Analysis of Combine Grain Yield Monitoring Systems: An evaluation of autonomous calibration of mass-flow sensor

by

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ABSTRACT

Yield monitor data is widely accepted as a valuable tool within the agricultural industry when making agronomic, financial, and management decisions and has been inaugural in the establishment of precision agriculture. Automation and sophistication of processes involved with yield monitoring systems has modernized farming through increased precision and efficiency. Traditional elevator mount mass-flow yield monitors are vulnerable to error due to insufficient calibrations and material flow inconsistencies resulting from threshing and separating processes. An advanced interconnected system that is able to autonomously analyze and adjust the mass-flow sensor calibration curve based on real-time data from the combine harvester has the potential to reduce error in comparison to traditional yield monitoring systems that require manual calibration of the mass-flow sensor. The accuracy of estimated yield using a traditional mass-flow yield monitoring system requiring manual calibration of the mass-flow sensor was compared with a yield monitoring system capable of autonomous mass-flow sensor calibration. A John Deere S790 combine harvester and grain cart with weigh scales threshed and weighed *Triticum aestivum* Linnaeus. The parameters examined were grain kernel moisture content, temperature, and weight of crop harvested with time. The weights of the harvested grain estimated by the respective calibration systems were compared to the weight measured in the grain cart for evaluation of yield accuracy and converted to bushels per acre for analysis. The average accuracy for the autonomous mass-flow sensor calibration system was 97.8% when compared with the average accuracy for the manual calibration yield monitoring system of 94.4%.

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1. INTRODUCTION

The integration of precision technology with yield monitoring systems has become an indispensable component in combine harvesters because of the accurate, site-specific data produced. The yield data generated allows producers to address spatial variability within a single field and use that information to make informed management decisions (Grisso et al., 2002). It is important that yield monitors are able to produce accurate results that accommodate changing variability of crop conditions, machine operation, and grain condition throughout a field and over a season. The dynamic relationships of these variables with yield monitor results and the challenges associated with correcting for them make these systems vulnerable to error if not calibrated correctly and adequately (Veal et al., 2010). Consequently, yield monitor performance is often compromised because maintaining correct calibration factors throughout harvest can be challenging as frequent calibrations are not always practical nor accessible (Grisso et al., 2009). Advanced yield monitoring systems capable of autonomous calibration have the potential to improve performance through increased precision and frequency of calibrations.

In order for yield monitors to produce accurate results, they must generate a calibration curve that stays current and can accommodate inherent variability encountered from machine operation, crop conditions, and field conditions. Traditional methods of calibration require knowledge on the weight of grain harvested from a known area, grain kernel moisture content, and grain flow rate through the combine to calculate a calibration factor used to estimate a geo-referenced yield (Luck, 2017). This method of calibration is time consuming, requires access to weigh scales, and needs to be repeated numerous times throughout harvest and at the different speeds that the harvest may encounter (Grisso et al., 2009). Since time is limited at harvest and weigh scales may be not accessible for calibration, an autonomous calibration yield monitoring system has been developed that continuously calibrates while harvesting without delays or the need for weigh scales. The purpose of this research was to examine yield accuracy between manual and autonomous calibration technologies of yield monitoring systems onboard a combine harvester. Evaluation of the two different techniques was completed by harvesting *Triticum aestivum* Linnaeus, alternating between the autonomous calibration yield monitoring system and the manual calibration yield monitoring system. A weigh scale provided accurate weights from each trial and a global positioning system along with header crop sensors ensured accurate area harvested for each trial.

In the following pages all related information regarding this study is divided into different sections. In the literature review section, literature related to the importance of mass-flow sensors, calibration, and yield monitors is examined. Also, literature related to the value of yield monitors and their applications is discussed. The materials and methodology section describes the equipment used, experimental design, and the detailed experimental procedures of the research. The results and discussion section identifies and explains the outcomes of the study. Results of this research will identify the role technology has in modern agriculture, the influence of autonomous calibration of mass-flow sensors in yield monitoring systems on accuracy of estimated yield, and the value of intensive data in agriculture.

2. LITERATURE REVIEW

2.1. Precision technology in yield monitors

Developments and advancements in precision technology have facilitated the transition to modern agriculture with sophisticated farming systems. Yield monitors have been at the forefront of the precision farming revolution due to their ability to function as a location-specific crop performance indicator that informs producers about variability in their fields (Blackmore 2003) These complex systems are filled with advanced technology, sensors, and software that provide the framework for which allow producers to assess and manage their farm (Blackmore 2003). Although there are numerous types of yield monitors, the mass-flow style of yield monitor using an impact plate to measure grain flow is the most common form of yield monitor system being used on today's combine harvesters (Franzen and Humburg 2019; Schuster et al., 2017). Other types of yield monitors use volumetric flow methods where grain flow is measured with fixed time intervals; these include paddle wheel sensor and infrared sensor (Arslan and Colvin 2002a). Volumetric flow methods claim to require less maintenance but have been associated with lower accuracy due to wheel slippage or timing interference (Chung et al., 2016; Shearer et al., 1999).

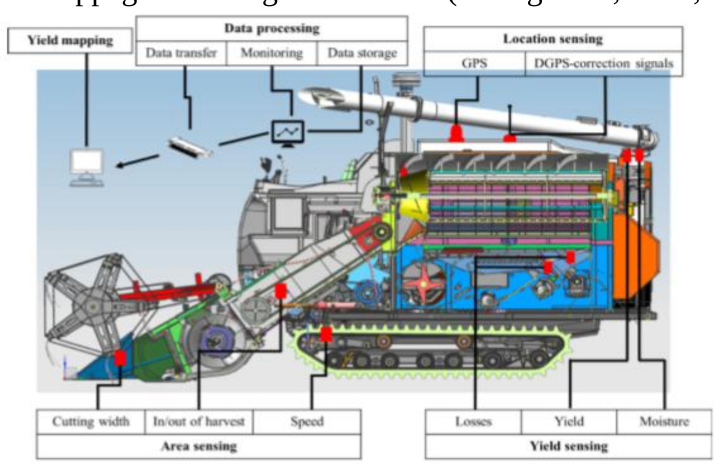

Figure 1. Schematic of yield monitoring and mapping components in a combine harvester (Chung et al. 2016).

Literature by Whelan and Taylor (2013) indicate that there are six fundamental concepts that a yield monitoring and mapping system must be able to efficiently detect, process and analyze: lean grain flow, grain moisture content, grain (elevator) speed, cutting height, harvester ground speed, and harvester location. The various sensors and devices mounted throughout the machine that is able to determine these parameters are shown in Figure 1. A global positioning system is the most common method for determining location where a differential global positioning system receiver, satellites, and a stationary receiver interact (Blackmore 2003). Some modern yield monitoring systems may have additional sensors to reduce error such as slope sensors where inclined topography is present, additional load cells involved with calibrations, and camera's in clean grain elevators and tank to optimize grain quality (Arslan and Colvin 2002a; John Deere 2018). With such large volumes of data being generated from multiple sensors and devices, software to make sense of the information is necessary. As a result, modern yield monitoring systems rely on sophisticated software to organize and manipulate the data into a form that is useful.

2.1.1. Information management systems

Information management systems are robust analytical software that process, analyze, and store large volumes of data from ubiquitous sources (Blackmore 2003). There are many different types of information management systems with various applications in agriculture however; literature from Blackmore (2003) indicates that geographical information system is the most common information management system found in combine harvester yield monitoring systems. Geographical information systems manipulate machine data and utilize location knowledge from global positioning systems to create geo-referenced maps of various areas and fields. Multiple maps can be combined to create an overlay that can be used to compare and show interactions between different variables of interest.

Many of today's yield monitoring systems also commonly utilize cloud-based computing technology within geographical information system software because it has allowed remote access to real-time performance parameters (Bo & Wang 2011). In some combine harvester this is accomplished via a wireless hotspot to transmit and store harvest information such as yield data in real-time to mobile tablets and devices (John Deere 2020). Comprehensive electronic infrastructure is a core necessity of these systems and provides the platform that enables the heterogeneous devices of the yield monitoring system to network synergistically as an interconnected mechanism (Bo & Wang 2011). This has enabled extensive repositories, processing, and analytic capabilities at a level of precision that previously was not possible due to technological limitations. As precision technology within yield monitors continues to improve it is expected that the volumes of data generated from the devices will increase, becoming increasingly reliant on information management systems. Information management systems play an integral role in maximizing yield monitor performance and accuracy because the management and analysis of large volumes of site-specific data.

2.2.Value of yield monitors in agriculture

Yield monitoring systems have a crucial role in precision agriculture systems and have become a standard component on combine harvesters due to their ability to effectively evaluate yield variability within a field. Advancements in yield monitors have encouraged the adoption of site-specific farming; providing the ability to monitor and map variables of the physical environment in real-time (Casady et al., 2010; Grisso et al., 2002). A valuable quality of these systems is the ability to treat each field as a heterogeneous unit instead of a single homogenous unit (Grisso et al., 2002). This allows for greater precision and productivity with the creation of prescription maps that make variable rate application of inputs possible. This helps to ensure that the appropriate amount of fertilizer is applied by using fertilizer rates based on the specific needs throughout the field; preventing over application or under application of fertilizer (Risius 2014; Casady et al., 2010). Location referenced yield monitors also help identify areas of concern and help address the potential causes such as compaction, seeding rate, and varietal differences (Grisso et al., 2002). With this information, producers are able to maximize productivity, efficiency, and profits through site-specific farming practices (Blackmore 2003).

Information produced by yield monitoring systems has encouraged producers to adopt more sustainable farming practices. Literature by Blackmore (2003) found that yield map comparisons with other agronomic maps representing crop productivity factors such as soil type and fertility help determine best management and farm practices. This information can also help producers plan for the future by identifying problem areas and reduce financial risk by justifying costs when deciding to go forward with costly farm improvements (Risius 2014; Blackmore 2003). Combine harvester yield monitoring systems have enabled producers to conduct their own on farm research to evaluate practices and inputs best suited to their farm (Griffin et al., 2008). Producers are able to make management decisions based on data generated with the same specific to their farm and practices.

2.2.1. Educated management decisions

Advancements in yield monitoring systems have given producers the ability to make educated farm management decisions based on site-specific yield data generated across the field and over a season. This information provides a fundamental basis for many agronomic decisions that are valuable to maximize productivity throughout a field (Chung et al., 2016). These decisions can include determining if field tiling is appropriate, what variety or crop is most suitable for that field, ideal irrigation rates, and if variable rate fertility applications are appropriate (Risius 2014). A producer can also use yield information to continuously make adjustments for the future by evaluating the impacts that different factors had on yield during harvest for future reference. Furthermore, yield maps are able to provide financial justification of new management decisions implemented such as different practices and varieties utilized in an attempt to increase field productivity and farm profits (Blackmore 2003).

