RESPONSE OF CORN YIELD TO IRRIGATION AND NITROGEN AND THE RELATIONSHIP BETWEEN YIELD AND NDVI MEASURED BY AERIAL IMAGERY

By

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IMAGERY

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Abstract: Nitrogen (N) and water are among the key components that effect crop growth and yield outcome in the Southern Great Plains. However, the effect of N and irrigation interaction on corn yields have not been studied in the area. The objectives of this study were to evaluate yield response of corn to various N and irrigation rates and interactions between N and irrigation, provide valuable insight on spatial variation across irrigation treatments in response to N, as well as evaluate the relationship between corn yield and normalized difference vegetation index (NDVI). The study was conducted at the McCaull Research and Demonstration Farm near Eva, in the Oklahoma Panhandle. The N treatments included five rates ranging from 0 to 336 kg N ha^{-1}. The irrigation rates included 25, 32, 38 mm of water per irrigation event. The corn responded to N rates significantly each year of study. However, the yield response to irrigation was visible only in 2019, which despite receiving above normal rainfall early in the season recorded the lowest amount of rainfall in mid and late season among the three years of study. No irrigation response was observed in 2018 and 2020 due to adequate replacement of water deficits along with timely rainfall. There was no interaction in N and irrigation rates that impacted corn yield, suggesting that irrigation and N rates were influencing yields independently. The highest irrigation rate (38 mm) presented the largest variability of yield increase with an optimum N rate of 235 kg N ha^{-1}for 2019 and 2020. In 2018, 336 kg N ha^{-1} was the optimum rate and showed the most variability within the 25 mm irrigation rate. A significant relationship in 2019 between NDVI and yield presented that the corn was in fact influenced by either irrigation or nitrogen while 2020 showed no true relationship. Over time Coefficient of Variation (CV) decreased with plant growth, supported by both 2019 and 2020 growing seasons. Our results indicate that despite the irrigation rates and capacities, corn yields in the Oklahoma Panhandle remain vulnerable to weather patterns and production scale mechanical challenges and relate to spectral reflectance measurements.

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CHAPTER I

CORN YIELD RESPONSE TO VARIABLE IRRIGATION AND NITROGEN RATES

Abstract

Nitrogen (N) and water are among the key components that effect crop growth and yield outcome in the Southern Great Plains. However, the effect of N and irrigation interaction on corn yields have not been studied in the area. The objectives of this study were to evaluate yield response of corn to various N and irrigation rates and interactions between N and irrigation, and provide valuable insight on spatial variation across irrigation treatments in response to N. The study was conducted at the McCaull Research and Demonstration Farm near Eva, in the Oklahoma Panhandle. The N treatments included five rates ranging from 0 to 336 kg N ha^{-1}. The irrigation rates included 25, 32, 38 mm of water per irrigation event. The corn responded to N rates significantly each year of study. However, the yield response to irrigation was visible only in 2019, which despite receiving above normal rainfall early in the season recorded the lowest amount of rainfall in mid and late season among the three years of study. No irrigation response was observed in 2018 and 2020 due to adequate replacement of water deficits along with timely rainfall. There was no interaction in N and irrigation rates that impacted corn yield, suggesting that irrigation and N rates were influencing yields independently. The highest irrigation rate (38 mm) presented the largest variability of yield increase with a maximized N rate of 235 kg N ha^{-1} for 2019 and 2020. In 2018, 336 kg N ha^{-1} was the maximized rate and showed the most

variability within the 25 mm irrigation rate. Our results indicate that despite the irrigation rates and capacities, corn yields in the Oklahoma Panhandle remain vulnerable to weather patterns and production scale mechanical challenges and relate to spectral reflectance measurements.

Introduction

Nitrogen (N) and water are among the key components that effect crop growth and yield outcome in the Southern Great Plains. Nitrogen is the principal constituent of numerous organic compounds like amino acids, proteins, nucleic acids, and alkaloids (Mengel et al., 2001). Water on the other hand, is an essential component of photosynthesis, regulates crop canopy temperature, and helps with absorption and transportation of nutrients throughout the plant body. Although nitrogen is essential for plant growth it is often found to be deficient in Oklahoma crops typically within a few growing seasons (Arnall, 2017a). Similarly, water is the major limiting factor in northwestern Oklahoma (which is also part of the Central High Plains region) due to low and uncertain precipitation. As a result, N and water play an important role in achieving yield potential of crops and net farm returns in western Oklahoma and in the Central High Plains of the USA. Corn is one of the major high water demanding crops, which also yields maximum yield per unit of irrigation applied in the region (Schlegal et al., 2016)). Nitrogen application is also the highest among all the other major crops produced in the region.

Nitrogen rates are particularly important when considering the maximum amount that should be used. There is great variance from year-to-year in the maximum application rate, making the values consistently different between growing seasons as well as locations. The goal should be to identify rates appropriate for the production environment suggesting farmers should adjust rates based on a reasonable yield goal and production practice (Bushong, 2014) while being courteous of potential N loss mechanisms. The application of N presents challenges. One of the most prominent challenges is its mobility, which can result in leaching. If excess N is applied, it has the potential to be lost from the soil system through leaching. Soils can especially become oversupplied when the N level exceeds crop removal (Dhital, 2016), which stresses the need to identify N rates that supply sufficient N for crop growth while minimizing this residual soil N which can result in leaching out of the root zone. Another challenge that frequently presents concern is that crop response to N fertilizer applications is often field- and season-specific and can vary widely within the same field (Doerge, 2002). In-field variability increases concerns with application emphasizing the seriousness of N management practices. Schmidt et al. (2002) observed significant variability in grain yield response to increasing N rates among in-field locations. Furthermore, in addition to yield deficiencies due to under application of N, over-application of nitrogen can also result in reduced crop performance.

In agriculture, irrigation accounts for approximately 80 percent of the United States' consumptive water use and about 90 percent specifically in the Western states. To minimize the chances of leaching and nutrient flow, irrigation systems are selected based on site conditions. The center pivot system is best known for the light and frequent application of water (Splinter, 1976). Bushong (2014) stated, in the Southern Great Plains of the United States, water is limited by relatively low rainfall and deep-water tables. The fluctuation of rainfall from year to year in the Oklahoma Panhandle can change the optimum irrigation required. Over many years, the use of water has significantly lowered the ground water level of the Ogallala Aquifer. According to the US Geological Survey (USGS), the water table in the Oklahoma Panhandle is approximately 73 meters below land surface. The USGS data retrieval expresses that the aquifer has decreased about four meters from predevelopment in 1950 to 2015 with a recharge rate of 6 cm per year (Ryder, 1996). Therefore, irrigation management that can better account for variations in rainfall amount and distribution during a growing season is essential in the Panhandle because the Ogallala Aquifer is the principal water supply for the area.

Previous studies have been focused on but are not limited to the impact of water and nitrogen on corn yield and water productivity indices based on linear-move sprinklers, N fertilizer recommendations based on region, and yield response based on fully irrigated versus water-stressed conditions (Rudnick and Irmak, 2013; Camp, 2010; Ogola et al. 2002). Several studies have reported effects of irrigation and nitrogen fertilizer use on corn (Eck, 1984; Al-Kaisi et al. 2003; Rudnick and Irmak, 2013). Eck (1984) showed that under furrow irrigation, adequate N slightly increased corn grain yield under stress and greatly increased yield with full irrigation, but excessive N did not reduce yield even with severe stress. Rudnick and Irmak (2013) reported that irrigation was most effective at increasing the grain yield above rainfed situations when N application rates were increased while using linear-move sprinklers. The higher N treatments experienced a larger increase in yield with increasing irrigation than the lower treatments where N check treatment had no grain yield response to irrigation.

A field scale setting naturally operates on a continuous schedule like on farm conditions. In addition, the expectation of mechanical complications which might disrupt a planned irrigation program can impact how farmers approach irrigation management. Farmers' irrigation methods are typically based on a fixed calendar date, visual observation of plant water needs, hand-feel of soil moisture, observing neighbors' irrigation practices, or a combination of these approaches (Irmak, 2012). The challenge presented within the experimental condition for this study is meant to better represent the on-farm conditions where mechanical systems could have operational challenges at any given time, halting the application process, resulting in the potential for unplanned delays in irrigation. This exemplifies a real-world scenario to understand how yield responds to both nitrogen and irrigation under less-than-ideal conditions where challenges such as breakdowns, etc. are hindering management and operation.

The objectives of this study were to (1) evaluate yield response of corn to various N and irrigation regimes (2) evaluate the impact of interaction of N and irrigation in corn production, (3) provide valuable insight of the benefits of maximizing N and irrigation management to increase yield and sustainability of irrigated corn production in the Southern Great Plains and (4) evaluate spatial variation across irrigation treatments in response to N. The Ogallala Aquifer, which loses water at a faster rate than replenished, sits beneath the farm indicating the importance of the research done here. Investigating the combined impact of N and irrigation on corn growth and yield is limited in the region. Therefore, this study explores the impact of different irrigation strategies and N application rates on corn yield in the Central High Plains. This study was set apart from previous studies in the aspect that irrigation management was restrained by a large-scale commercial farm setting.

Methodology

Site Description and Experimental Design

The research project was conducted during 2018-2020 growing seasons at the Oklahoma State University's McCaull Research and Demonstration Farm located in Oklahoma Panhandle (Lat: -101.789563; Longitude: 36.932259; Elevation: 1067 m). The Oklahoma Mesonet classifies this region to be semi-arid with an annual precipitation of 450 mm. Majority of the rainfall is received during growing season from April-September. The mean annual temperature in the region is 13.9^{o}C. The major soil type (> 90%) at the experimental site was Gruver Clay Loam (Fine, mixed, super active, mesic Aridic Paleustoll) with 1-3% slope. The soil pH in the area ranges from 7.2-8.0.

The experiment was laid out in a split block (also referred to as strip-block) design using commercial equipment intended for large scale field operations. A split-block analysis considers the presence of two different sizes of experimental units used to test the effect of an entire plot treatment and a split block treatment (Kowalski 2003). Split-block analyses are typically used in agriculture for precision in comparison of interactions, in this case between irrigation and nitrogen rates with yield. In this design, the water treatments (vertical) were primary plots while the N treatments (horizontal) were sub plots containing eight rows of corn. There were three irrigation treatments and five N treatments. This experimental design was followed due to the nature of complexity for random distribution of the experimental units on large scale, such as N treatments which could be efficiently applied in bands with large equipment. The N treatments were laid in long strips/bands which run across the water treatments (Figure 1.1). In 2018, the irrigation zones were 18-degree slices of the pivot. In 2019 and 2020, the size of the irrigation zones was reduced to 15-degree slices of the pivot to allow space for other experiments on the pivot. For this same reason the replicates were reduced to 3 in 2020. In 2018 each N strip was 6.1 m wide which consisted of 12 rows spaced 50.8 cm. In 2019 and 2020, the strip till machines and planters were configured to have 12 rows which were 76.2 cm apart, so the plots were 9.14 m wide. The subplot length varied from 79 to 103m in 2018. In 2019 and 2020 subplot lengths were approximately 65 to 86 m in length. In 2018, an Orthman 1tRIPr (Orthman, Lexington NE) strip till machine was used to inject liquid 32-0-0 fertilizer. In 2019 a DMI (Case IH, Racine, WI) and in 2020 a Krause Gladiator (Kuhn, Brodhead, WI) strip till machine was used to inject anhydrous ammonia (82-0-0). The irrigation treatments were executed by controlling the speed of the pivot using a FieldNet telemetry system (Lindsay Irrigation, Omaha, NE).

Treatment, Planting, Crop Management, and Statistical Approach

The three-year (2018-2020) study was conducted on two 51-hectare (ha) center pivots. Composite soil samples (>25 subsamples) were taken before N application to determine residual nutrient status of the field. Subsamples were collected with 44.5 mm diameter Giddings probe (Giddings Machine Company) to a depth of 61 cm. The cores were segmented into 0-15 and 15-61 cm depths. Subsamples were combined and mixed in a bucket prior to analysis by the Oklahoma State University Soil, Water, and Forage analytical laboratory. The analysis results are shown in Table 1.1.

Table 1.1. Analysis of pre-season composite soil samples collected from 0-15 and 15-61 cm.

