benchmarking and USDA yield reporting, the yield monitor is a valuable tool for producers. When accurate, it produces valuable spatial data that is otherwise unavailable and enables instant evaluation of cropping practice decisions. Accuracy of the produced data drives better business decisions that operates on variable margins and deals with a constantly changing environment of hybrids and recommended practices that benefit from field evaluations to determine their value to a producer. Manufacturers are also pushing the limits of spatial placement of chemicals when application rates are determined and evaluated from spatial yield data. This requires accuracy not only on larger aggregate weights, but also on a specific spatial point or load level.

Characterization of current impact based yield monitors in this research extended beyond previous published works to provide observations of the accuracy of well calibrated yield monitors. The number of replications produced in this study allowed for strong conclusions to be drawn about impact based yield monitor accuracy that previously were limited by small samples sizes. The analysis developed the boundaries for expected in field yield monitor performance from an unbiased research perspective that previously relied on manufacturer claims of accuracy. The developed guidelines for yield comparisons for agronomic test plots provided yield differential bounds and recommendations that guide decision making processes in determining the importance of replicates when utilizing yield monitors for single load comparisons.

The season long evaluation of yield monitor performance developed knowledge of the effects of a seasonal multipoint calibration and the driving factors that determine if the calibration remains relevant and has no literature to compare against. Test stand evaluations had previously been completed in this area to determine some of the factors driving yield monitor shifts in accuracy, but the range of moisture contents, grain quality, flow rates, and number of replicates had not been produced in lab environments.

The development of the automatic calibration algorithm was proven to effectively estimate partial tank weights and successfully calibrate the impact based yield monitor. This process removed the operator from the calibration, a process that has not changed since the introduction of the yield monitor and improved seasonal yield monitor calibration accuracy. The process and algorithm developed in Chapter 2 provides the knowledge to extend the automatic calibration yield monitor to multiple crop types and machine configurations. Additionally, the calibration algorithm can be coupled with any yield monitor system for calibration and is not reliant the impact based yield monitor.

The growth of data farming in recent years with services aggregating yield and agronomic data to provide recommendations rely on accurate yield data to produce founded recommendations to their customers. The work presented provided a unique solution to a common issue presented in a continuously data driven environment. Regardless of the variability of the calibration system, the automation removes operator error from the process and ensures that the harvesters are calibrated. The known accuracy of the partial tank weight system coupled with the characterization of the impact based yield monitor error provides the knowledge needed to make decisions from yield data that is produced from different harvester if calibrated with the automatic calibration system.

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