2.2.2. Yield mapping

The integration of global positioning systems within yield monitoring systems has enabled generation of large volumes of geo-referenced yield information. The data generated is often organized into a yield map; a visual representation of a field's site-specific yield and functions as a guide for producers to view the variability throughout the field (Arslan & Colvin 2002a). Yield mapping differs from previous management practices as productivity factors in a field such as soil type or fertility are not assumed to be homogenous across its entirety (Grisso et al., 2002). Instead, a yield map is able to address spatial variation present in a field by using global position system technologies and software to identify site-specific yield fluctuations within the field (Casady et al., 2010). A study by Griffin et al., (2008) has indicated that yield mapping capabilities in harvesters have also shown significance when conducting on farm research. Producers who had access to yield mapping technologies at harvest where more likely to conduct on farm trials and felt more confident when making management decisions. Yield mapping data can also be used to set production and performance benchmarks for future reference.

2.3. Yield estimation

To determine the instantaneous yield, the combine harvester's onboard computer system relies on input from various sensors and knowledge from manually entered information (Luck & Fulton 2004). Luck and Fulton (2004) discuss the process and components involved with yield estimation using a standard well-known formula (Eq. 1). The mass-flow rate, distance travelled, and harvested moisture content of the grain are all measured automatically by sensors mounted throughout the combine. The remaining parameters; logging interval, header cut width, bushel weight, moisture content, and conversion factor from ft^2 to acres are constants that must be entered in by the operator. However, newer combine harvesters may also be equipped with additional sensors such as header cut width sensors to accurately identify area harvested or slope sensors that measure terrain pitch (John Deere 2018). It is important that all parameters required by the formula are precise to ensure accurate estimation of yield. Instantaneous yield is typically calculated using the following equation:

$$Yield\left(\frac{bu}{ac}\right) = \left[(\mathbf{43,560}) * \left(\frac{m*t}{d*w*p}\right) * \left(\frac{100-MC_{harvest}}{100-MC_{market}}\right)\right] \quad \textbf{(1)}$$

Where:

m=mass flow rate estimated from the impact plate sensor (lb/sec);

t=logging interval of the yield monitoring system (sec);

d=distance traveled between logged data points (ft);

w= header cut width setting (ft);

p= grain density or test weight (lb/bu);

$MC_{harvest}$ = moisture content measured from the yield monitor moisture sensor (%);

MC_{market} = marketable moisture content (%), and;

43,560 = conversion factor from ft^2 to acres.

2.4. Yield monitor performance

Yield monitors are intricate systems with many interconnected sensors that work together to estimate yield. The most important component in a mass-flow style yield monitoring system is the impact plate of the mass-flow sensor which is typically mounted at the top of the clean grain auger (Arslan and Colvin 2002a). The grain passing through to the clean grain tank exerts a force on the impact plate creating a voltage reading that is proportional to the impact received by the grain, indicating grain flow. It is important to ensure that the mass-flow sensor is properly calibrated as Reinke et al. (2011) have identified the largest contributor to yield estimate accuracy to be involved with the mass-flow sensor. In optimal conditions with proper operation, calibration of the mass-flow sensor, and installation of yield monitoring systems reliable and accurate yield data is possible (Lems et al., 2016).

Although yield monitors have become sophisticated systems with advanced technology, they have limitations. Research by Simbahan et al. (2004) indicated that there are various systematic and random factors that make yield measurement vulnerable to error. The different sources of error may occur naturally, be a result of machine operation and management, or a result of mechanical failure during the yield measurement process. Some sources of error may be preventable whereas others are unavoidable, but techniques to minimize the impact of the error on yield estimation can be effective (Luck and Fulton 2004). The commitment of time and resources needed to effectively calibrate yield monitoring systems is another limitation that can be a significant drawback (Grisso et al., 2002).

2.4.1. Accuracy

The accuracy of yield monitor data has become increasingly important with the shift towards site-specific farming. Although there is some discrepancy within literature of the level of precision that can be achieved, it is generally agreed upon that yield monitor accuracy has significantly improved over the last 30 years (Chung et al., 2016). Many commercial yield monitoring systems claim to be accurate within 3.0% when proper calibration and operation is performed (Risius 2014; Fulton et al., 2009). However, according to Grisso et al. (2002), "the advertised accuracies of continuous yield monitors vary from 0.5 to 4%, if the yield monitors are installed and used correctly" whereas Arslan and Colvin (2002a) found that yield monitor measurements were able to produce results that were accurate within 2.0% in a laboratory setting but found that the error commonly increased up to 5.0% when on a field scale. Furthermore, literature by Reynes et al. (2002) found that on a field scale error up to 9.17% is possible. While many studies have shown that accurate yield monitor results can be achieved with proper calibration and operation, it is important to consider the circumstances at the time of harvest and what the purpose of the yield data is to determine what level of accuracy is reasonable.

The accuracy of yield monitor data that is deemed to be appropriate is dependent on the producer's intentions. For example, literature by Arslan and Colvin (2002b) suggest that a higher degree of accuracy is needed for the purposes of buying and selling grain than would be needed to make connections between yields and variable applications. It is also important to consider the conditions present at the time of harvest, as it is unrealistic to expect highly accurate results in extremely and variable conditions (Arslan and Colvin 2002b). Regardless of the purpose of the yield data or harvest conditions, improving the accuracy is desirable. Some ways to maximize yield monitor accuracy include performing multiple quality calibrations of the mass-flow sensor and re-calibrating frequently as well as ensuring in-cab parameters are entered correctly (Lems et al., 2004). Literature by Lems et al. (2004) also suggests periodically checking the moisture sensor, mass-flow sensor, and ground speed sensor for accuracy is necessary to maximize yield monitoring system performance.

2.4.2. Calibration

The mass-flow sensor is considered one of the most critical components involved with yield monitoring systems and just like any other sensor it needs to be calibrated (Luck & Fulton 2004). The calibration procedure for the mass-flow sensor is time consuming but absolutely vital for accurate yield measurements. The calibration process generates a calibration curve, which is able to relate the output from the mass-flow sensor to grain weights for an estimation of the yield (John Deere 2018). Typically this process involves repetitively weighing the harvested grain from a known area at difference ground speeds (Lems et al., 2014). Luck (2017) emphasizes the importance behind quality calibrations because a poorly generated calibration curve lead to poorly estimated yield results; the same results used for yield mapping and management decisions. However, quality calibrations are not always practical or accessible as it requires access to weigh scales and can delay harvest (Luck 2017).

To ensure accuracy, quality mass-flow sensor calibrations must be done for each type of grain being harvested each year. The calibrations must also be repeated throughout the harvest season and as conditions change since mass-flow sensor readings are influenced by moisture content, test weight, and crop type (Grisso et al., 2009). Literature from Grisso et al. (2009) indicates that a higher level of accuracy is achieved when several loads are used in the calibration and that each load should be of sufficient and similar size. Literature by Veal et al.

(2010) found that using too few calibration points and calibrating outside of operating parameters are other sources of calibration error that will negatively affect the accuracy of estimated yield. It is also important that mass-flow sensor calibrations occur on level ground with uniform crop to ensure the area covered and force exerted on the impact plate is accurate (Arslan and Colvin 2002a).

2.4.3. Error in yield monitors

Yield monitors have become a valuable component on combine harvesters but using them to obtain reliable data on a field scale can be challenging. Literature by Arslan and Colvin (2002a) indicate that a number of different factors can influence the yield estimation as any factor that alters the way grain flows through the combine or the striking characteristics on the impact plate will introduce error. Although calibration is likely the single largest potential contributor to error, other sources can also have a significant impact (Arslan and Colvin 2002a)**.**

Some of the common operator errors include incorrect header width entered, improper calibration, and harvesting outside of the calibration parameters (Veal et at., 2010; Arslan and Colvin 2002a). Operators need to be sure that the correct in-cab parameters such as crop type and the bushel weight are selected to ensure estimated yield accuracy (Lems et al., 2016). Luck and Fulton (2004) stress that some error is unavoidable but that methods to minimize the impact they have on yield data produced are effective. Cleaning sensors throughout the harvest season is important to prevent build up of material and dust that can interfere with the sensors ability to accurately function. Arslan and Colvin (2002a) explain that grain passing over moisture sensing plate can leave deposits that affect moisture readings and that overestimated moisture readings from a malfunctioning sensor will underestimate yield. Aside from changing the bushel weight of the grain, a change in moisture content of the grain will also alter the impact characteristics of the grain striking the impact plate. Maintaining a consistent ground speed and header height when harvesting prevents surges of grain from striking the impact plate and also prevents inconsistencies in lag time; the time lapsed from when the grain enters the combine to when it strikes the impact plate (Casady et al., 2010). Correct header height, header width, and ground speed while harvesting also ensures that the data is only recorded while actively threshing over the proper area. Literature by Luck and Fulton (2004) discuss the importance behind consistent header height and ground speed. Although consistent header height and sudden stops are not always avoidable, prevention is important as the resulting error in estimated yield can be upwards of 1000.0 bushels per acre. Positional errors from global position systems or wandering errors will incorrectly calculate the area covered and consequently influence the accuracy of yield data. Tall trees, building, or adverse weather conditions can also reduce signal strength of the global positioning system (Blackmore 2003).

2.4.4. Limitations

Although advances in technology have addressed many of the challenges previously limiting yield monitor accuracy, other restrictions for use still exist. Important limitations of yield monitoring systems such terrain pitch, slope, lag time, and moisture sensor capabilities were discussed in literature by Luck and Fulton (2004) and Franzen and Humberg (2016). Yield monitoring systems are not able to accurately represent yield when harvesting on slopes as the force of grain hitting the impact plate is affected by the degree of inclination (Luck and Fulton 2004). Similarly, literature by Franzen and Humburg (2016) state “Anything that changes the impact force will be detected as a change in grain flow rate. While combining uphill, gravity can force the grain harder against the sensor plate to indicate more flow. While combining downhill, gravity can reduce the indicated flow because the grain is being thrown upward”. This finding is consistent with other literature by Burks et al. (2004) who concluded that harvesting on slopes of 6.0-9.0% introduced error that were as high as 60.7% when travelling downhill and 18.2% travelling uphill. This error may also be in part due to the inability of harvesters to precisely measure the distance travelled when travelling up or down a slope (Grisso et al. 2002). Even with the creation of slope sensors on modern harvesters, the effect of slope on yield estimation accuracy cannot be completely eliminated (Arslan and Colvin 2002a).

Luck and Fulton (2004) also found that from the time the crop enters the header to striking the impact plate 10-15 seconds has passed. This delay, known as lag time is a result of the time required for the grain to be threshed and separated before reaching the clean grain tank, causing the yield to be incorrectly referenced to the geographic location of where it initially entered the combine harvester. Sudden stops or accelerations change the flow of material and send surges of material through the combine harvester which also influence the force of grain striking the impact plate and the distance travelled during that period (Franzen and Humburg 2016). A final consideration that Luck and Fulton (2004) outline is that typical moisture sensors accurately read values that range from 10.0-33.0%, therefore yield estimation is susceptible to error when harvesting a crop with a grain kernel moisture content outside of this range.

3. MATERIALS AND METHODS

3.1. Site description

Field studies were carried out over two harvest seasons; fall of 2018 and fall of 2019. Relatively dry, but consistent conditions throughout the entire growing season and harvest for the 2018 crop resulted in a uniform crop and an easy uninterrupted harvest without weather delays. Extremely dry conditions during the 2019 growing season with late season precipitation resulted in stunted, uneven crop. Late season precipitation in the form of rain and snow frequently shut down harvest for extended period's time ranging from hours to days depending on the volume of moisture received. Most often the weather only permitted a couple hours of harvesting at a time before a storm would move through, making it very challenging to find two full days of good weather and dry crop. Since the precipitation was extremely variable across fields, the moisture contents of the grain kernels at the time of harvest were inconsistent.