Year	**Depth (cm)**	**pH**	**NO_3-N**	**P**	**K**	**SO_4-S**	**Ca**	**Mg**	**Zn**
			(ppm)						
2018	0-15	8	4.7	50	684	5.3	3012	680	-
	15-61		4.1						
2019	0-15	8.3	6.4	21	596	5	2646	761	0.9
	15-61		4.1						
2020	0-15	8.1	11	30.5	561	5.5	2045	645.5	1.3
	15-61		7.3						

The corn crop was subjected to five different N rates as well as three irrigation treatments. In 2018, N treatments were applied on March 21 and included 112, 168, 224, 280 and 336 kg N ha^{-1}. In 2019, N rates of 0, 78, 157, 235, and 314 kg N ha^{-1} were applied on April 4, and in 2020 the same N rates were applied on March 26th. In addition to these N treatments all plots received a blended fertilizer containing 12% N, 40% P2O5, 10% S, and 1% Zn at the rate of 45.4 kg ha^{-1}. The fertilization treatments were applied in three replicated strips around the pivot (Figure 1.1).

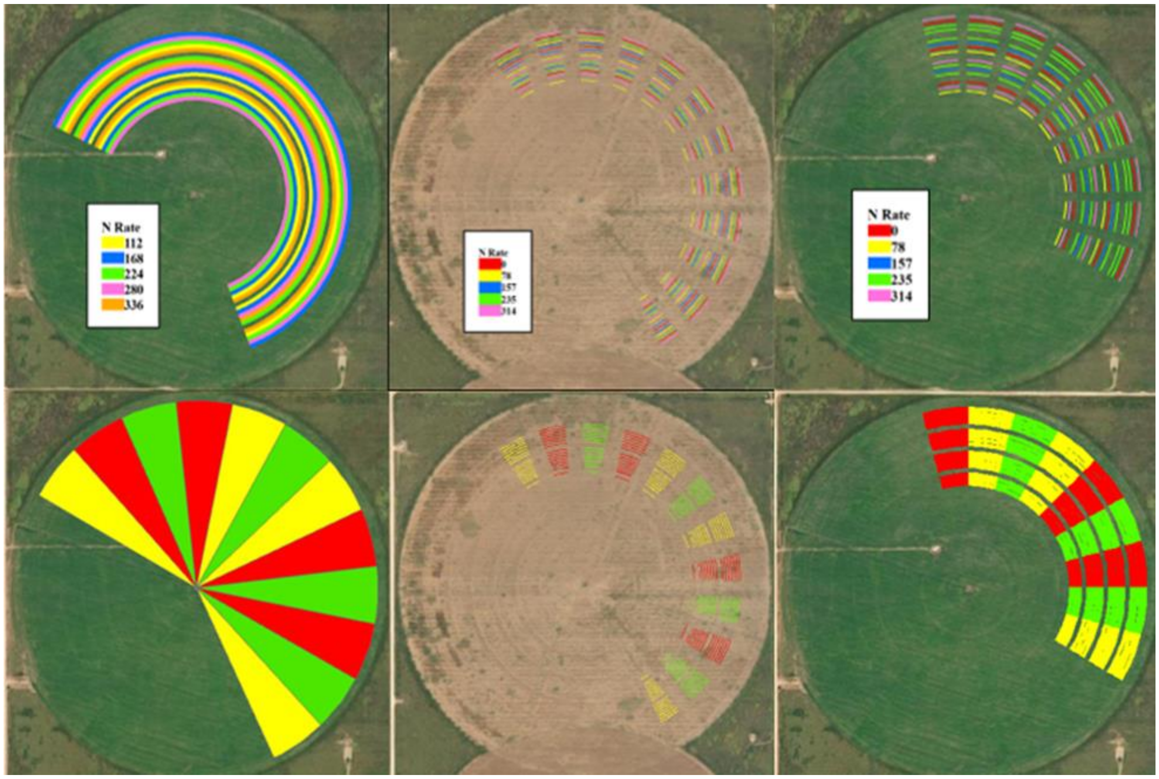

Figure 1.1. (Top row): Orientation of N rate fertilization in 2018, 2019, and 2020, respectively (kg ha^{-1}). (Bottom row): Placement of the 25 mm (red), 32 mm (yellow), and 38 mm (green) irrigation treatments using the pivot telemetry and speed control in 2018, 2019, and 2020, respectively.

In the year 2018, there was not a zero N check. A zero N check was omitted in the first year because the initial focus of this study was to evaluate/demonstrate corn yield response within a range of N rates that farmers would potentially use. The limited yield response in 2018 demonstrated the need for a zero N check in the remaining years.

The irrigation treatments included 25 mm, 32 mm, and 38 mm per irrigation event. These irrigation treatments were applied approximately on five-day intervals because the pivot was discharging 2271 L min^{-1}. This discharge rate would supply 32 mm to the whole pivot every 5 days which is a common capacity for the region when irrigating corn. Also, this capacity can supply approximately 672 mm of irrigation during the typical irrigation season between May 15 and Sept. 1, which when combined with the average rainfall for the region during this time, 226 mm, is nearly sufficient to replace the typical seasonal ET experienced in this area. The pre-irrigation rates of 152 mm, 0 mm, and 76 mm were applied in 2018, 2019, and 2020, respectively. 2019 had excessive rainfall (see Figure 1.2) in the months prior to planting, therefore making pre-water irrigation unnecessary. Gruver Clay loam soil has a plant available water capacity of 4.6 mm per mm in its top 1.2 meters. If 50% of this is assumed readily available this soil can provide for a maximum allowable deficit of 109 mm. The pivot was constantly monitored and provided maintenance as the growing seasons progressed, each year, to ensure efficient use. The irrigation system would be shut off during a rainfall event if the rainfall amount plus the irrigation amount was greater than evapotranspiration for that day if the soil profile was estimated as full for the 32 mm treatment. Irrigation was terminated at the end of the growing season when the crop was at growth stage R5.75, or if excess rainfall occurred as was the case in 2020 when the pivot got stuck. The last irrigation events occurred on Sept. 2, 2018, Sept. 8, 2019, and Aug. 27, 2020.

The corn crops were planted on April 26, 2018, May 15, 2019, and May 7, 2020, at a seeding rate of 74,000 seeds ha^{-1} with Pioneer 1197 AM hybrid and was harvested on October 17, 10, 06 in 2018, 2019, and 2020, respectively. The crop was managed with standard agronomic practices as recommended by the Oklahoma Cooperative Extension for corn in the Oklahoma Panhandle. These agronomic operations included pre- and post-emergence herbicide applications as well as insecticide application. The crop was planted in rotation with wheat; therefore, the crop was planted on an adjacent pivot in the second year with no considerable changes in slopes or soil type. In 2018, the crop was harvested through a John Deere (Model No. 9770) Combine. Each plot was harvested individually and was weighed on a weigh wagon scale. In 2019 and 2020, the combine used had a calibrated yield monitor and generated yield maps for the field. Periodically, during harvest, grain was weighed in a weigh wagon to ensure the accuracy of the yield monitor data which was used to calculate plot weights. Yields were stated at 15.5% moisture. The data from yield maps were extracted with the help of ArcGIS and R programming. Shape files corresponding to individual plots were created in ArcGIS and R codes were written to extract data from yield maps using shapefiles.

The yield response as a function of irrigation, crop response to N and irrigation as well as associated interactions were analyzed using SAS statistical software package (SAS institute, Cary, NC). An analysis of variations (ANOVA) was conducted for crop response to N and irrigation using Proc GLM at a 95% confidence interval. The strength of developed relationships was measured based on the interaction of yield with both nitrogen and irrigation rate. No interaction between N and irrigation was observed, therefore, the data for N and irrigation effects is presented independently. A nonlinear (linear-linear-plateau) model was established for the analyses of the yield response as a function of irrigation using Proc NLIN at a 95% confidence, creating plateaus of the maximized yield rate as a function of N.

Results and Discussion

Weather Conditions

Weather data was obtained from the Oklahoma Mesonet station (Eva) located less than half mile from the experiment sites. Both 2018 and 2020 started with a drier May and June. However, July and August of both years witnessed average rainfall. In contrast, the 2019 witnessed a wet spring, registering above normal rainfall in May, but the rainfall remained significantly below normal for the rest of the season. The average annual rainfall for the Texas County region is 456 mm. The total amounts of rainfall received were 471, 343, and 354 mm in 2018, 2019, and 2020, respectively. The rainfall patterns were relatively well distributed in 2018 and 2020 compared to 2019, which received nearly half of its rainfall in the month of May as seen in Figure 1.2. Crop ET discussed was provided by the Oklahoma Mesonet. For understanding of crop ET calculations, visit the Oklahoma Mesonet site (http://weather.ok.gov).

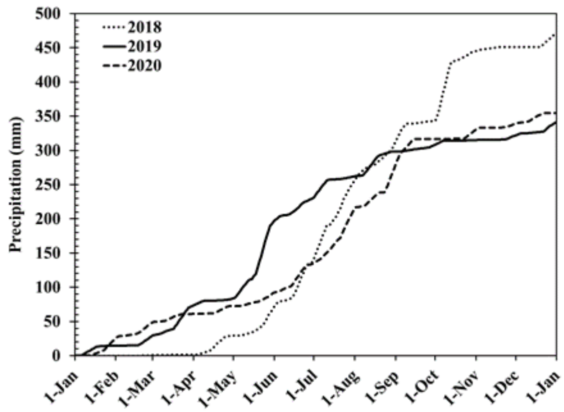

Figure 1.2. Cumulative rainfall totals in mm for each year.

Treatment Effects on Corn Yield

The corn grain yields (Mg ha^{-1}) for all N and irrigation treatments for each growing season are presented in Table 1.2. Corn yield response to N rates was significant at all levels of irrigation (Table 1.2). In general, corn yield increased with N rate for a given irrigation regime. The lowest yields were recorded for lowest N and irrigation treatments. The yield difference was most prominent in 2019, followed by 2020, and 2018. However, it should be noted that 2018 did not have a 0 N treatment and was the best growing season of the study due to timely rainfalls. The improvement of yield for lower N rates with irrigation in 2019 and 2020 provides evidence that N uptake improved with irrigation. These gains were more prominent in 2019, when the yield improved consistently for each N rate with increase in irrigation rate showing greater magnitude than the other growing seasons. This difference occurred because irrigation was a major limiting factor in 2019, but not in 2018 and 2020, discussed later. In our results, the yield response of corn to N rates for any given irrigation regime followed a quadratic pattern, similar to what was reported by Rudnick et al. (2013). Irrespective of the year or irrigation, in general, the corn yield was not significantly different for the largest three N rates for any given irrigation regime. However, there was no significant interaction between irrigation and N rates, but both variables interacted with site-year. Therefore, the data was pooled across irrigation for discussion on yield response to N.

Table 1.2. Evaluation of yield response for each growing season under 25-, 32-, and 38-mm conditions at various N rates (ANOVA, α=0.05).

Year	Irrigation Rate (mm)	N Rate (kg N/ha)	Yield (Mg/ha)	Total Irrigation (mm)	In Season Rainfall (mm)	Crop ET (mm)
2018	25	112	13.14a	437	254	905
		168	14.00b	437	254	905
		224	15.01c	437	254	905
		280	14.89c	437	254	905
		336	15.39c	437	254	905
	32	112	13.18a	530	254	905
		168	13.96ab	530	254	905
		224	14.67bc	530	254	905
		280	15.08c	530	254	905
		336	15.46c	530	254	905
	38	112	13.39a	624	254	905
		168	14.29b	624	254	905
		224	14.97bc	624	254	905
		280	15.24c	624	254	905
		336	15.38c	624	254	905
2019	25	0	8.13a	359	112	816
		78	8.05a	359	112	816
		157	10.65ab	359	112	816
		235	11.37b	359	112	816
		314	9.89ab	359	112	816
	32	0	9.32a	448	112	816
		78	9.51a	448	112	816
		157	12.11b	448	112	816
		235	12.65b	448	112	816
		314	11.51ab	448	112	816
	38	0	10.03a	541	112	816
		78	10.66ab	541	112	816
		157	13.49c	541	112	816
		235	13.99c	541	112	816
		314	12.90bc	541	112	816
2020	25	0	10.98a	424	244	912
		78	12.81ab	424	244	912
		157	12.48ab	424	244	912
		235	13.98b	424	244	912
		314	13.46b	424	244	912
	32	0	11.64a	526	244	912
		78	13.50b	526	244	912
		157	13.19b	526	244	912
		235	14.01b	526	244	912
		314	13.88b	526	244	912
	38	0	11.82a	627	244	912

	78	13.67b	627	244	912
	157	13.21ab	627	244	912
	235	14.44b	627	244	912
	314	14.12b	627	244	912

Figure 1.3 shows the yield response to N rates pooled across irrigation rates for each year of study. Significant yield differences were observed for different N rates for all growing seasons. Overall, the yield increased with N rates, especially in 2018, though there was slight decline for highest N rate in 2019, and 2020, which it was not statistically significant ($p<0.05$). The greatest increase in yield was recorded in 2019 from 78 kg N ha^{-1} to 157 kg N ha^{-1} with an average increase of 3.26 Mg ha^{-1}. No yield differences ($p<0.05$) were observed between two highest rates of N in 2018, and slight differences for the highest three N rates was observed in 2019 and 2020. These results suggest that there is potential for decreasing N fertilization in the Southern Great Plains, where common application rate of N is 300 kg N ha^{-1}. Similar results were reported by Al-Kaisi et al. (2003) in Northeast Colorado where authors found that N requirements for the area may be nearly half that what are usually applied to the corn fields.

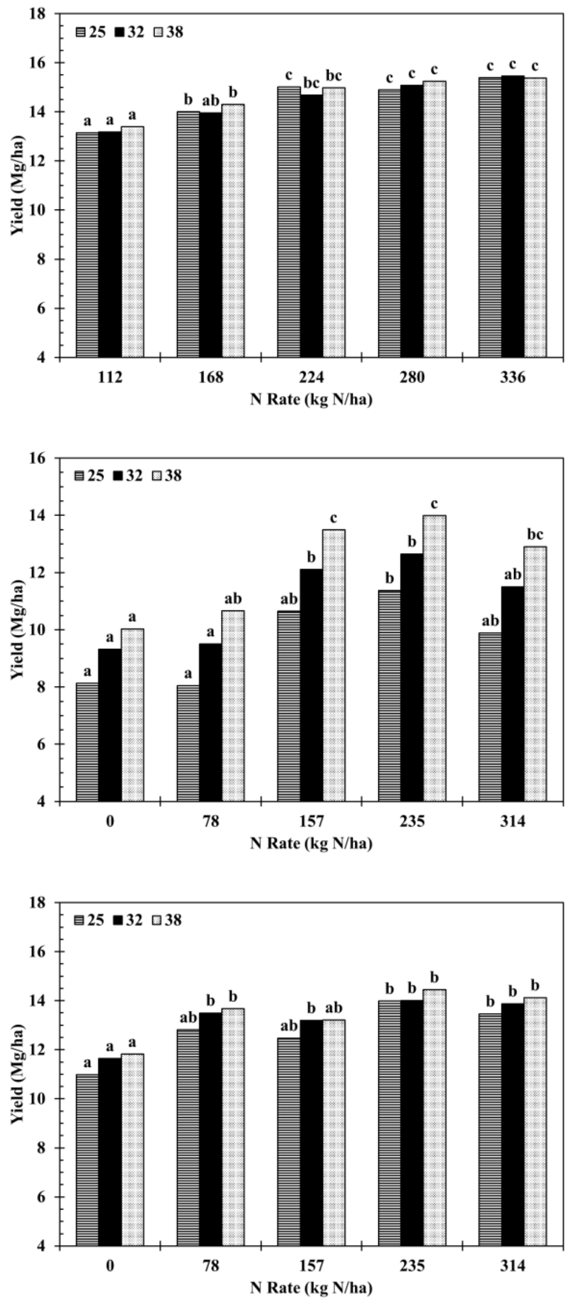

Figure 1.3. Corn yield response to pre-plant nitrogen for 2018 (top), 2019 (middle), and 2020 (bottom), pooled across irrigation rates (25, 32, and 38 mm, α=0.05).

Other Studies have also reported results presenting no interaction between N and irrigation. Ogola et al. (2002) reported that there were no interactions between N and water regime on the grain yield in any of the three experiments; however, they had independent effects. Yield values for rainfed at 0- and 100-kg N ha^{-1} were 7.2 and 8.3 Mg ha^{-1}, respectively, and for irrigated at 0- and 100-kg N ha^{-1} were 8.1 and 11.4 Mg ha^{-1}, respectively. Like Derby (2005), yield values (at 100 kg N ha^{-1}: rainfed and irrigated yields were 8.5- and 13.45-Mg ha^{-1}, respectively) were significantly increased with irrigation. Zamora Re (2019) presented no interactions between irrigation and N fertility rates on final grain yield through three growing seasons. The N regimes as well as irrigation had significant effect on the yield response; however, there was no influence of interaction of N and irrigation together.

In contrast, several early investigations have reported strong relation between soil moisture and N, where soil moisture enhance corn response to N uptake (Martin et al., 1982; Russelle et al., 1981). More recent studies from Al-Kaisi et al. (2003), Paolo et al. (2006) and O'Neill et al. (2004) reported a significant interaction between N and irrigation treatments, which showed improved uptake of water and N when available in sufficient amounts. Rudnick (2013) presents data that shows an interaction between nitrogen and irrigation in both growing seasons involved. The 2012 experiment showed that 0 kg N ha^{-1} had nearly no grain yield response to irrigation, unlike the highest treatment, which was 252 kg N ha^{-1} resulting in a strong positive grain yield response to irrigation. This interaction was likely found due to a combination of effects from N and water deficiency on the crop, which were not apparent in this study conducted in the Oklahoma Panhandle. Gheysari (2009) emphasized that the interaction of irrigation and nitrogen showed a quadratic trend as a function of N application for a given irrigation depth.

Irrigation Effects on Corn Yield

Figure 1.4 shows the distribution of irrigation applied during each growing season as well as the water balance calculated as the difference between the Mesonet estimated ET and the measured rainfall at the Mesonet station near the McCaull Research and Demonstration Farm (Labeled Eva on mesonet.org). In 2018, the lack of pre-plant rainfall (Figure 1.2) resulted in the utilization of 150 mm of pre-irrigation on all treatments to facilitate strip tillage and planting. In

May, the 32 mm treatment meant to replace 100% of the water deficit replaced 89%. Due to mechanical breakdowns of the pivot which delayed irrigation this treatment was only able to replace 79% of the deficit occurring in June. In July 85% of deficit replacement was achieved. Followed by 82% during August. When the irrigation applied between planting and September 15 is compared to the water deficit, we find that the treatments replaced 75, 90, and 107% of the deficit, respectively. If the pre-water is included in the irrigation totals the lowest irrigation treatment of 25 mm per application supplied 100% of the water deficit. This explains the lack of yield response to irrigation as shown in Figure 1.5.

In 2019, preseason rainfall and persistent rainfall throughout May and much of June delayed initiation of irrigation. Irrigation initiation was attempted on June 16, but multiple mechanical failures delayed the first irrigation until June 23. Mechanical failures plagued the system through much of July as well. Given the capacity to irrigation every 5 days with the 32 mm rate, the maximum monthly irrigation should have been 198 mm, in contrast 153 mm were applied in July 2019 because of mechanical failure. In August, the pivot and pumping plant had fewer problems, as a result 185 mm of irrigation was achieved with the 32 mm treatment. However, the deficit during July and August was 243 and 202 mm, respectively. Therefore, the 32 mm treatment was only capable of replacing 70% of the calculated seasonal deficit and the 38 mm treatment only replaced 84% of the deficit. These deficits were sufficiently different to results in the response of yield to total seasonal irrigation shown in Figure 1.5.

Data from Al-Kaisi et al. (2003) shows that plant N uptake response to irrigation depends on the growing conditions or production environments and the growth stage of the crop. In 2019, the crop did not show any visual water or N stress signs early in the season, indicating the crop had access to sufficient water and N during early phase of the crop growth due to early season rainfalls. The water deficit occurred after reproductive stages of the crop had started at which point the crop's potential to obtain N was compromised. Therefore, despite having significant irrigation impact in 2019, a larger water deficit might be required to see the interaction of N and irrigation from beginning of the crop growth.

In 2020, the irrigation season was started with the application of 76 mm of pre-plant irrigation to facilitated strip tillage and planting. In May the 32 mm treatment replaced 100% of the estimated deficit. However, in June, July, and August this treatment was inadequate and only replaced 71, 75, and 88% of the deficit. In fact, when the pre-irrigation and seasonal irrigation applications are totaled, they replaced 73, 87.5, and 102% of the deficit. The lack of significant impact of irrigation treatment on yield presented in Figure 1.5 suggest that the replacement of 73% of the deficit was sufficient to achieve maximized yield.

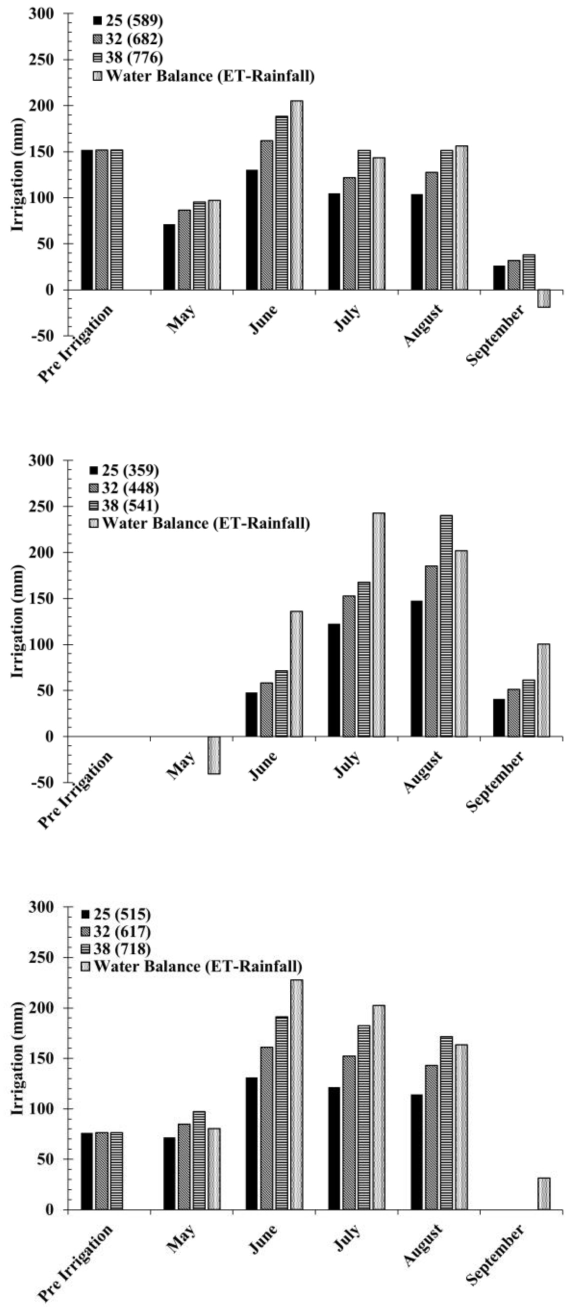

Figure 1.4. Distribution of irrigation by pre-irrigation and month for 2018 (top), 2019 (middle), and 2020 (bottom) growing seasons and the water balance as determined by the difference between the Mesonet estimated ET and measured rainfall. Total irrigation from May to September is in parenthesis.

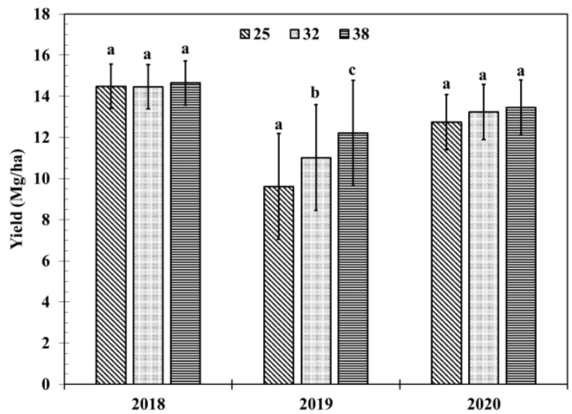

Figure 1.5. Yield production pooled across irrigation rate (mm) for each growing season. Yield between irrigation rates (i.e., comparing irrigation rates within the same growing season) represented by the same letter are not statistically different (α=0.05).