In the fall of 2018 research took place approximately 8 miles north of Ste. Rose Du Lac, Manitoba, Canada. The duration of the research spanned a period of two days, August 14th and August 15th over 196.1 acres. Two different varieties of *T. aestivum* with similar physiological maturity were used; Viewfield and Brandon. The outdoor air temperature averaged 20.6°C during the harvest period on August 14th and 30.2°C on August 15th. Conditions were dry.

In the fall of 2019 research took place 13 miles north of Dauphin, Manitoba, Canada. Multiple attempts were made before finally getting two full days of harvest where the weather cooperated; August 15th and August 16th. A total of 184.4 acres with two different varieties of *T. aestivum* were used; Tisdale and Brandon. The outdoor air temperature averaged 19.1 and

23.8°C on August 15th and August 16th, respectively. Initially conditions were dry, but isolated thunderstorms and precipitation caused delays throughout harvest.

3.2. Harvest equipment and materials

3.2.1. Combine harvester and header

The combine harvester used to thresh and separate the crop of *T. aestivum* was a 2018 John Deere S790 (Fig. 2). This is a class 9, rotary combine with a single rotor and was used for research in both the 2018 and 2019 harvest seasons.

A 2018 John Deere 640FD straight cut header fed the crop into the combine. This is a flex draper header and has a 40.0ft cut width with a double knife drive and pickup reel as well as crop sensors.

Figure 2. 2018 John Deere S790 combine harvester with open hopper top and flex draper header attached.

3.2.2. Tractor and grain cart

For the 2018 harvest a 2018 Brandt 1322XR grain cart (Fig. 3a) equipped with weigh scales inside the cart was used. The grain cart was powered by a John Deere tractor through the drawbar. Harvest tracker kept track of the scale weights of the clean grain unloaded into the grain cart.

For the 2019 season a 2011 Unverferth 1315 grain cart (Fig. 3b) equipped with weigh scales mounted inside the cart was used to weigh the clean grain. A Versatile 375 powered the grain cart by PTO and a monitor inside the cab recorded and tracked the weights of clean grain unloaded by the combine harvester. The scales in the grain cart were zeroed each time after unloading into grain trucks.

Figure 3. Grain cart wagon used for data collection; (a) 2018 Brandt 1322XR used for 2018 harvest; (b) 2011 Unverferth 1315 used for 2019 harvest.

3.2.3. Calibration technologies

Autonomous calibration The combine harvester was equipped with ActiveYield® technology, the technology responsible for the yield estimates produced with autonomous calibration of the mass-flow sensor. Three load cells mounted in the clean grain tank of the combine harvester along with software use the change of weight of the grain measured by the load cells as the grain fills the tank to continuously calibrate the system (Fig. 4). The weight measured in the clean grain automatically zeroes out after each load.

Figure 4. Three load cells mounted in the clean grain tank of 2018 John Deere S790 combine harvester. Load cells are identified by red arrows.

Manual calibration The combine harvester was also equipped with the Greenstar® yield monitoring system. This is a classic type of mass-flow yield monitoring system that requires manual calibration of the mass-flow sensor with each crop type and throughout harvest as crop conditions change. Preloaded software generates a location specific yield estimate based on input from sensors and the calibration curve.

3.2.4. Moisture tester

An external grain kernel moisture content tester was needed to ensure the combine harvesters onboard grain kernel moisture content sensor was accurate and to apply any corrections if needed. A calibration of the ambient air temperature is also necessary with this series of combine to accurately measure the grain kernel moisture content.

3.2.5. Tandem grain trucks

Tandem grain trucks were loaded with the harvested wheat by the grain cart after each load was weighed and recorded. The trucks hauled the grain to the farmer's main yard for bin storage where samples were taken to verify the bushel weight of the grain and the grain kernel moisture content at the commercial elevator.

3.2.6. Grain crop – *T. aestivum*

2018 crop Both fields used for research were level and uniform, with the exception of a few low spots with weeds. Each field had a uniform seeding date, implying that all crop harvested for research had endured similar growing conditions. Each field was treated the same across its entirety with variety, seeding depth, fertility and pesticides. Some slight difference in the varieties of *T. aestivum* used in the research exist; on a typical year Viewfield is a semi-dwarf variety and reach maturity in 101 days whereas Brandon is taller and reaches maturity in 107 days.

2019 crop Both fields used for research were level and as uniform as possible given the challenges presented by un-ideal growing conditions. Extremely dry conditions resulted in inconsistent crop with variation in thickness and height across the fields. Near the end of the growing season storms resulted in sporadic and uneven precipitation. Similar to the crop in 2018, each field was seeded at the same time and depth with one variety per field. Each field received the same fertility and pesticide inputs to minimize inconsistency. On a typical year both varieties of *T. aestivum* have a similar physiological maturity where, Tisdale; a medium height variety will reach physiological maturity in 101 days and Brandon; a variety with shorter height will take slightly longer to reach maturity.

3.3. Material set-up

3.3.1. Field

The headlands of the fields used for research were harvested first and omitted from the research because of typical inconsistencies associated with the outer edges of the field such as soil compaction. A bushel weight was determined by the grain elevator from a representative sample of harvested wheat taken from a uniform and consistent area of the field. Additionally, a representative sample of the harvested *T. aestivum* was also taken to test the grain kernel moisture content to ensure the grain was appropriate for harvest.

3.3.2. Combine harvester

The combine harvester threshing and separating settings needed to be adjusted so that grain volume and quality is maximized during operation. The settings were chosen by the producer and remained unchanged for both the manual calibration yield monitoring system and the autonomous calibration yield monitoring system for each field throughout the day. It was also important that the combine harvester travel at a consistent speed throughout the dauration of each field, the producer determined that 5.5mph was ideal for the 2018 harvest and 5.0mph for the 2019 harvest. The same header was used for the duration of the research and was set with the same rigidity throughout the research and also to maintain a consistent cut height. Combine harvester settings for each *T. aestivum* variety harvested during the 2018 season and 2019 are summarized in Table 1a and Table 1b, respectively.

Table 1a. 2018 threshing and separating settings in the combine harvester for two varieties of *T. aestivum*.

	Brandon	Viewfield
Rotor speed (rpm)	900.0	1000.0
Threshing clearance (mm)	7.0	5.0
Sieve (mm)	1.0	1.0
Chaffer (mm)	16.0	16.0
Fan speed (rpm)	1200.0	1200.0
Average ground speed (mph)	5.5	5.6

Table 1b. 2019 threshing and separating settings in the combine harvester for two varieties of *T. aestivum*.

	Brandon	Tisdale
Rotor speed (rpm)	1000.0	1000.0
Threshing clearance (mm)	9.0	8.0
Sieve (mm)	4.0	4.0
Chaffer (mm)	14.0	14.0
Fan speed (rpm)	1250.0	1250.0
Average ground speed (mph)	5.0	4.7

3.3.3. Grain cart and weigh scales

The grain cart used for the 2018 season was calibrated by the dealer after the 2017 harvest season and was stored in a shed to ensure accuracy for the 2018 season. Similarly, the grain cart used for the 2019 season was calibrated after the 2018 harvest season and parked in storage. Prior to use, the grain cart was completely cleaned out of any grain that may have been left over from previous crop. To minimize any error in scale readings the grain cart was parked stationary in one location on level ground in the field as movement across the field has potential to offset scale readings. Also, the measured weights of grain harvested and unloaded into tandem trucks for the research determined by the grain cart were compared to the weight measured by the grain elevator to confirm accuracy.

3.3.4. Calibration

Moisture sensor The onboard grain kernel moisture content sensor in the combine harvester needed to be calibrated to ensure proper moisture readings were measured. To do this, a Quantum digital grain moisture meter determined the true percentage of moisture present in the grain kernels to be compared to the readings generated by the combine harvester grain kernel moisture content sensor (Fig. 5). A sample of harvested grain that was representative of the field conditions was taken and measured with an external grain kernel moisture content tester. A triple beam balance was used to measure out a sample of 250.0g which was then placed into the dump cylinder of the grain kernel moisture content tester. The function calibrate knob is turned until the dial reading reads zero. Next the grain was then let down into the canister and the dial knob was turned to draw the needle on the dial reading as close as possible to zero. The value on the meter and the temperature of the grain is used to obtain the moisture percentage of the grain kernels by reading from the provided chart. This value was compared to the grain kernel moisture content reading onboard the combine harvester and any offset was corrected, in the research no correction needed to be made.

Figure 5. Quantum digital grain kernel moisture meter.

Mass-flow sensor A vibration calibration of the mass-flow sensor was conducted at each field prior to harvest and every time the header was attached. With the header attached, the calibration is conducted to compensate for vibration induced error from machine operation while harvesting.

A multi-point calibration method was used to calibrate the mass-flow sensor of the traditional manual calibration yield monitoring system. This process involved multiple calibration loads at varying crop flow rates which was accomplished by harvesting at different ground speeds. Each calibration load was unloaded in the grain cart to be weighed; it was important that all loads were over 3000.0lbs and similar in size. The weight of the harvested wheat was entered into the combine harvester calibration software along with the acres harvested respective to each load in order to calibrate the mass-flow sensor and generate a current calibration curve. For the 2018 season, six 4500.0lb loads were used and the combine harvested 1.5 acres for each load. The weight of grain harvested was weighed in the grain cart after each 1.5 acre harvested at the relevant speed. A total of 9.0 acres were used for the manual calibration yield monitoring system before actual yield results were recorded**.** The same procedure was followed for calibration during the 2019 season with the only differences being the harvesting speeds used and 2.1 acre loads for a total of 12.4 acres used. Calibration procedures were conducted by a John Deere technician to ensure a proper and quality calibration was done. The grounds speeds reflect calibration recommendations; conducting two loads at normal harvesting speed and two loads each at 0.5mph faster and slower than normal harvesting speed. The ground speeds used in the multi-point calibration are shown in Table 2.

Table 2. Multi-point calibration of mass-flow sensor ground speeds for six loads in 2018 and 2019.

Calibration	1	2	3	4	5	6
2018 Speed (mph)	6.5	6.0	5.5	5.5	5.0	4.5
2019 Speed (mph)	6.0	5.5	5.0	5.0	4.5	4.0

3.4. Experimental procedure

The combine harvested adjacent plots of *T. aestivum* alternating between the autonomous calibration yield monitoring system and the manual calibration yield monitoring system. The combine harvester would harvest the appropriate plot and then drive over to where the grain cart was parked to unload. The weight of the grain was measured by the grain cart to determine the true yield and then unloaded into a tandem truck to be hauled to a bin for storage. Other parameters recorded from each plot in each calibration system were grain kernel moisture content, area harvested in acres, time, and the estimated yield in bushels per acre generated by the yield monitoring system. This information allowed for yield estimate accuracy comparisons of the manual calibration yield monitor system and the autonomous calibration yield monitoring system. Field information on the breakdown of acres, distribution, and use in research is outlined in Table 3. Crop in low spots or areas that were distinctively not uniform with the majority of the field were not included and left out of the research to prevent skewed grain kernel moisture content readings.