The lack of yield response to irrigation in 2 of 3 years of this study was expected. Recall that the three irrigation treatments were meant to replace 80, 100, and 120 % of expected soil water deficit created during a typical year in this region. Despite the supplemental irrigation, rainfall amount and patterns play a vital role in crop yields in the Southern Great Plains (Raz-Yaseef, 2015). This is because the low well capacities found in the High Plains region of the Southern Great Plains are insufficient to meet crop ET demand during peak growth periods for corn. In such scenarios, the profile storage as well as seasonal rainfall become very important to achieve yield goals. Furthermore, the biomass growth of crop during vegetative crop stages also determines the crop ET demand during later stages (Mengel, 2001; Payero et al. 2006; Murley et al., 2018). Corn registers its peak ET demand during reproductive stages which are more sensitive to water stress than vegetative growth stages. In our study, the reproductive stages of corn started in the first week of July. The above normal rainfall received through July in 2018 and 2020 helped meeting crop ET demand and recharging soil profile. This well-timed rainfall synchronized with critical growth stages of crop, dissolved yield differences among the irrigation treatment despite the dry start of the cropping season. As such, the poor rainfall in July added to stress of the low water treatments resulting in lower crop yields than high water treatments in 2019. Late start of irrigation in 2019 meant that crop relied heavily on profile storage to meet ET demand, especially for low water rates. As a result, the yield response to irrigation rates were more visible in 2019 than the other two years of the study. These results indicate, that despite the irrigation rates and irrigation capacities, the corn yields in Southern Great Plains remain vulnerable to weather patterns, especially rainfall timings and patterns. Our results agree with previous studies which also reported year-to-year variations in precipitation exerts a strong influence on crop yields in the Great Plains (Wienhold, 1995, Al-Kaisi et al. 2003; Rudnick and Irmak, 2013). The year-to-year variation to irrigation response in our study agree with previously reported by Rudnick and Irmak (2013) in Nebraska, and Al-Kaisi et al. (2003) in Northeast Colorado.

Nitrogen Effects on Corn Yield

Acting independent from irrigation, nitrogen data was evaluated across the various N regimes for each growing season (Figure 1.6). In 2018, the maximum N rate of 336 kg N ha^{-1} maximized yield at 15.41 Mg ha^{-1}, however this was not significantly greater than yield achieved with 280 kg N ha^{-1}. In 2019 and 2020, the 235 kg N ha^{-1} rate achieved maximum yields of 12.67 and 14.15 Mg ha^{-1}, which were not significantly different than the 157 kg N ha^{-1} rate.

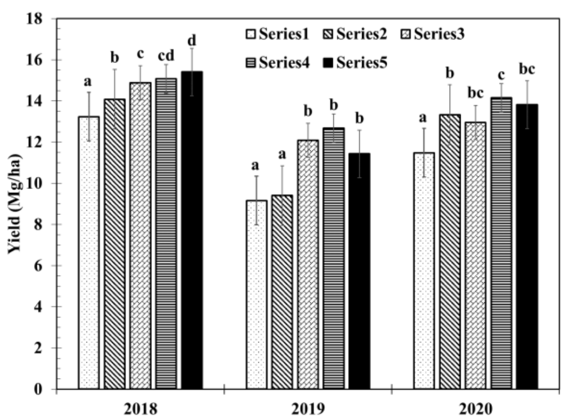

Figure 1.6. Corn yield response pooled across nitrogen rates for each season (α=0.05). Yield between nitrogen rates (i.e., comparing nitrogen rates within the same growing season) represented by the same letter are not statistically different(α=0.05). Series 1 represents the lowest nitrogen rate (i.e., 112 kg N ha^{-1} for 2018, and 0 kg N ha^{-1} for 2019 and 2020) and the following series represent N rates within each year as they increase with Series 5 being the highest N rate (i.e., 336 kg N ha^{-1} for 2018, and 314 kg N ha^{-1} for 2019 and 2020).

Nitrogen Effects on Corn Yield by Irrigation

The variability of response to N within irrigation slice was evaluated for each growing season (Table 1.3). The percent increase between the lowest N rate versus the highest yielding N rate indicates the corn crop responsiveness to nitrogen. In general, 2018 and 2020 had lower response; however, it appeared that in 2018 the yield optimized at 336 kg N ha^{-1} whereas in 2020, 235 kg N ha^{-1} was the optimum value. The responsiveness in 2019 was expected. The 2018 growing season showed the most variability within the 25 mm irrigation rate whereas in 2019 and 2020, the highest irrigation rate (38 mm) presented the largest variability of yield increase.

Table 1.3. Percent increase of yield within slices for each growing season.

	Slice	Lowest N		Highest Yielding N		% Increase
		N Rate (kg N/ha)	Yield (Mg/ha)	N Rate (kg N/ha)	Yield (Mg/ha)	
2018	1	112	14.1	336	15.6	10
	2	112	12.2	336	14.8	21
	3	112	12.6	336	15	19
	4	112	12.6	336	15.6	24
	5	112	12.1	280	14.7	21
	6	112	12.9	280	15.1	17
	7	112	12.4	336	15.8	28
	8	112	13.4	336	15.6	16
	9	112	14.1	336	15.8	11
	10	112	14.3	336	15.5	8
	11	112	13.8	336	15.7	13
	12	112	14.1	336	16	14
2019	7	0	9.7	235	12.9	33
	8	0	9.3	235	11.7	26
	9	0	11.5	157	13.1	14
	10	0	8.5	235	11	30
	11	0	9.3	235	11.8	28
	12	0	10.3	235	13.7	34
	13	0	9.4	235	12.6	33
	14	0	6.9	235	10.6	54
	15	0	10.5	235	14.6	39
	16	0	7.8	314	12.4	59
	17	0	7.9	314	14.6	85

	18	0	8.8	235	13.2	49
	1	0	11.2	314	14.3	27
	2	0	11.3	314	13.9	23
	3	0	10.4	235	13.7	32
	4	0	11	235	14.2	29
2020	5	0	10.7	235	14.1	32
	6	0	11.8	235	14.8	26
	7	0	11.1	235	14.2	29
	8	0	13.2	235	14.7	11
	9	0	12.6	235	14.7	17

Note: * indicates slices with 25 mm irrigation rate, + are slices for 32 mm irrigation rates, and all other slices are 38 mm.

The linear-linear-plateau models (Appendix 1, Figure A1.7-1.9) created for each slice are available. The plateau values indicate maximized yield as a function of N rate for each corresponding slice. Each model was best fit, and a point of intersection was established. The point of intersection is an indicator of the N rate that achieved optimum yield, the positive slope indicates a difference in yield values amongst N rates, and the plateaus argue the lack of numerical difference in yield at a given N rate. Unlike the percent increase for the growing seasons, the analyses showed a general trend of optimum N at 235 kg N ha^{-1} for 2018, 157 kg N ha^{-1} for 2019, and 78 kg N ha^{-1} for 2020; however, there is variability of optimum N value within slices for the given year. Compared to the increase of yield from lowest N to highest yield N, the plateaus show that higher yielding environments have less variability. Similar in field variability was found in a study conducted in both Kansas and Nebraska. Schmidt et al (2002) presented results that showed significant variability in grain yield response to increasing N rates among in-field locations; however, these results compared variability to organic matter.

Conclusion

Yield was quantified and evaluated for five N application rates under three irrigation regimes at 80, 100, and 120% water rates. The yield increased with increase in N rates, especially in the 2018. The greatest increase of yield response was in 2019 from 78 kg N ha^{-1} to 157 kg N ha^{-1}, which increased yield by 2.67 Mg ha^{-1}. In 2018 and 2020, the interaction of yield with irrigation was similar presenting no significant difference between the three regimes; however, 2019 had significant difference between each irrigation treatment. The yield with highest water treatment in 2019 was lower than yield registered for lowest water treatments in 2018 and 2020. This demonstrates that the rainfall patterns in 2019 which delivered over half the seasonal rain prior to June 1st were much less productive than in 2018 and 2020 when rainfall was limited during the early season. The mechanical failures that occur at the on-set of most irrigation seasons were much more impactful during 2019 as they occurred in the middle of the season instead of during the pre-irrigation, which was the case in 2018 and 2020.

The present research differs from previous studies on nitrogen and irrigation management techniques because it was conducted on production-scale fields. This resulted in conditions where irrigation could not be applied to meet soil water deficits estimated from the Mesonet ET minus rainfall due to mechanical failure combined with irrigation rates that were less than estimated ET. In 2018 and 2020 these deficits did not impact yield due to the utilization of pre-irrigation. However, in 2019 the mechanical failures that occurred in June and July limited corn yield in the irrigation treatment supplying 32 mm per application which can generally replace water deficit under average conditions.

CHAPTER II

RELATIONSHIP BETWEEN CORN YIELD AND NDVI MEASURED BY AERIAL IMAGERY

Abstract

Remote sensing is the process of acquiring information from remote platforms. Passive sensors can be used to measure the amount of light that is reflected from a natural source like the sun and to provide monitoring of soil properties and vegetative indices like NDVI. The normalized difference vegetation index (NDVI) is a measure of reflectance that could be used to predict yield values; however, the imagery collection process is challenging. Some of the challenges include shadows or timing of irrigation. The Coefficient of Variation (CV) is a statistical method to check variability within values, specifically NDVI values for this study. The objective of this study was to develop a relationship between yield and NDVI. A significant relationship in 2019 was presented, however, 2020 showed no true relationship between yield and NDVI. Over time CV decreased with plant growth, supported by both 2019 and 2020 growing seasons. Our results indicate that NDVI does in fact relate to yield supported by the CV values decreasing as more vegetation appeared proving relationships between either irrigation or nitrogen (N).

Introduction

Remote sensing is the process of acquiring information about objects from remote platforms such as ground-based booms, aircrafts, or satellites (NRC, 1997). Remote sensing can be done by either an active sensor, which emits their own light and measures the reflectance of spectra, or by a passive sensor, which registers the amount of light reflected from a natural source like the sun (Maresma, 2020). In agriculture, these sensors can conduct monitoring of soil properties and vegetative indices (Haung, 2018) such as NDVI.

Normalized difference vegetation index (NDVI) is a common measurement used to determine plant health through light absorption and reflectance (Arnall, 2017b) defined as the ratio of spectral reflectance measurements found in near-infrared (NIR) minus the reflectance in the red (visible) region, divided by the sum of NIR and red (Wang, 2016; Arnall, 2017b; Maresma, 2020). Teal et al. (2006) stated that NDVI values could be used to predict corn yield potential. However, these predictions could have factors that influence them. Changes in the angle of or reflectance of the sun, temperature or timing of irrigation or fertilization can all impact accuracy and results of NDVI (Raun et el., 2005b; Maresma, 2020). Normalized difference vegetation index is known to decrease in sensitivity as the plant canopy closes (Thomason, 2007).

To possibly validate the accuracy of the NDVI values, the Coefficient of Variation (CV) is often used to distinguish the variability within NDVI. The CV is defined as the standard deviation divided by the mean value (Fu, 2013). A low CV predicts a field to be more responsive and capable of greater yield compared to field elements with high CV values (Raun et al., 2005a). Lukina et al. (2000) showed that as the vegetation coverage increased, the CV of NDVI values decreased.

Ceres Imaging, a commercial provider, offers high-resolution multispectral imagery that can capture the canopy density as well as the plant health and nutrient availability within a field. An NDVI measurement alongside a Chlorophyll Index is used to provide growers with aerial imagery of their fields. Chloryphyll (Chl) is the primary contributor of green color in leaves and nitrogen is a major component of the Chl molecule (Benitez, 2010). Ceres uses a passive sensor mounted on a manned aircraft to obtain data.

The objective of this study was to evaluate the relationship between yield and NDVI measured by Ceres aerial imaging in the Southern Great Plains. The change in coefficient of variation over time was also evaluated.