Table 3. Distribution and utilization of harvest area in acres by the autonomous calibration yield monitoring system (AC) and the manual calibration yield monitoring system (MC) for all fields in 2018 and 2019.

	2018		2019	
	Field 1	Field 2	Field 1	Field 2
Total area	160.0	140.0	150.0	155.0
AC	52.0	41.0	41.0	46.0
MC	45.0	58.0	37.0	48.0
Calibration	9.0	0.0	12.0	0.0
Headlands/Other	54.0	26.0	59.0	60.0

3.4.1. Yield data

2018 In Field 1, data using the *T. aestivum* variety Brandon were recorded from a total of 20 loads; 10 loads using the autonomous calibration yield monitor system and 10 loads using the manual calibration yield monitor system. For the manual calibration yield monitor system the average load size was 16102.0lbs over an average area of 4.5 acres whereas the average load size for the autonomous calibration yield monitoring system was 18118.0lbs over an average area of 5.2 acres. The average grain kernel moisture content in Field 1 was 14.4% and the bushel weight of the grain was 64.0lbs.

In Field 2, data using the *T. aestivum* variety Viewfield were recorded from a total of 16 loads; 8 loads using the autonomous calibration yield monitor system and 8 loads using the manual calibration yield monitor system. For the manual calibration yield monitoring system the average load size was 18227.0lbs over an average area of 7.2 acres whereas the average load size for the autonomous calibration yield monitoring system was 12456.4lbs over an average area of

5.2 acres. In Field 2, the average grain kernel moisture content was 13.9% and one bushel of threshed grain weighed 63.0lbs.

2019 Data using the *T. aestivum* variety Tisdale were recorded from a total of 8 loads for the manual calibration yield monitor system and 9 loads for the autonomous calibration yield monitor system on Field 1. The average load size for the manual calibration yield monitor system and the autonomous calibration yield monitor system was 10206.3lbs over an average area of 4.6 acres and 9583.3lbs over an average area of 4.6 acres, respectively. On average the grain kernel moisture content was 14.5% and the weight of one bushel of threshed grain was 60.0lbs.

In Field 2, data using the *T. aestivum* variety Brandon were recorded using 6 loads from the manual calibration yield monitor system and 7 loads from the autonomous calibration yield monitor system. On average, the manual calibration yield monitor system load size was 13765.0lbs over an area of 7.9 acres and 12270.0lbs over an area of 6.6 acres for the autonomous calibration yield monitor system. The average grain kernel moisture content was 13.1% and the bushel weight of the threshed grain was 66.0lbs.

3.5. Data collection

3.5.1. Estimated yield

Autonomous calibration The estimated yield relied on numerous sensors onboard the combine harvester to ensure specific criteria was met before yield would be estimated and recorded. To minimize error, recording of data began while harvesting once the load was of sufficient size of 2000.0lbs and continued to record data up to 6600.0lbs or until the header was disengaged. The loads were deemed unacceptable for use and were rejected if any of the following conditions occurred while harvesting; interruption of grain flow through combine harvester from abrupt acceleration or deceleration, inconsistent grain flow in combine harvester from variable crop conditions, a load size of less than 2000.0lbs or terrain slope that exceeds ±4°. In the event that any one of those conditions were met the data gathered during that load was discarded and no data was recorded. The estimated yield was then automatically computed by the combine harvester.

Manual calibration The manual calibration yield monitoring system did not have the same technology to omit loads when conditions fell outside of ideal calibration conditions. Recording of data began as soon as the combine harvester header was engaged regardless of the size of the load, terrain pitch, or speed and ended when the header disengaged. For this reason, all loads were monitored manually to ensure a sufficient and similar size was met, as well as for consistent crop flow. The estimated yield was automatically computed by the combine harvester's onboard yield monitoring software.

3.5.2. True yield

For each harvested load, the true yield was recorded so that a comparison to the estimated yield for the respective system could be made. To find the true yield of each load, the grain harvested by the combine was unloaded into the stationary grain cart and weighed. This value, along with knowledge of the bushel weight of the crop, and area harvested was used to calculate the true yield using Equation 2. The area harvested for the load was measured by the global positioning system with knowledge of the combine harvester's header size. The final value computed is representative of the true yield of the load.

$$\boldsymbol{True\ Yield}\left(\frac{bu}{ac}\right)=\left(\frac{\left(\frac{W_g}{W_{bu}}\right)}{Area}\right) \quad \textbf{(2)}$$

Where:

W_g= weight of the harvested grain from the load (lbs);

W_{bu}=bushel weight of the crop (lbs/bu), and;

Area=area harvested for the load (ac).

3.6. Data analysis

To determine how accurate each mass-flow yield monitoring system was, the yield estimates produced with the manual calibration yield monitoring system and the autonomous calibration yield monitor system were compared to the respective true yields. The accuracies of each calibration system were represented as a percentage of the estimated yield to the true yield and functioned as an average. Using these percentages, a comparison of accuracy of estimated yield was then made between the autonomous calibration yield monitor and manual calibration yield monitor.

4. RESULTS

4.1. Estimated yield accuracy

Throughout the two harvest seasons, the accuracy of the yield estimated by the autonomous calibration yield monitoring system and the manual calibration yield monitoring system were examined through evaluation of the yield data year to year and field to field. A two-sample t-test with unequal variances confirmed that the difference in population means of the accuracy of the estimated yield from each yield monitor system to be significant (α=0.05) in all fields and years except Field 2 in 2019 (Table 4). Accuracy and consistency of the yield estimated by the autonomous calibration yield monitoring system was greatest on both a field scale and year to year. On average, the estimated yields were accurate within 2.3% of the true yield; 3.4% more accurate than the yield estimated by the manual calibration yield monitoring system.

Table 5 summarizes the average accuracies of the estimated yields for each field and year for both calibration methods in the yield monitoring systems researched. The most accurate yield estimates produced from both the autonomous calibration yield monitoring system and the manual calibration yield monitoring system occurred in 2018, but in separate fields (Table 5). Also in 2018, the largest t-values occurred suggesting the greatest likelihood of a significant difference between the means (Table 4). The 2018 data indicates that the manual calibration yield monitoring system was most accurate on Field 2 whereas the accuracy of yield estimates produced by the autonomous calibration yield monitoring system remained relatively neutral between the two fields albeit slightly greater precision on Field 1. Opposite to the outcomes observed in 2018, in 2019 the manual calibration yield monitoring system was most accurate on Field 1 and the autonomous calibration yield monitoring system was most accurate on Field 2. Furthermore, there were greater differences in the accuracies between each field in 2019 than compared to 2018.

Referring to Figure 6, the estimated yields produced by the manual calibration yield monitoring system were more erratic between individual fields and years. The greatest variation for yield estimates produced by the manual calibration yield monitoring system occurred in 2019 in Field 2 where the average error in estimated yields dropped to 7.0%, the lowest accuracy experienced. This level of error is considerably higher than that in any other field of any year. The accuracy of average estimated yields in Table 5 also indicate that estimated yield in Field 1 were on average 2.2% more accurate than that of Field 2 in 2019; where as in 2018 in Field 2 were on average 1.1% more accurate than the yield estimates produced in Field 1. This higher level of accuracy observed in 2018 in Field 2 is consistent across every load in the research with the exception of two loads demonstrated in Table 6.

Similar to the yield estimates produced with the manual calibration yield monitoring system, the yield estimates produced using the autonomous calibration yield monitoring system also experienced the largest difference in average field accuracies in 2019 with a difference of 0.6%. Throughout the research, the autonomous calibration yield monitoring system remained the most consistent in terms of average field accuracies as the average accuracies of the yield estimates produced in each field within a year remained very similar. However, unlike the outcomes from the manual calibration yield monitoring system in 2018, no observable trend is identified where the yield estimated in one field is consistently more accurate than the other. Overall, the lowest accuracy in estimated yields and largest variation in average accuracies of estimated yields between the fields occurred in 2019 for both the manual calibration yield monitoring system and the autonomous calibration yield monitoring system.

Table 4. Results of two-sample t-test for unequal variances for the accuracy of estimated yields in field 1 and field 2 in 2018 and 2019 using a two-tailed t-test (α=0.05).

	2018		2019	
	Field 1	Field 2	Field 1	Field 2
p-value	1.9E-06	4.6E-04	3.7E-02	0.1
t-value	7.3	5.1	2.4	1.8

Table 5. Average accuracies of the yield estimates produced on each field by autonomous calibration yield monitoring system and manual calibration yield monitoring system in 2018 and 2019.

	2018				2019			
	Autonomous calibration		Manual calibration		Autonomous calibration		Manual calibration	
	Field 1	Field 2	Field 1	Field 2	Field 1	Field 2	Field 1	Field 2
Average Accuracy (%)	98.1	97.9	94.0	95.1	97.1	97.8	95.2	93.0
Average Accuracy (%)	98.0		94.6		97.5		94.1	

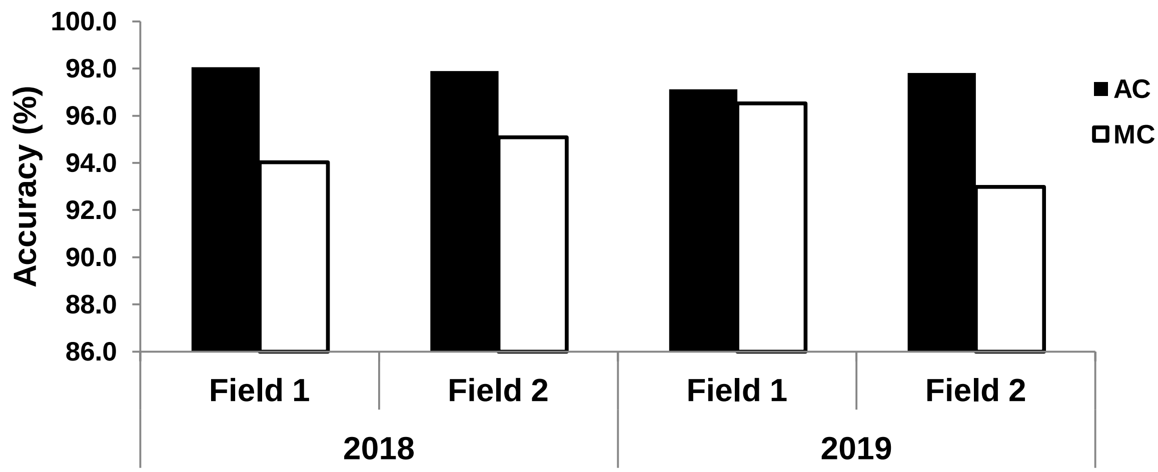

Figure 6. Average accuracy of yield estimated using autonomous calibration yield monitoring system (AC) and manual calibration yield monitoring system (MC) in field 1 and field 2 over 2018 and 2019 harvest.

Table 6. Accuracy of yield estimated with manual calibration yield monitoring system and autonomous calibration yield monitoring system for each load in 2018 on field 1 and field 2.

	Manual calibration		Autonomous calibration	
	Field 1	Field 2	Field 1	Field 2
Load	Accuracy (%)	Accuracy (%)	Accuracy (%)	Accuracy (%)
1	94.7	95.0	99.5	99.3
2	95.6	95.4	98.9	96.3
3	93.4	96.4	97.5	97.1
4	93.1	95.2	97.7	96.6
5	93.4	94.9	96.7	98.1
6	97.1	94.3	98.1	96.6
7	93.0	94.4	99.4	99.7
8	93.6	95.1	97.5	99.4
9	94.4		98.5	
10	92.1		96.8	

4.1.1. Manual calibration

The manual calibration yield monitoring system was able to estimate yields that were on average 94.3% accurate with error that ranging from +7.9 to -2.7%. The estimated yield is consistently over-estimated in both years in all fields with the exception of the last load in Field 1 of 2019; this trend is demonstrated in 2018 by Figure 7a and Figure 7b and in 2019 by Figure 7c and Figure 7d. The produced yield estimates used for the research over the 2018 and 2019 harvest had very similar average accuracies that differed only by 0.5% between years and 1.6% between fields despite experiencing different growing conditions. In both years, the variety Brandon had the lowest accuracy of estimated yield.

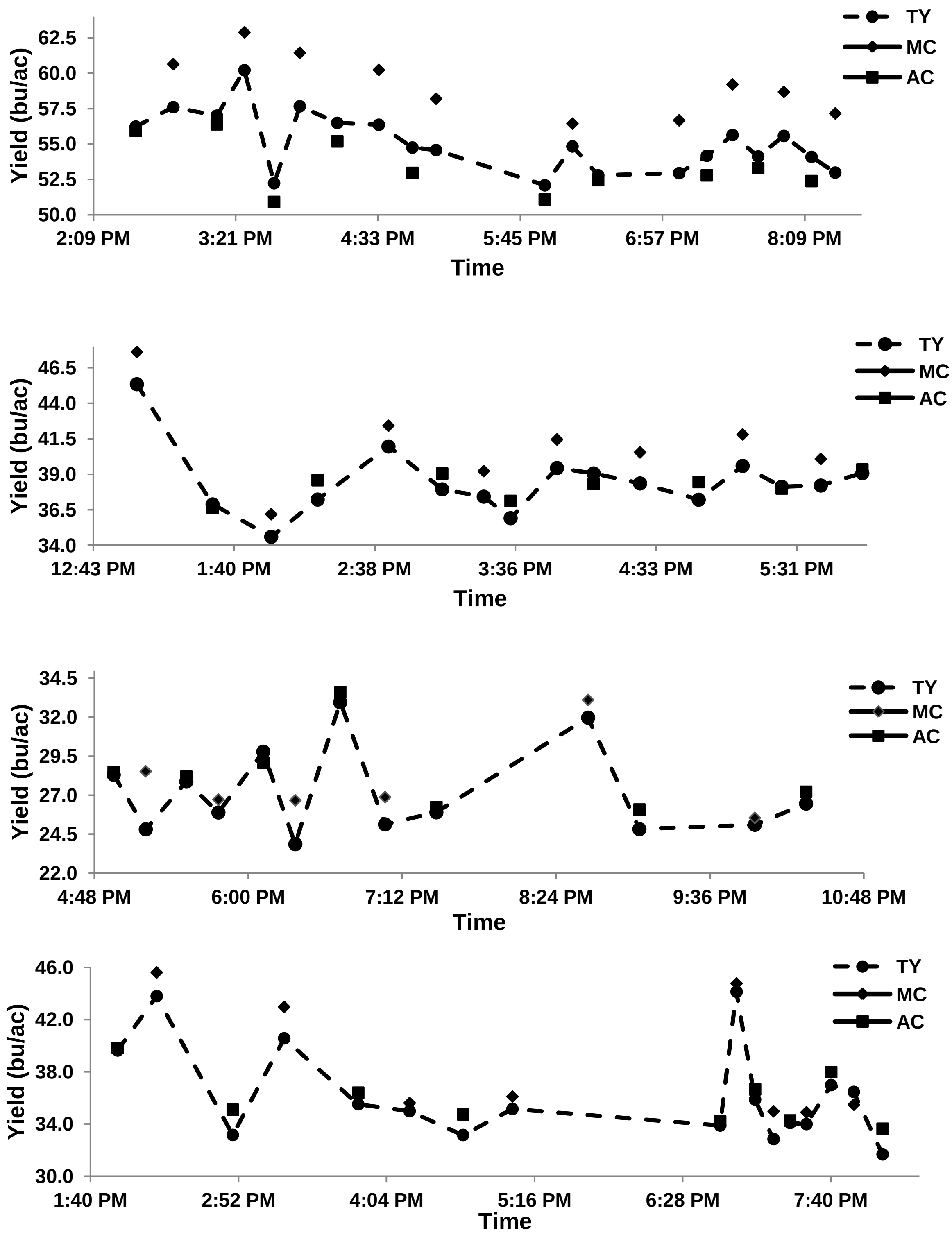

Figure 7. True yield (TY) and estimated yield of *T. aestivum* harvested with manual calibration yield monitoring system (MC) and autonomous calibration yield monitoring system (AC) in; (a) field 1 during 2018 harvest; (b) field 2 during 2018 harvest; (c) field 1 during 2019 harvest; (d) field 2 during 2019 harvest.

4.1.2. Autonomous calibration

The autonomous yield monitoring system was able to produce results that were on average, 97.7% accurate over the duration of the research. The estimated yield values are demonstrated in Table 6 and had error that ranged from -3.3 to +3.7% in 2018 and, +8.4 to +0.6% in 2019. In 2018 on average, Field 1 was underestimated each load by an average of 2.0% whereas Field 2 averaged 1.4% overestimation, although both overestimation and underestimation did occur (Fig. 7b). In 2019, Field 1 was overestimated by 2.3% and Field 2 was overestimated by 3.3% for an average overestimation of 2.8%. The generated yield estimates used for the research over 2018 and 2019 had similar levels of accuracy that on average only differed by 0.5% between years and 0.4% between fields.

4.1.3. Factors influencing estimated yield accuracy

Grain kernel moisture content A direct relationship between grain kernel moisture content and yield estimate accuracy exists for the manual calibration yield monitoring system. As grain kernel moisture content increases, the accuracy of the estimated yield increases with the exception of Field 1 in 2019 where no effect is observed (Fig. 8a and Fig. 8c). In 2018, this trend is strongest in Field 2 as compared to Field 1 where a flatter trend line and lower correlation are demonstrated. However, this observation is not completely consistent when examining the relationship with the outcomes from the autonomous calibration yield monitoring system. The accuracy of yield estimate by the autonomous calibration yield monitoring system remained relatively unchanged in Field 1 and Field 2 in 2018 despite slightly increasing as grain kernel moisture content decreased (Fig. 8b). In 2019, the accuracy of the estimated yield showed a greater response at different grain kernel moisture contents as indicated by the steeper slopes and larger correlation values, but each field experienced an opposite effect (Fig. 8d). Overall, the accuracy of the yield estimated from the manual calibration yield monitoring systems appears to be greatest at higher grain kernel moisture contents whereas the influence of grain kernel moisture content on the accuracy of yield estimated using the autonomous calibration yield monitoring system is inconsistent.

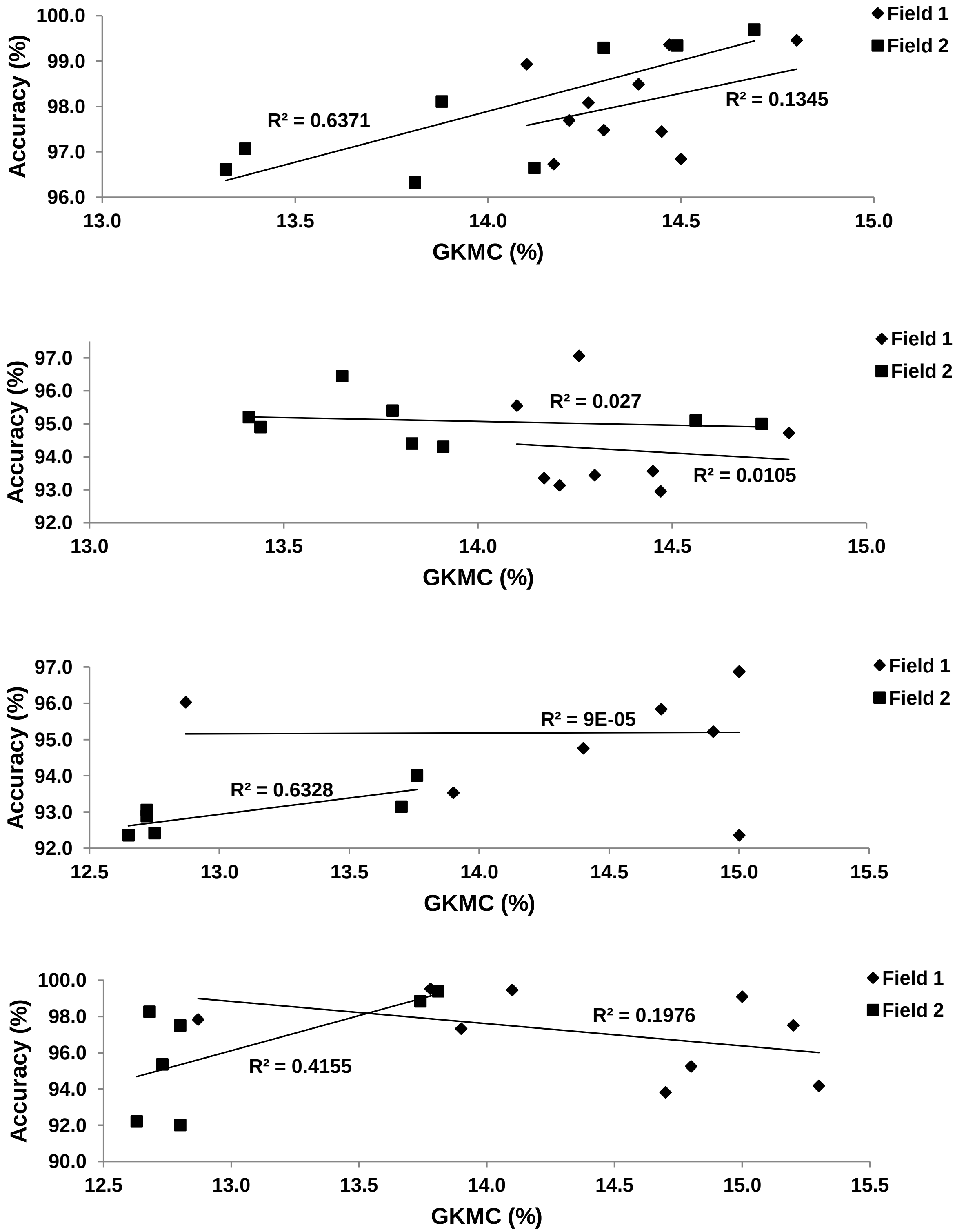

Figure 8. Relationship of grain kernel moisture content (GKMC) and accuracy of yield estimated for field 1 and field 2; (a) with manual calibration yield monitoring system in 2018; (b) with autonomous calibration yield monitoring system in 2018; (c) with manual calibration yield monitoring system in 2019; (d) with autonomous calibration yield monitoring system in 2019.