Methodology

Site Description, Treatment, Planting, Crop Management, and Experimental Design

The research project was conducted during 2018-2020 growing seasons at the Oklahoma State University's McCaull Research and Demonstration Farm located in Oklahoma Panhandle (Lat: -101.789563; Longitude: 36.932259; Elevation: 1067 m); however, imagery by Ceres was only taken in 2019 and 2020. The site characteristics, treatment plans, planting dates, and all crop management are adequate to the previous chapter.

The experiment was laid out in a split block design using commercial equipment and are compatible with the design from Chapter 1.

Spectral Reflectance Measurements and Statistical Approach

Spectral reflectance measurements were conducted over two growing seasons above canopy level. In 2019, the flights were conducted from July through September for a total of eleven flights, while in 2020, the flights spanned April through September for a total of nine measurements. The spectral reflectance measurements of the experiment field were acquired through Ceres Imaging from a fixed wing aircraft providing surface reflectance multispectral GeoTIFFS. Images were collected on cloud free days between about 10 am and 2 pm at a temporal cadence of once every one to two weeks. The images were captured at an average resolution of 0.86 in 2019 and 0.89 m in 2020 per pixel. Many factors were obtained during the flights, but for the purpose of this study the NDVI index was closely evaluated. The equation for this NDVI calculation is shown below.

$$NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}}$$

where ρ_NIR – Fraction of the emitted NIR radiation returned from the sensed area (reflectance), centered at 717 nanometers (nm)

ρ_RED- Fraction of the emitted Red radiation returned from the sensed area (reflectance), centered at 671 nm

Each image was orthorectified and atmospherically corrected by Ceres Imaging using publicly available meteorological data and standard atmospheric modeling with the SMARTS model developed by the National Renewable Energy Laboratory, US Department of Energy (Gueymard, 1995). The multispectral bands collected were green (550 nm), red (670 nm), red edge (717 nm), and near infrared (800 nm), with 10 nm bandwidths (FWHM). The resolution varied with flight altitude at time of data collection but ranged from 0.69 to 0.93 in 2019 and 0.85 to 0.93 m in 2020 for VNIR.

The manned aircraft used a passive sensor meaning the values of NDVI provided will not reach 1.0 like intended. However, the values are still precise. The values of a passive sensor do not measure based on direct reflectance from an active light but rather from the sun, causing the values to fluctuate up and down more freely. Therefore, regression is used to obtain the best fit of the data.

The CV was also calculated from the aerial imagery measurements taking the standard deviation of an NDVI measurement divided by the mean NDVI value. CV is a relative measure of variation meaning the values vary depending on the data. In agricultural experiments, the CV can be used for the inferential purpose of an experiment to be conducted in a new location (Bhat and Rao, 2007). In data like this study, it is important to recognize that the standard deviation is typically a constant value. So, when the mean is small, the CV has high values and as the mean gets larger, the CV decreases. The behavior of CV is supported by Schauberger (2018).

The data from GeoTIFFS was extracted with the help of ArcGIS and R programming. Shape files corresponding to individual plots were created in ArcGIS and R codes were written to extract data from GeoTIFFS using shapefiles. NDVI and CV response through the growing seasons were analyzed using SAS statistical software package (SAS institute, Cary, NC). A predictive analysis using linear regression (PROC REG) was used to find the relationship between NDVI plot mean and yield as well as CV and yield at a 95% confidence interval for 2019-2020.

Results and Discussion

NDVI Relationship with Yield

The summary of NDVI and CV effects on yield for 2019 and 2020 with respect to date flown are shown in Table 2.1. Notice in 2019, the flights started in mid-July and 2020 the flights started prior to the May 7th planting date. The relationship between NDVI and corn yield had a strong response through the 2019 growing season; however, there were exceptions on a few dates that encountered challenges with solar radiation, shadows, or pivot placement etc. For instance, on flight date 7/11/2019, the scatter in the plot (Figure A2.1), along with the NDVI p-value of 0.4904 indicated one of these challenges. On this day, there was a solar radiation value of 22.43 MJ m^{-2}, which was well below the average of 26.12 MJ m^{-2} for the month of July. Those solar radiation values account for solar energy that is reaching the earth (Oklahoma Mesonet, Eva, OK). It is likely that clouds were a great influence on this day. On 7/29/2019 (Figure A2.3), the flight resulted in a similar p value ($p = 0.4618$) to 7/11/2019; however, the solar radiation reached an above average value of 28.11 MJ m^{-2} signifying clouds were likely not the problem, but possibly shadows from the angle of flight, or even the imagery picking up that the corn had started to tassel, which would have covered the crop's canopy, at this point in the season.

In general, there was an increasing trend in the slopes of the 2019 regression analyses of NDVI (Figure A2.1-2.11). The positive trend suggests an increase in vegetation coverage or perhaps greener vegetation. This suggests the corn was influenced as the season approached harvest (October 10) and supported by the findings in Chapter 1. Chapter 1 states the 2019 growing season had independent response to irrigation and nitrogen, which validates the robust NDVI values. The p-values of NDVI decreasing as the crop nears maturity is like Thomason (2007). All the R^2 values have significance in 2019. Ceres images picked up yield variability but could not be detected if it was solely based on irrigation or nitrogen specifically. The CV of NDVI for 2019 had a decreasing trend over the course of the season illustrated by low yields correlating to higher CV values (Figures A2.12-2.22) and exhibited significance (Table 2.1). The decline of CV values was not due to decrease in NDVI standard deviation overtime but rather due to the mean getting larger and the standard deviation remaining constant. The decline in CV values as the mean gets larger corresponds to results presented by Schauberger et al (2018). The variability values decreased as the season progressed due to increase of green vegetation coverage (Figures 2.12-2.19) and then began increasing again when the plants began to dry out (Figure A2.20). The observed decrease in CV over time was also observed by Lukina et al (2000).

A general negative trend in both the NDVI and CV was observed for the 2020 season. Given the early start date in 2020, small NDVI values for the months of April through June were apparent (Figures A2.23-2.26). The reason for this circumstance is due to the field having little biomass at this time. The remainder of the season presented a weak relationship between yield and NDVI given by statistical values in Table 2.1 and supported by Chapter 1 results as they stated weak response to N and irrigation. 9/02/2020 (Figure A2.31) presents a significant NDVI value only because the crop was showing late season deficit to either N or irrigation. The generally negative trend had no true relationship with yield. Since the imagery for the 2020 growing season was started in April, prior to planting, the ground was bare and therefore, explains the large CV values for the 4/23/2020 flight (Figure A2.32). The CV resulted in high values because the mean was extremely small and the standard deviation relatively constant, like the late season flight on September 2. The flights in June (Figures A2.33-2.35) showed a slope that was positive or close to zero (essentially a flatline) because the R^2 values were so small, suggesting in these flights the relationship between yield and CV was zero. Like 2019, the variation of CV increased as yield decreased when the crop started failing towards the end of the season.

Table 2.1. Evaluation of NDVI and CV effects on corn yield for both 2019 and 2020 (α=0.05).

Date Flown	NDVI			CV		
	R^2	**P Value**	**Equation**	**R^2**	**P Value**	**Equation**
7/11/2019	0.4904	<0.0001	y = 68.21x-23.02	0.1882	<0.0001	y = -0.71x+13.36
7/25/2019	0.72	<0.0001	y = 71.54x-27.60	0.2754	<0.0001	y = -0.65x+13.45
7/29/2019	0.4618	<0.0001	y = 98.84x-39.20	0.3328	<0.0001	y = -2.80x+16.45
8/5/2019	0.5998	<0.0001	y = 138.6x-60.10	0.2725	<0.0001	y = -1.93x+14.24
8/13/2019	0.6999	<0.0001	y = 89.43x-37.52	0.4972	<0.0001	y = -1.78x+15.09
8/19/2019	0.7762	<0.0001	y = 98.71x-41.36	0.5188	<0.0001	y = -1.50x+14.16
8/29/2019	0.6486	<0.0001	y = 80.11x-33.08	0.4798	<0.0001	y = -1.52x+13.96
9/5/2019	0.6241	<0.0001	y = 75.10x-28.17	0.4337	<0.0001	y = -1.22x+13.89
9/10/2019	0.6523	<0.0001	y = 34.03x+4.04	0.5158	<0.0001	y = -0.47x+13.59
9/17/2019	0.6216	<0.0001	y = 24.33x+2.2907	0.4419	<0.0001	y = -0.26x+13.71
9/23/2019	0.5211	<0.0001	y = 16.69x+7.65	0.2906	<0.0001	y = -0.12x+13.85
4/23/2020	0.0446	0.0457	y = -107.76x+12.19	0.0439	0.0474	y = -.015x+14.02
6/1/2020	0.0513	0.0318	y = -34.50+14.55	0.0107	0.331	y = -0.024x+12.79
6/15/2020	0.063	0.017	y = -15.27x+14.86	5E-06	0.9834	y = -0.0007x+13.16
6/25/2020	0.0059	0.4707	y = -3.40x+14.31	0.0028	0.6179	y = -0.019x+13.34

7/8/2020	0.0272	0.12	y = 16.63x+5.82	0.0478	0.0384	y = -0.25x+13.82
7/20/2020	0.0932	0.0034	y = -30.86x+25.36	0.0253	0.1346	y = -0.30x+14.86
8/4/2020	0.3419	<0.0001	y = -76.98x+45.18	0.0105	0.3358	y = -0.213x+13.46
8/18/2020	0.061	0.0189	y = 18.15x+6.56	0.5549	<0.0001	y = -0.55x+14.85
9/2/2020	0.2043	<0.0001	y = 20.16x+6.29	0.5751	<0.0001	y = -0.29x+14.33

Aerial Images and Their Relationship with NDVI

The aerial images provided by the aircraft had several limitations (i.e. solar radiation, shadows, etc.); however, given the challenges of the environment they were justified. In 2019, the response of NDVI was apparent since there was an effect of both irrigation and nitrogen in prior analyses. In 2020, however, the yield difference varied slightly from low to high rates of both nitrogen and irrigation making it much harder for the imagery to register a response to or form a relationship with NDVI from an average altitude of 4300 meters.

In the future, one way to better the accuracy of this study would be to do a double measurement. To do so, a lower canopy active sensor and LiDAR instrumentation would be needed. The lower canopy active sensor would be able to look at the chlorophyll levels in the lower canopy while the LiDAR would be taken from above to obtain the chlorophyll levels of the upper canopy. This way, the biomass of the lower and higher levels of the corn would be considered, especially since corn first shows chlorosis at second and third leaf (Arnall, 2017b).

Conclusion

Aerial imagery was quantified and evaluated for several dates in 2019 and 2020 growing seasons. Though some challenges were presented with flight imagery, a significant relationship in 2019 between NDVI and yield presented that the corn was in fact influenced by either irrigation or nitrogen as the season progressed. However, 2020 showed no true relationship between yield and NDVI which was most likely influenced by the slight difference in yield values at variable nitrogen and irrigation rates. Over time CV decreased with plant growth, supported by both 2019 and 2020 growing seasons. Variability began increasing again after the crop started to dry out as harvest approaches. The normalized difference vegetation index and coefficient of variation relationship with yield varies with growing season and conditions.

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APPENDICES

APPENDIX A

Regression analyses graphs for yield in response to N within respective irrigation treatment and growing season

Figure A1.7. 2018 corn yield response to N within respective slice (irrigation rate).