Time The trend lines for the manual calibration yield monitoring system in Figure 9a and Figure 9b illustrate that the overall accuracy of the estimated yields decreased with time in 2018. Field 2 experienced the greatest decline in accuracy with time when compared to Field 1, supported by the larger correlation (Fig. 9b). This trend is also observed with the yield estimates produced using the autonomous calibration yield monitoring system in Field 1 but not in Field 2 where accuracy of the estimated yields increased with time (Fig. 9b). In 2019, the accuracy of yield estimated with the manual calibration yield monitoring system continued to decrease as time continued in Field 1 and Field 2, demonstrated in Figure 9c and Figure 9d, respectively. The large correlation and steep downward slope of the trend line in Figure 9d supports that the greatest decline in accuracy occurred in Field 2. The relatively flat trend line in Figure 9c and the correlation value of $9x10^{-05}$ indicates that the autonomous calibration yield monitoring system experienced very little variation in accuracy of estimated yields. Similar to Field 1 in 2019, time had little effect on accuracy of the yields estimated by the autonomous calibration yield monitoring system on Field 2 in 2019.

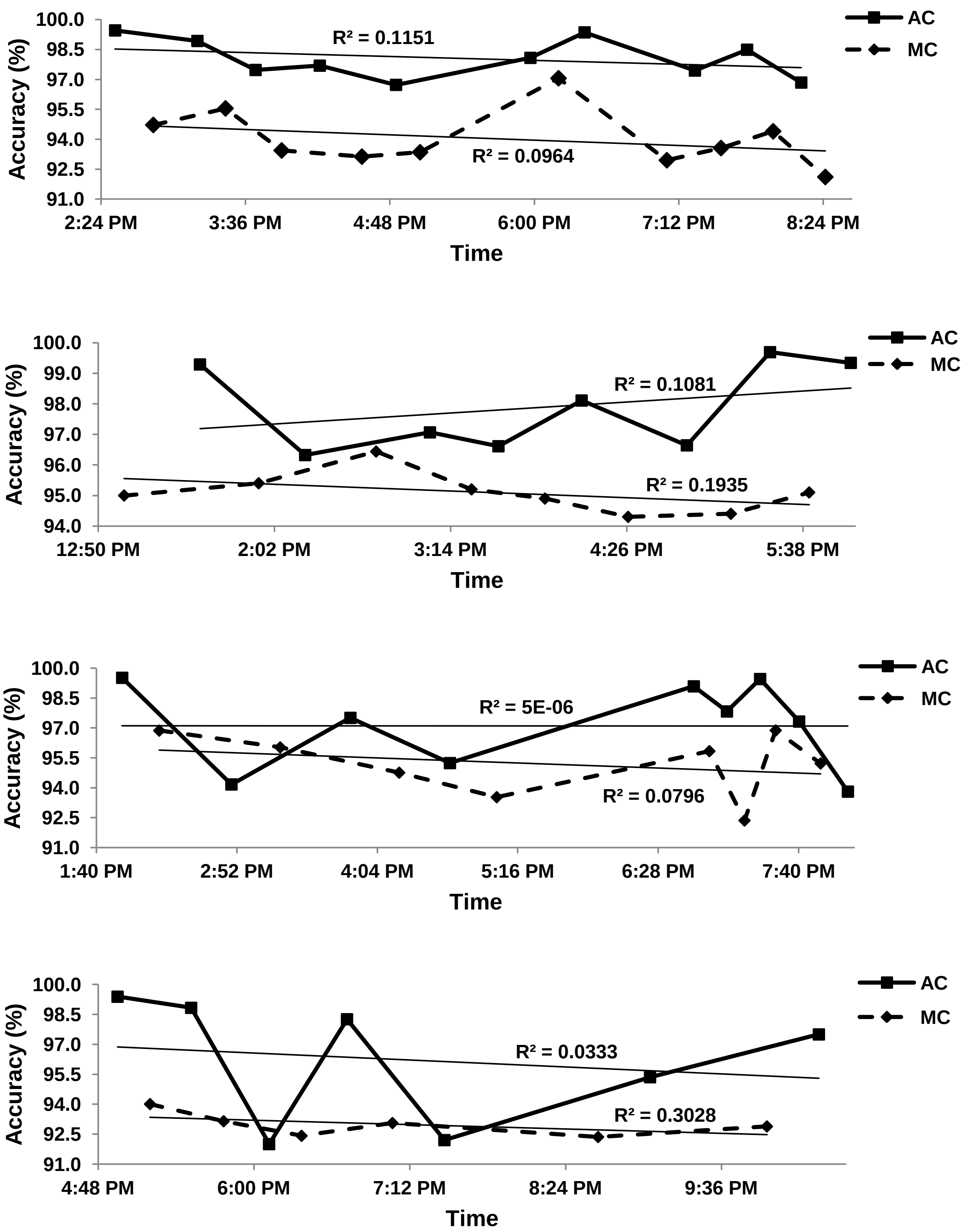

Figure 9. Relationship of accuracy of yield estimated by manual calibration yield monitoring system (MC) and autonomous calibration yield monitoring system (AC) at the time of each load harvested on; (a) field 1 in 2018; (b) field 2 in 2018; (c) field 1 in 2019; (d) field 2 in 2019.

Ambient air temperature An inverse relationship between the moisture contents of the grain kernels and the ambient air temperature at the time of harvest was found to be consistent throughout the entire research. Regardless of the year, time of the day, or field, as the ambient air temperature increased or decreased, the grain kernel moisture content responded inversely (Fig. 10a, Fig 10b, Fig. 10c, and Fig. 10d). Also, an association between the time of day and the ambient air temperature is observable in Figure 10a, Figure 10c, and Figure 10d where the ambient air temperature begins to decrease between 6:00PM and 7:00PM. The amount of time passing did not show any relation to the ambient air temperature because no consistent trend was identified throughout the research where after a set amount of time had passed the temperature would change. Thus, time itself did not have any effect on the ambient air temperature, but the time of the day at which harvest occurred did.

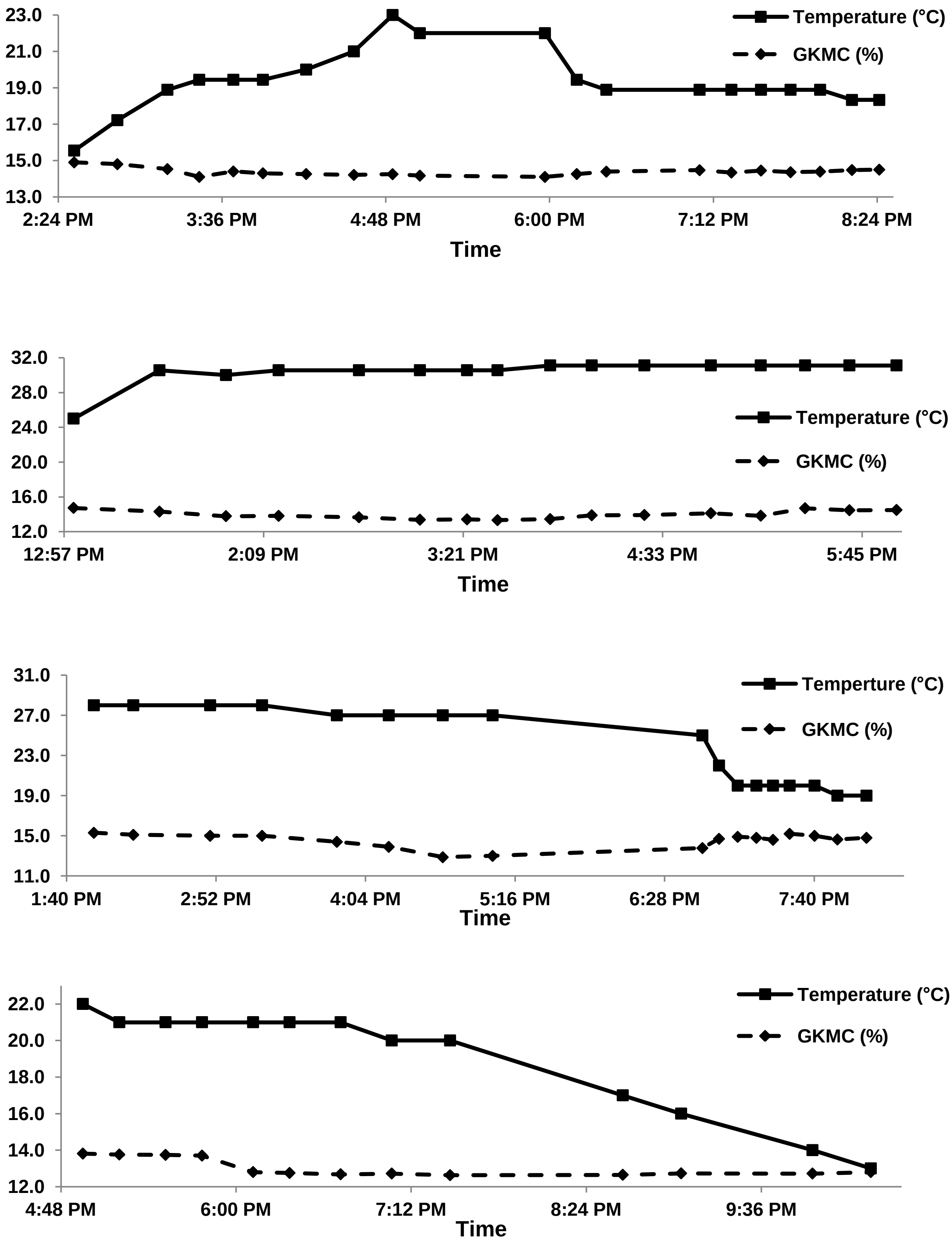

Figure 10. Effect grain kernel moisture content (GKMC) of *T. aestivum* harvested and environmental temperature with time for all loads harvested on; (a) field 1 in 2018; (b) field 2 in 2018; (c) field 1 in 2019; (d) field 2 in 2019.

5. DISCUSSION

5.1. Estimated yield accuracy

When properly calibrated, manufacturers claim yield estimates from mass-flow yield monitoring systems to be accurate within 3.0% however; this is not always the case as shown by other research conducted at a field scale (Deere & Company 2012). The manual calibration yield monitoring system was able to produce estimates that were on average accurate within 5.4% in 2018 and 5.9% in 2019 of the true yield. Although this is well below the level of precision that can be achieved in a controlled environment, it is consistent with other research conducted at a field scale. Literature by Reynes et al. (2002) reviewed several variations of mass-flow yield monitors and found error in estimated yield to be as great as 9.17% when all reasonable measures are taken to ensure accuracy. Although an overall average error of 5.7% in estimated yield is greater than what manufacturers suggest can be achieved it is consistent with other research conducted on field scales. The estimated yields produced using autonomous calibration yield monitoring system fall within what is supported by manufacturers where on average results fell within the 3.0% accuracy claims.

It is likely that the yield estimates produced using the autonomous calibration yield monitoring system were more accurate due to the ability to continually calibrate to adjust with changing crop conditions. The autonomous calibration yield monitoring system also ensures that each mass-flow sensor calibration is precise and of high quality. Specific criteria that each load must meet before being used in a calibration functions as a failsafe, preventing any inaccurate or poor adjustments of the calibration curve (John Deere 2018). Literature by Reynes et al. (2002) indicate that consistent crop is important for maximizing for accuracy with yield monitors as varying flow rates of grain hitting the impact plate of the mass-flow sensor can result in lower accuracy. This was consistent with the outcomes throughout this study as on average, the most accurate yield estimation results were produced in 2018.