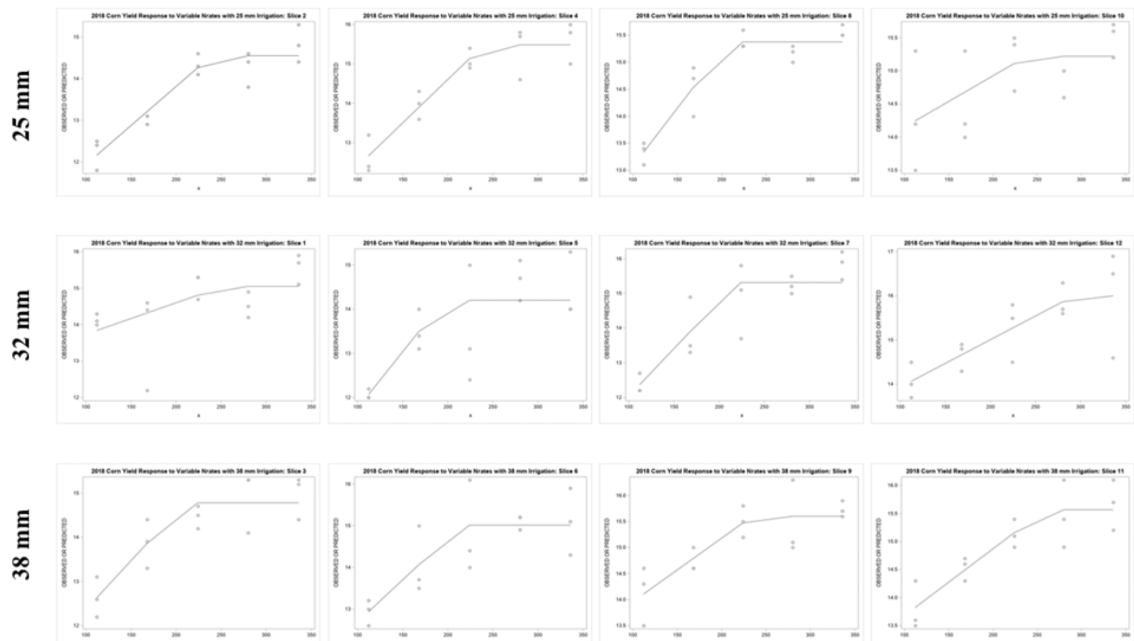


Figure A1.8. 2019 corn yield response to N within respective slice (irrigation rate).

25 mm

32 mm

38 mm

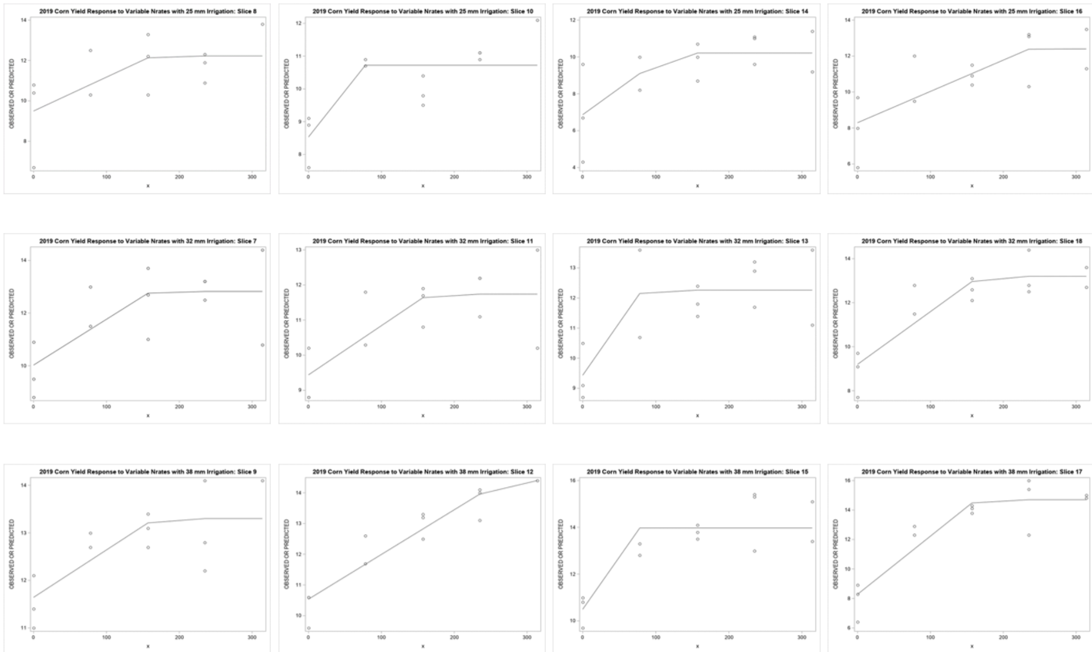
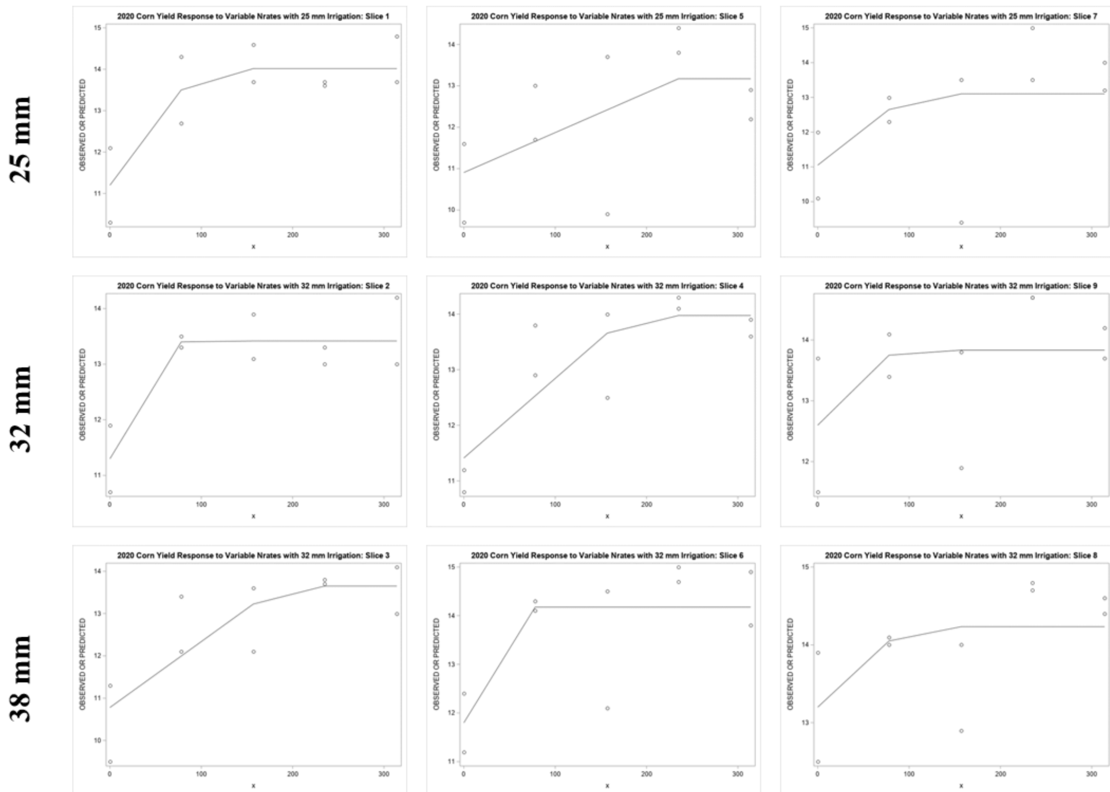


Figure A1.9. 2020 corn yield response to N within respective slice (irrigation rate).



APPENDIX B

Regression analyses graphs for mean NDVI and CV for respective flights within growing season 2019 and 2020

Figure A2.1. Regression analysis of NDVI average versus yield on 7/11/2019 (McCaull Research Farm, n=180, α=0.05).

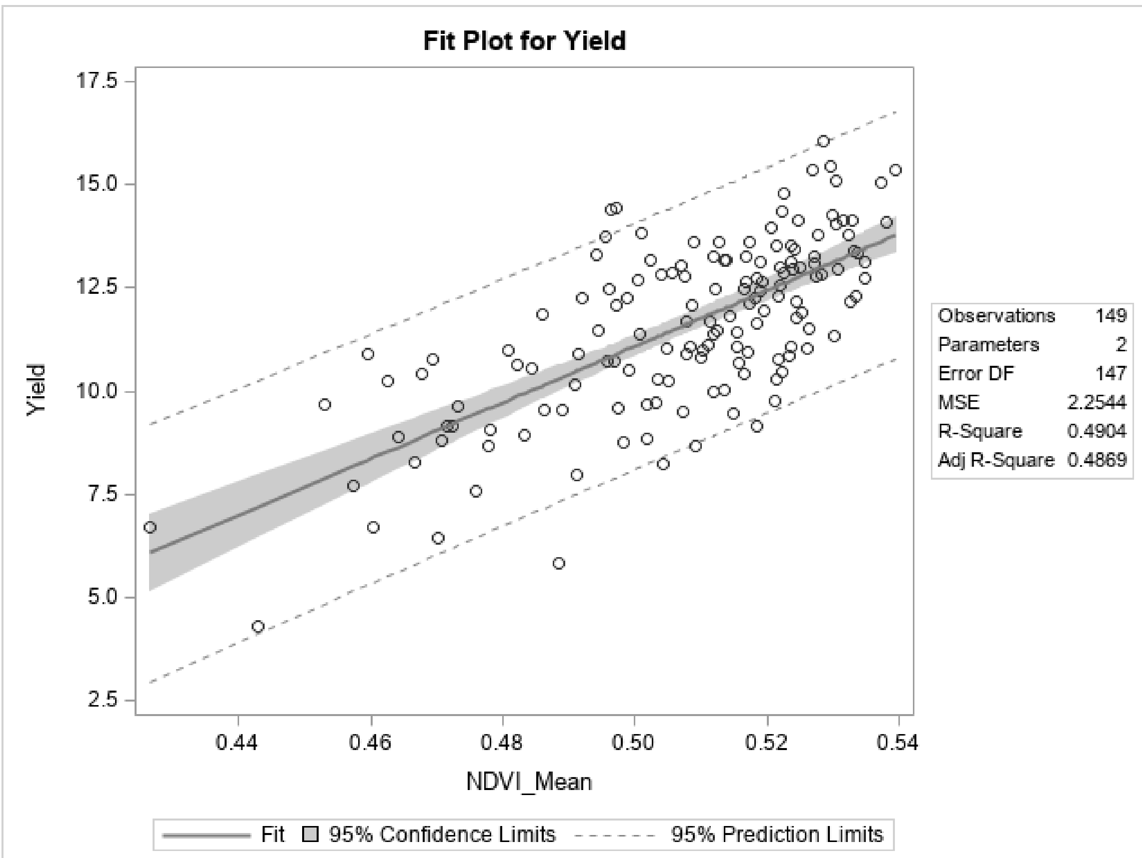


Figure A2.2. Regression analysis of NDVI average versus yield on 7/25/2019 (McCaull Research Farm, n=180, α=0.05).

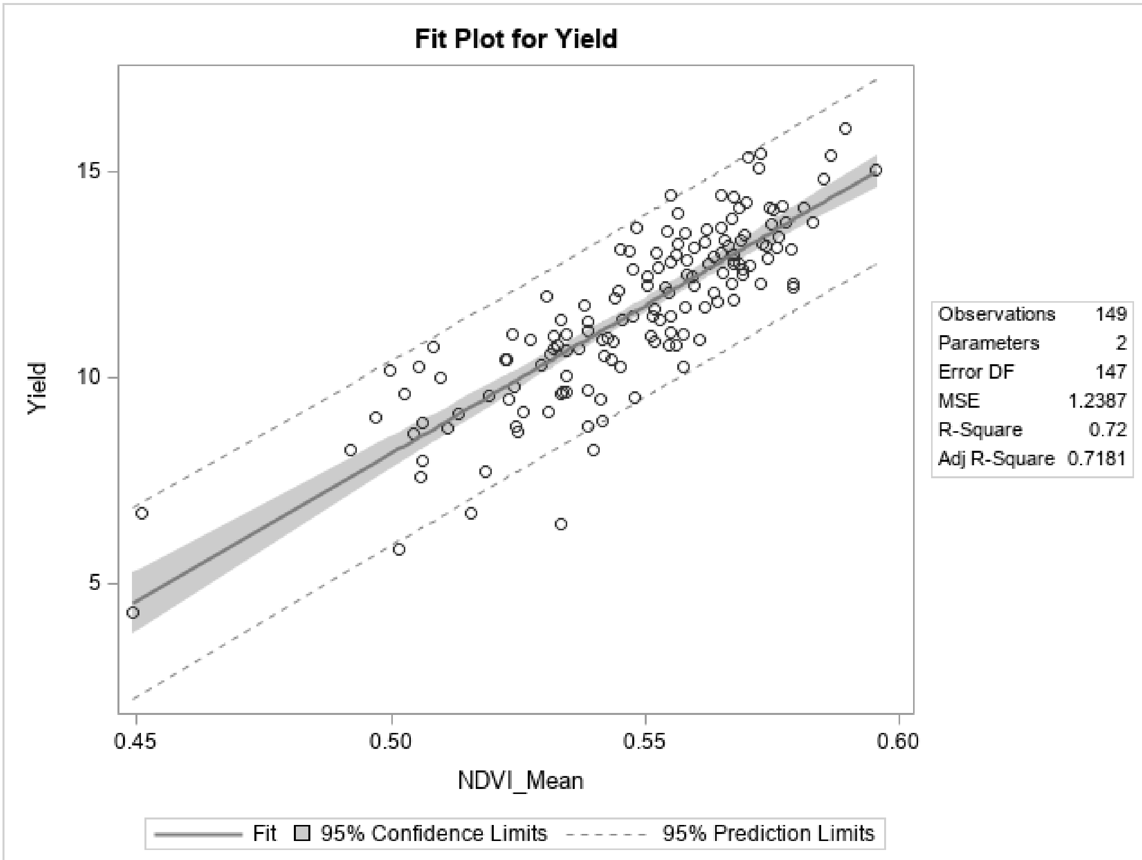


Figure A2.3. Regression analysis of NDVI average versus yield on 7/29/2019 (McCaull Research Farm, n=180, α=0.05).