There is a high likelihood that the difference between the mean accuracies of the yield estimated by the manual calibration yield monitoring system and the autonomous calibration yield monitoring system in 2018 is not due to sampling error or chance, supporting the difference in capabilities between the two systems to accommodate variability. The greatest probability of a significant difference in mean yield accuracy occurred on Field 1 in 2018 where the p-value of 1.9E-06 is less than the standard level of significance (α=0.05) and the probability of obtaining the t-value of 7.3 or greater is 0.0009%. Such small likelihood of a significant difference of accuracy in mean yields in Field 1 in 2018 makes sense as the autonomous calibration yield monitoring system was most accurate and consistent whereas the manual calibration yield monitoring system was least accurate. The lower p-value and higher t-value found in Field 2 in 2018 also imply that the difference in average accuracy of the yields estimated with the manual calibration yield monitoring system and the autonomous calibration yield monitoring system is significant and not due chance or sampling error. The lowest p-values and higher t-values found in 2018 are due to lower variation among the sample populations as the two-sample t-test performs better with lower variation.

Variable crop conditions and flow rates produced a negative effect similar to that discussed in literature by Reynes et al. (2002) where inaccuracy of yield estimates was greatest in 2019; the year with the most inconsistency in crop conditions. The lower likelihood of a significant difference between the means of the accuracy in yield estimated by the autonomous calibration yield monitoring system and the manual calibration yield monitoring system in 2019 demonstrates the influence that poor crop and inconsistent conditions has on the ability of yield monitoring systems to produce significant results. This was most evident on Field 2 where even though the yield estimated by the autonomous calibration yield monitoring system was overall more accurate, the low t-value of 1.8 and p-value of 0.1 is greater than the level of significance (α=0.05) indicating no significant difference. This outcome is likely because the yield estimates from both the autonomous calibration yield monitoring system and the manual calibration yield monitoring system had greater variability which makes it hard to conclude that a significant difference exists; even though the mean accuracy of the estimated yield for the manual calibration yield monitoring system is lower. In Field 1, the p-value was higher than in 2018, but still lower than the level of significance (α=0.05) supporting that the significant difference between the mean accuracies of the estimated yields is not due to chance or sampling error.

The changes in average accuracies between Field 1 and Field 2 in 2018 were also minimal in comparison to the differences observed in between fields in 2019 indicating that consistent crop conditions are essential for consistent yield estimates regardless of the calibration system used. It is important to note that although the distribution of data was not normal for the t-tests calculated in 2018 and in 2019, a normal distribution was still assumed because prior knowledge of the populations finds a normal distribution. The reliability of the two-sample t-test assuming unequal variances decreases with skewed distributions and small sample sizes due to increased variance and random error limiting the detection of smaller differences between the means of the yields estimated from each yield monitoring system. Thus it is likely that with a larger sample size a significant difference would have been detected on Field 2 in 2019.

The adverse effect that inconsistent crop conditions had on the accuracy of yield estimated was most prominent with the manual calibration yield monitoring system. Throughout 2019, the yield estimated using the manual calibration yield monitoring system experienced greater variability between fields and overall lower accuracy with estimated yield in comparison to 2018. Conversely, the accuracy of the yield estimated by autonomous calibration yield monitoring system remained relatively consistent in each year and between fields despite the different year to year conditions, implying that the autonomous calibration yield monitoring system is more consistent under all conditions. Overall, variable conditions did negatively affect the abilities of both yield monitoring systems to accurately estimate yield but the extent is inconclusive due to limited data. It is possible that the impact that variable crop conditions had on accuracy was undervalued since the fields and days selected for use in this research were chosen based on uniformity and consistency. Had more fields with a wider range of conditions been studied it is likely that a stronger relationship may have been identified between the effect of variable conditions and estimated yield accuracy.

Another possible explanation for the higher accuracy of estimated yield in 2018 may be a result of the larger average load size used as literature by Grisso et al. (2002b) suggests that a direct relationship exists between the load size of grain in the clean grain tank and accuracy of yield estimates. If this were true, then the highest accuracy of estimated yields should be found in the fields with the biggest average load sizes and it would be expected that the most accurate yield estimation for the manual calibration yield monitoring system to be in Field 2 in 2018, not Field 1 of 2019. However, this is true for the average accuracy of yield estimated using the autonomous calibration yield monitoring system as accuracy did increased with load size. Literature has also proven that this relationship is only true until a minimum threshold load size is reached, about 4000.0lbs according to Grisso et al. (2002b) or 2000.0lbs according to John Deere (2018) thus, it is unlikely the load size is completely responsible for the variation in estimated yield accuracies recorded in each field as all loads exceeded 4000.0lbs. Another consideration is that the weight measured by the grain cart was rounded to factors of ten, limiting the precision. It is more likely that other factors such as variable conditions played a larger role in the variation between the accuracies of the estimated yields.

As previously discussed, 2019 growing conditions were extremely dry initially with erratic storms and precipitation throughout harvest that resulted in variation among crop, grain kernel moisture contents, and bushel weights of the grain. It is also known that yield estimates produced by yield monitoring systems are most accurate when frequently re-calibration occurs and when crop conditions remain uniform (M. Darr 2019). Since the crop conditions in Field 1 were closer to the conditions experienced during calibration procedure it is expected that accuracy was higher. Conversely, as a result of inconsistent growing conditions the harvest conditions experienced in Field 2 were different than the conditions at what the calibrations initially took place at in Field 1 which may explain the lower accuracy of the estimated yields. However, this theory does not support the outcomes in 2018, as the manual calibration yield monitoring system was slightly more accurate in Field 2. The reason this relationship was not observed in 2018 is likely because the crop conditions stayed consistent enough with no significant changes over the two day period for a significant decline in accuracy warranting re-calibration to be observed.

It is also possible that the varietal differences or differing growing characteristics influenced the resulting accuracy of the yield estimated. Of the three varieties evaluated throughout the research, the lowest precision in estimated yield from the manual calibration yield monitoring system consistently occurred with variety Brandon. A potential explanation may be because Brandon is a slightly taller variety and thus, there is more biomass to be processed and exposed to changing crop conditions. Also, literature from Fulton et al. (2018) indicates that changes in density of crop can influence the accuracy of yield monitors. In this case there was a change in yield between the two fields and within Field 1 as initially the crop had a greater density; the yield was greater than at the end of the field when calibration took place. A further possible explanation is that in Field 2 is that the crop may have been more consistent. Although it is not possible to confidently determine the underlying reason behind the outcome it is likely that a combination of field consistencies and variety characteristics are responsible for the differences in accuracy between Field 1 and Field 2 in 2018.

5.2. Factors influencing estimated yield accuracy

5.2.1. Grain kernel moisture content

Knowing that 60.0lbs per bushel is the standard normal weight for one bushel of *T. aestivum* at 13.5% moisture and referring to the overall higher than normal bushel weights with the respective grain kernel moisture content readings for each load in each field, it makes sense that typically, changing grain kernel moisture contents negatively affected the accuracy of estimated yields (Luck & Fulton 2004). Literature by Casady et al. (2010) indicates that changes in grain kernel moisture content readings have an adversely affect the accuracy of estimated yield because the bushel weight of the grain is dependent on the grain kernel moisture content. This is demonstrated through comparisons of the accuracy in Figure 9 and the grain kernel moisture contents in Figure 10 at similar times where the accuracy of the yield estimated is typically reduced with grain kernel moisture content changes for both fields for each year. Not specifically the value of the grain kernel moisture content, but the point where the grain kernel moisture changes that has the effect. Literature by Arslan and Colvin (2002a) has also found that changing moisture contents also alters the impact characteristics of the grain striking the impact plate. The minimal affect that changing grain kernel moisture contents had on the accuracy of the yields estimated by the autonomous calibration yield monitoring system are likely a result of the continuous calibrations that enable the calibration curve to accommodate variation. This is also why in 2018 there is no effect on the accuracy in either field. However, in 2019 the results are inconclusive as the accuracy of estimated yield on each field had an opposite effect.

The manually calibrated yield monitoring system was pre-loaded with specific moisture content calibration curves from factory that assumes a preset weight of 60.0lbs per bushel of *T. aestivum* with a grain kernel moisture content of 13.5% (Deere & Company 2002). These values are equal to 0.23% moisture per pound of wheat when estimating yield whereas in actuality the grain harvested averaged 0.22% moisture per pound in both Field 1 and Field 2 in 2018. Therefore, it is possible that the increasing grain kernel moisture content readings approached the parameters closer to the value at the time of calibration as indicated with higher accuracy at higher grain kernel moisture contents for 2018 in Figure 8a. This is also consistent with the findings in 2019 when examining the relationship between the accuracy of the estimated yield and grain kernel moisture content in Field 2 from Figure 8c. Literature from M. Darr (2019) and B.D. Luck (2017) indicate that changes in the weight of the grain being harvested can negatively influence the accuracy of the yield estimated from yield monitoring systems. Accuracy increases as grain kernel moisture content per pound nears closer to the standard moisture reading of 0.23% per pound of *T. aestivum*, which in this case occurs as the grain kernel moisture content increases due the higher than normal bushel weights of *T. aestivum*. Overall, the grain kernel moisture content seems to have an effect on the accuracy of yield estimated from yield monitoring systems but the extent is unknown.

5.2.2. Time and mechanical malfunction

Similar to any other device or sensor, proper maintenance and operation are fundamental to ensure integrity and accuracy of data produced. Overtime, sensors are prone to inaccuracy, and as time passes without re-calibrations, sensors become vulnerable to error. For this reason, the decline in accuracy of yield estimated using the manual calibration yield monitor system with time in 2019 was expected. The variable conditions were likely extreme enough to warrant a re-calibration multiple times throughout the harvest to ensure accurate results. However this does not explain the increase in accuracy of yield estimated using the manual calibration yield monitoring system from Field 1 to Field 2 in 2018.

It is possible that material and debris had accumulated on the grain kernel moisture content sensor plates interfering with the sensors ability to accurately measure the capacitance resulting in incorrect grain kernel moisture content readings. Shearer et al. (1999) discusses that material and dust can build up on the sensor from harvest and can cause incorrect readings if not cleaned regularly. Erratic grain kernel moisture content readings are frequently a result of dirty sensor plates and are common in extreme and variable conditions (Casady et al. 2010). This may explain why the grain kernel moisture contents and accuracy typically had opposite responses between Field and Field 2 during the 2019 harvest for both yield monitoring systems (Figure 8c and Figure 8d).

Literature by Grisso et al. (2009) also discusses the effect that a malfunctioning or improperly calibrated moisture sensor can have on the accuracy of yield estimates. Improper moisture sensor calibration can introduce error into yield results as underestimated grain kernel moisture content readings will result in an overestimation of yield. Since changing grain kernel moisture contents should have minimal effect on accuracy of yield estimated using the autonomous calibration yield monitoring system, it is possible that build up of material such as dirt or plant sap over the sensing plates or an electronic malfunction may partially explain the inconsistent relationship with accuracy of yield estimated and time. This may also explain why the grain kernel moisture content and time did not follow a similar pattern. However, with more data, a more consistent trend would be likely found. Thus, even with proper calibration, overtime the buildup of dust and material over the sensor, or sensor malfunction can interfere with the accuracy of estimated yield.