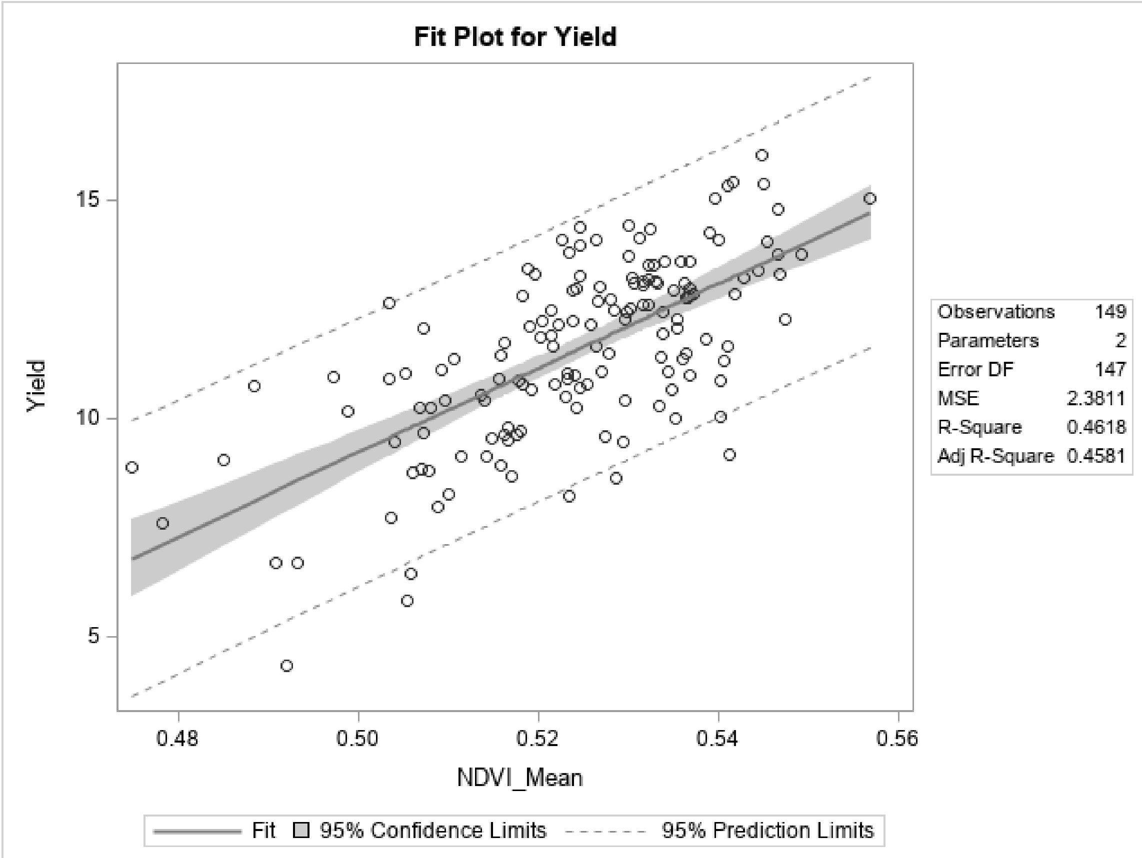


Figure A2.4. Regression analysis of NDVI average versus yield on 8/05/2019 (McCaull Research Farm, n=180, α=0.05).

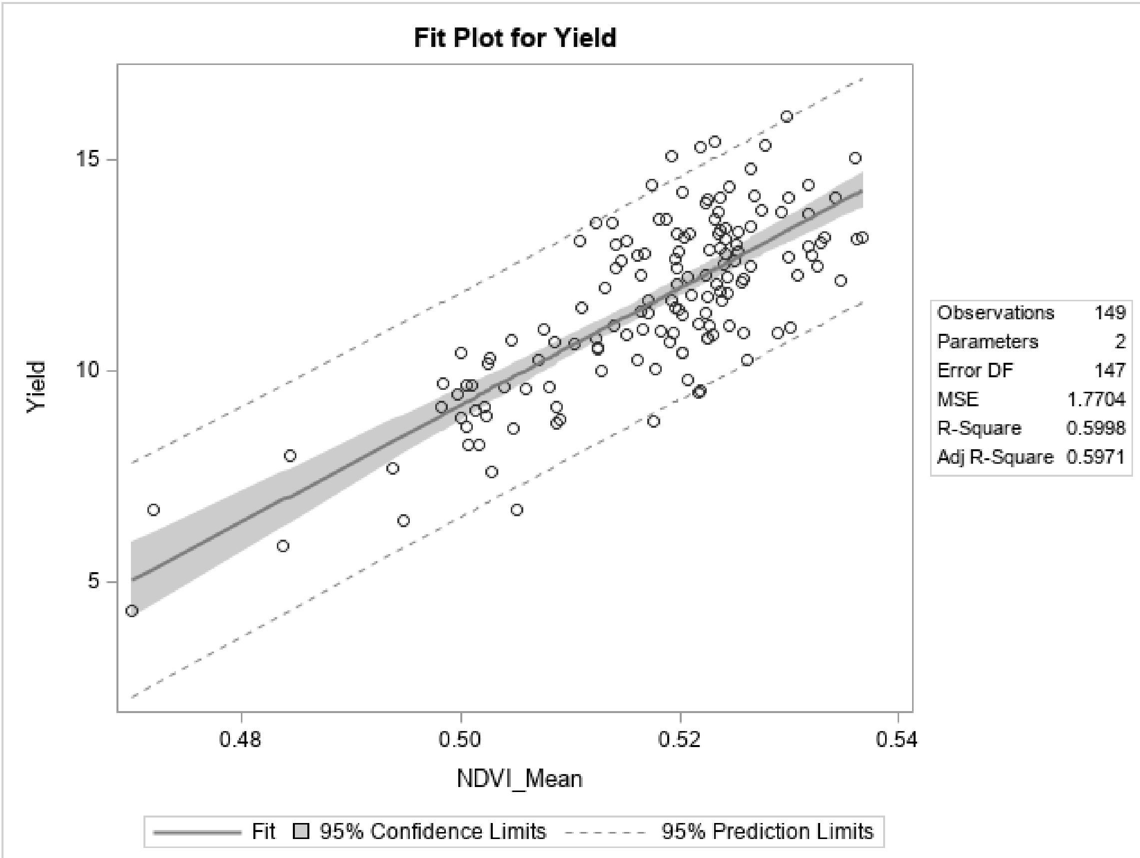


Figure A2.5. Regression analysis of NDVI average versus yield on 8/13/2019 (McCaull Research Farm, n=180, α=0.05).

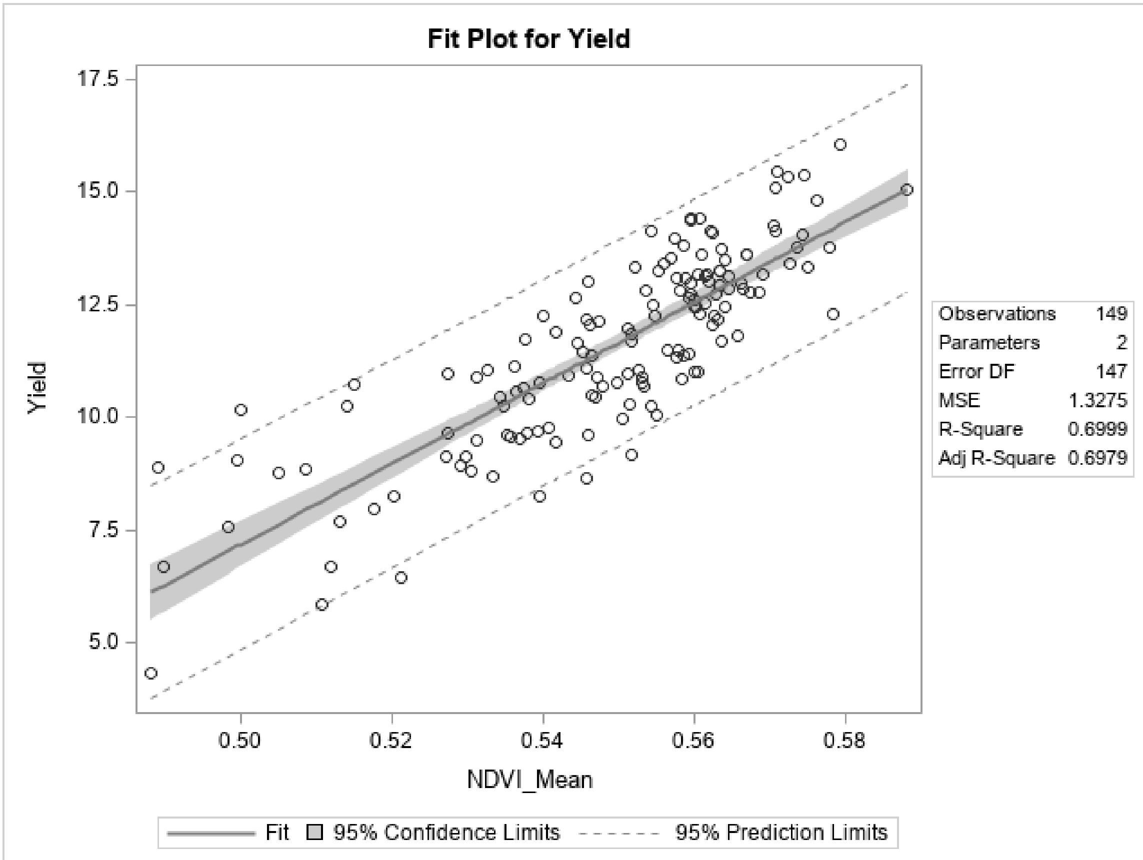


Figure A2.6. Regression analysis of NDVI average versus yield on 8/19/2019 (McCaull Research Farm, n=180, α=0.05).