5.2.3. Ambient air temperature

Key connections between the grain kernel moisture content, mass density of the grain, and temperature were discussed by Reynes et al. (2002) linking to the accuracy of estimated yield. The inverse relationship between ambient air temperature at the time of harvest and the grain kernel moisture content indicates that there is a direct connection, and since accuracy has been shown to be affected by the grain kernel moisture contents it can be said that the temperature indirectly affects the accuracy of the estimated yield. The time at harvest also showed to have an indirect effect on the accuracy of the estimated yield, most likely because of the affect of cooling ambient air temperatures as the sun set. This makes sense because at warmer temperatures, the air can hold more moisture, which in turn dries the grain kernels down to lower moisture content. It is also important to note what is not taken into consideration, which is the role that the humidity may have played with influencing the grain kernel moisture contents. The ambient air temperature, grain kernel moisture content, and time have an interconnected relationship, which is why re-calibration as conditions change is important, and also why the autonomous calibration yield monitoring system was most accurate. This finding is supported by literature from B.D. Luck (2017) emphasizing the importance of re-calibration as crop conditions change to ensure yield estimate accuracy. Estimated yield generated from yield monitoring systems are most precise when calibrations occur frequently to accurately represent the current conditions of the crop, thus experiencing a change in crop conditions without re-calibration will negatively influence the accuracy of estimated yield. Similar findings are reported by M. Darr (2019) stating that re-calibration is necessary when significant changes occur with grain kernel moisture content and test weights of the grain.

6. CONCLUSION

Precision technology is a fundamental component in the transition towards modern agriculture and the shift toward farm automation. In this study, the accuracy of yield estimates generated using autonomous calibration of the mass-flow sensor in the onboard yield monitor of a combine harvester was evaluated and compared to the traditional method of manual mass-flow sensor calibration. When the mass-flow sensor was automatically and continually calibrated the yield was estimated with greater precision and consistency, indicating that frequent and quality calibration of the mass-flow sensor was key for maximizing precision in estimated yield.

Inconsistent crop conditions negatively affected the accuracy of estimated yield in both the autonomous and manual calibration methods with the greatest impact on estimated yield accuracy from the manual calibration yield monitoring system. The inability of the manual calibration system to accommodate changing crop conditions was reflected by larger error in estimated yield over time and especially during periods of changing temperature and grain kernel moisture contents. However, the extent of the influence from varying grain kernel moisture content and temperature is unknown due to limited data. When the mass-flow sensor was automatically calibrated the impact of such variations in crop conditions was minimized due to continual adjustment of the mass-flow sensor calibration curve to represent the specific crop conditions being experienced.

Implementing autonomous calibration of the mass-flow sensor in combine harvester yield monitors eliminated many of the challenges that are associated with traditional manual calibration methods without sacrificing the quality of the yield data. The ability to gather precise and reliable yield data without the need to stop for time consuming calibrations throughout the harvest season not only created a more efficient process but increased the frequency of calibrations as well. Also, elimination of specialized equipment that is typically required for manual calibration make accurate yield data accessible to producers without access to weigh scales or grain carts and help offset the costs of new technology. Yield data produced using the autonomous calibration yield monitoring system exceeded that produced by the manual calibration method in regards to precision and consistency. Autonomous calibration of the mass-flow sensor in combine harvester yield monitors is a valuable technology that effectively and efficiently generates precise yield data.

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8. APPENDIX 1 – DATA

2018 data – Field 1

Yield monitoring system	Load	Time	Grain kernel moisture content (%)	Temperature (°C)	Acres	Combine yield (bu/ac)	Scale weight (lbs)	True yield (bu/ac)	Accuracy (%)
AC	1	2:31 PM	14.9	15.6	8.1	55.9	29080.0	56.2	99.5
MC	2	2:50 PM	14.8	17.2	4.5	60.6	16700.0	57.6	94.7
AC	3	3:12 PM	14.5	18.9	5.6	56.4	20320.0	57.0	98.9
MC	4	3:26 PM	14.1	19.4	4.5	62.9	17380.0	60.2	95.5
AC	5	3:41 PM	14.4	19.4	6.6	50.9	22060.0	52.2	97.5
MC	6	3:54 PM	14.3	19.4	4.5	61.4	16680.0	57.7	93.4
AC	7	4:13 PM	14.3	20.0	4.5	55.2	16380.0	56.5	97.7
MC	8	4:34 PM	14.2	21.0	4.5	60.2	16340.0	56.4	93.1
AC	9	4:51 PM	14.3	23.0	4.5	53.0	15840.0	54.8	96.7
MC	10	5:03 PM	14.2	22.0	4.5	58.2	15680.0	54.6	93.3
AC	11	5:58 PM	14.1	22.0	4.7	51.1	15500.0	52.1	98.1
MC	12	6:12 PM	14.3	19.4	4.4	56.4	15580.0	54.8	97.1
AC	13	6:25 PM	14.4	18.9	4.6	52.5	15440.0	52.8	99.4
MC	14	7:06 PM	14.5	18.9	4.5	56.7	15280.0	52.9	93.0
AC	15	7:20 PM	14.3	18.9	4.7	52.8	16260.0	54.2	97.4
MC	16	7:33 PM	14.5	18.9	4.5	59.2	15980.0	55.6	93.6
AC	17	7:46 PM	14.4	18.9	4.3	53.3	14860.0	54.1	98.5
MC	18	7:59 PM	14.4	18.9	4.5	57.2	16040.0	55.6	94.4
AC	19	8:13 PM	14.5	18.3	4.5	52.4	15440.0	54.1	96.8
MC	20	8:25 PM	14.5	18.3	4.5	57.2	15360.0	53.0	92.1

2018 data – Field 2

Yield monitoring system	Load	Time	Grain kernel moisture content (%)	Temperature (°C)	Acres	Combine yield (bu/ac)	Scale weight (lbs)	True yield (bu/ac)	Accuracy (%)
MC	1	1:01 PM	14.7	25.0	8.0	38.1	23216.0	36.3	95.0
AC	2	1:32 PM	14.3	30.6	4.0	36.6	9440.0	36.9	99.3
MC	3	1:56 PM	13.8	30.0	7.0	29.0	15520.0	27.7	95.4
AC	4	2:15 PM	13.8	30.6	4.7	38.6	11246.0	37.2	96.3
MC	5	2:44 PM	13.7	30.6	8.2	33.9	21456.0	32.8	96.4
AC	6	3:06 PM	13.4	30.6	7.6	39.1	18480.0	37.9	97.1
MC	7	3:23 PM	13.4	30.6	6.1	31.4	14720.0	29.9	95.2
AC	8	3:34 PM	13.3	30.6	5.3	37.1	12090.0	35.9	96.6
MC	9	3:53 PM	13.4	31.1	8.5	33.2	21488.0	31.6	94.9
AC	10	4:08 PM	13.9	31.1	4.6	38.3	11575.0	39.1	98.1
MC	11	4:27 PM	13.9	31.1	6.0	32.4	14768.0	30.7	94.3
AC	12	4:51 PM	14.1	31.1	5.0	38.5	11860.0	37.2	96.6
MC	13	5:09 PM	13.8	31.1	7.3	33.4	18528.0	31.7	94.4
AC	14	5:25 PM	14.7	31.1	5.3	38.0	12980.0	38.1	99.7
MC	15	5:41 PM	14.5	31.1	6.6	32.1	16120.0	30.6	95.1
AC	16	5:58 PM	14.5	31.1	4.8	39.3	11980.0	39.1	99.3

2019 data – Field 1

Yield monitoring system	Load	Time	Grain kernel moisture content (%)	Temperature (°C)	Acres	Combine yield (bu/ac)	Scale weight (lbs)	True yield (bu/ac)	Accuracy (%)
AC	1	1:54 PM	15.3	28.0	4.5	39.8	10700.0	39.6	99.5
MC	2	2:13 PM	15.1	28.0	4.6	45.6	12090.0	43.8	95.9
AC	3	2:50 PM	15.0	28.0	4.6	35.1	9150.0	33.2	94.2
MC	4	3:15 PM	15.0	28.0	4.5	43.0	11070.0	40.6	94.1
AC	5	3:51 PM	14.4	27.0	4.6	36.4	9800.0	35.5	97.5
MC	6	4:16 PM	13.9	27.0	4.6	36.5	9650.0	35.0	95.5
AC	7	4:42 PM	12.9	27.0	4.5	34.7	8950.0	33.1	95.2
MC	8	5:06 PM	13.0	27.0	4.7	36.6	9910.0	35.1	96.0
AC	9	6:47 PM	13.8	25.0	4.6	34.2	9350.0	33.9	99.1
MC	10	6:55 PM	14.7	22.0	4.6	46.0	12180.0	44.1	95.7
AC	11	7:04 PM	14.9	20.0	4.6	36.6	9900.0	35.9	97.8
MC	12	7:13 PM	14.8	20.0	4.7	35.0	9260.0	32.8	93.5
AC	13	7:21 PM	14.6	20.0	4.5	34.3	9200.0	34.1	99.5
MC	14	7:29 PM	15.2	20.0	4.6	35.9	9380.0	34.0	94.3
AC	15	7:41 PM	15.0	20.0	4.8	38.0	10650.0	37.0	97.3
MC	16	7:52 PM	14.6	19.0	4.6	36.8	8130.0	35.5	96.4
AC	17	8:06 PM	14.8	19.0	4.5	33.6	8550.0	31.7	93.8

2019 data – Field 2

Yield monitoring system	Load	Time	Grain kernel moisture content (%)	Temperature (°C)	Acres	Combine yield (bu/ac)	Scale weight (lbs)	True yield (bu/ac)	Accuracy (%)
AC	1	4:57 PM	13.8	22.0	5.4	28.5	10090.0	28.3	99.4
MC	2	5:12 PM	13.8	21.0	7.9	28.5	12930.0	24.8	85.0
AC	3	5:31 PM	13.7	21.0	5.6	28.2	10300.0	27.9	98.8
MC	4	5:46 PM	13.7	21.0	8.0	26.7	13670.0	25.9	96.8
AC	5	6:07 PM	12.8	21.0	5.2	29.1	10230.0	29.8	99.5
MC	6	6:22 PM	12.8	21.0	8.0	26.7	12600.0	23.9	88.2
AC	7	6:43 PM	12.7	21.0	9.4	33.6	20450.0	33.0	98.2
MC	8	7:04 PM	12.7	20.0	7.9	26.9	13100.0	25.1	93.1
AC	9	7:28 PM	12.6	20.0	5.5	26.2	9400.0	25.9	92.2
MC	10	8:39 PM	12.7	17.0	8.0	33.1	16880.0	32.0	96.4
AC	11	9:03 PM	12.7	16.0	7.6	26.1	12450.0	24.8	95.4
MC	12	9:57 PM	12.7	14.0	8.1	25.6	13410.0	25.1	98.2
AC	13	10:21 PM	12.8	13.0	7.3	27.2	12750.0	26.5	97.5