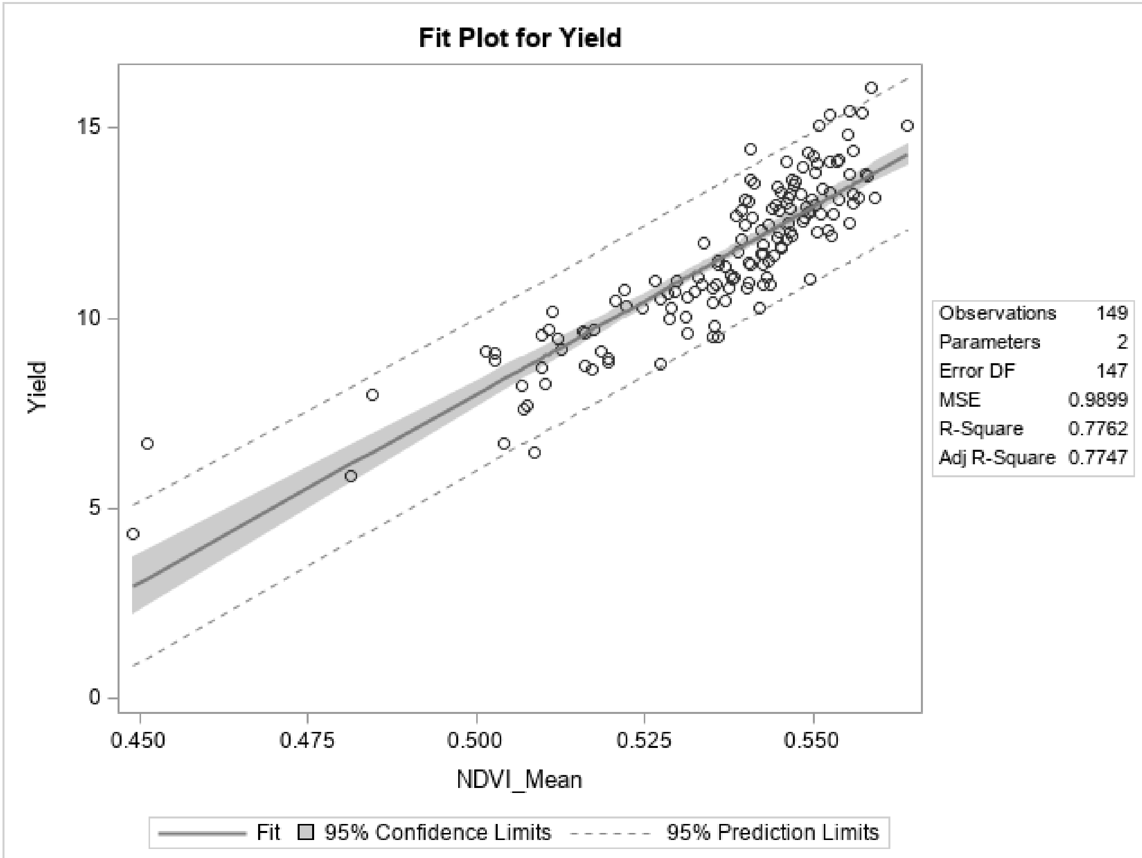


Figure A2.7. Regression analysis of NDVI average versus yield on 8/29/2019 (McCaull Research Farm, n=180, α=0.05).

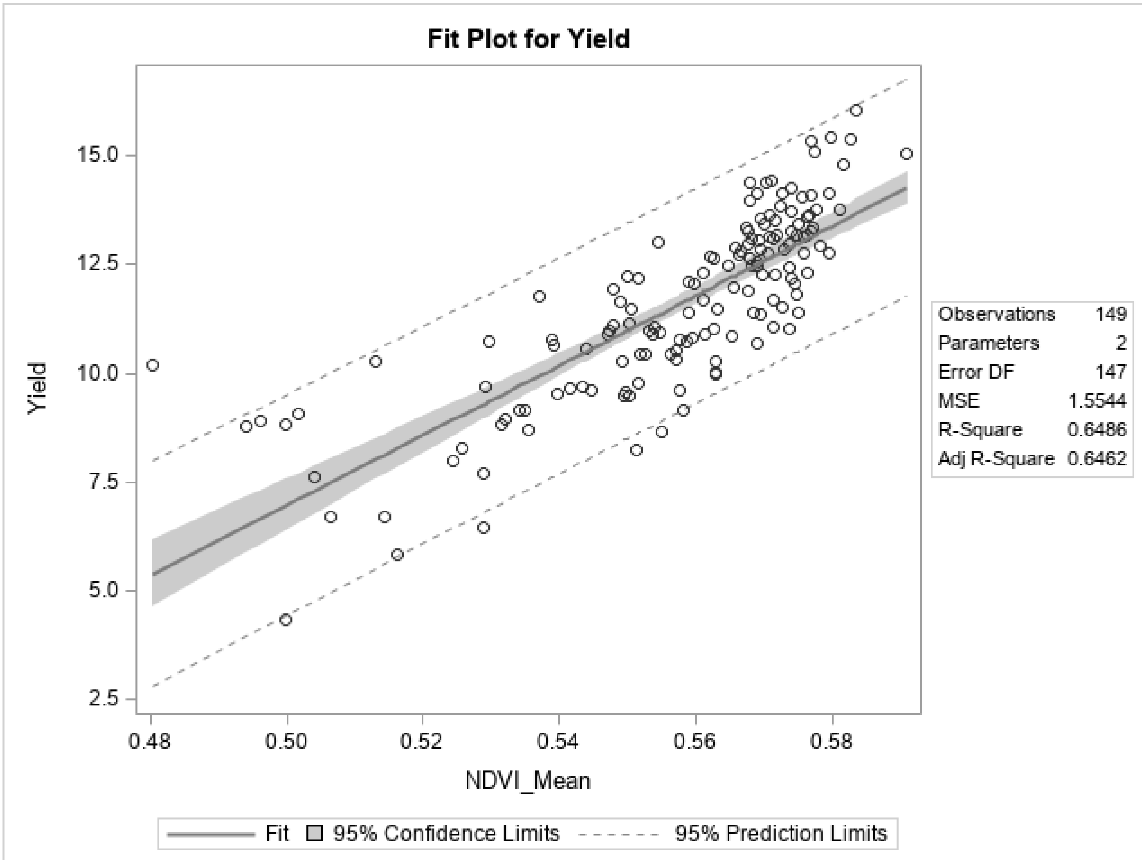


Figure A2.8. Regression analysis of NDVI average versus yield on 9/05/2019 (McCaull Research Farm, n=180, α=0.05).

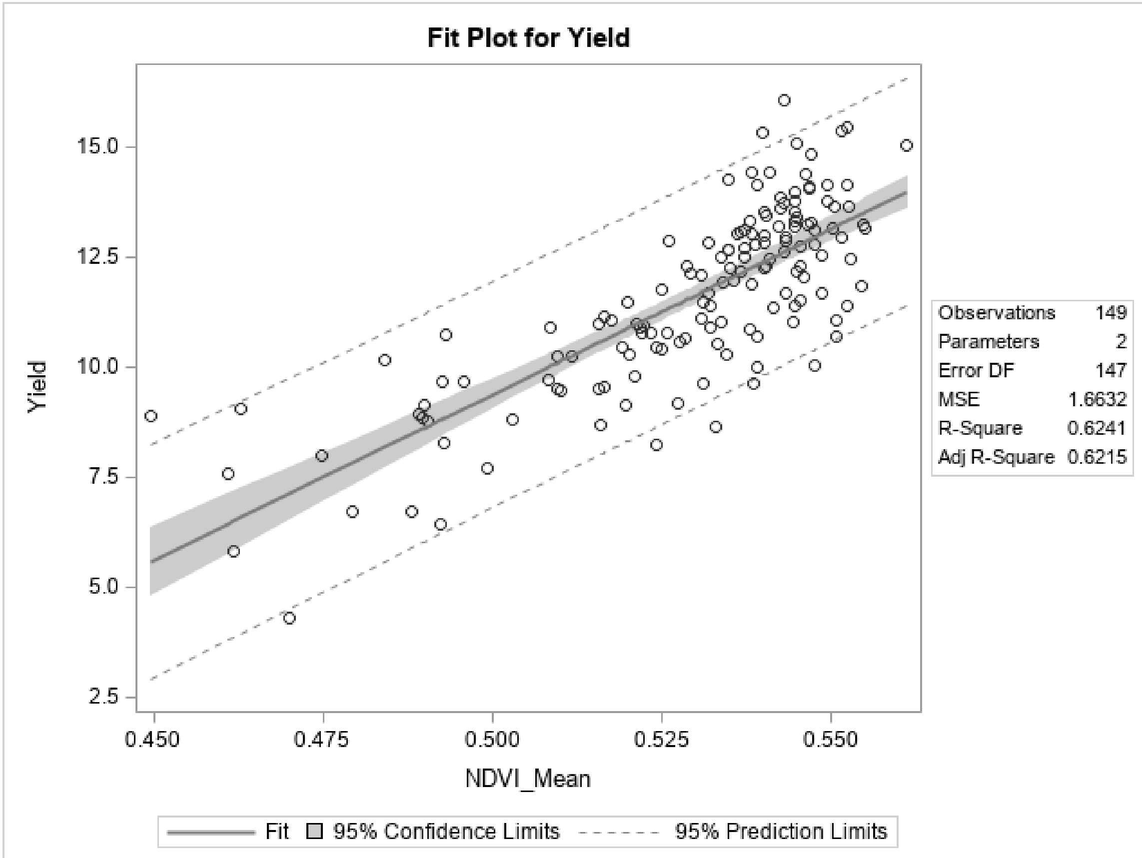


Figure A2.9. Regression analysis of NDVI average versus yield on 9/10/2019 (McCaull Research Farm, n=180, α=0.05).

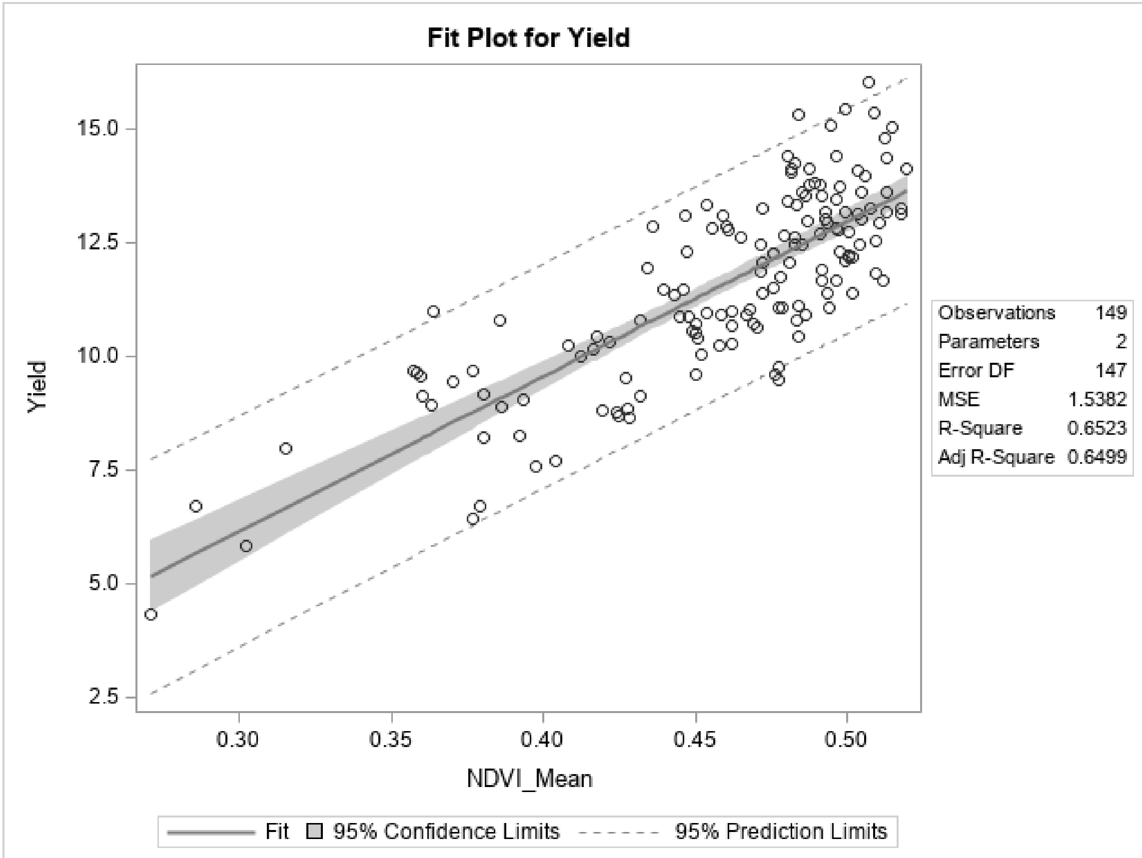


Figure A2.10. Regression analysis of NDVI average versus yield on 9/17/2019 (McCaull Research Farm, n=180, α=0.05).

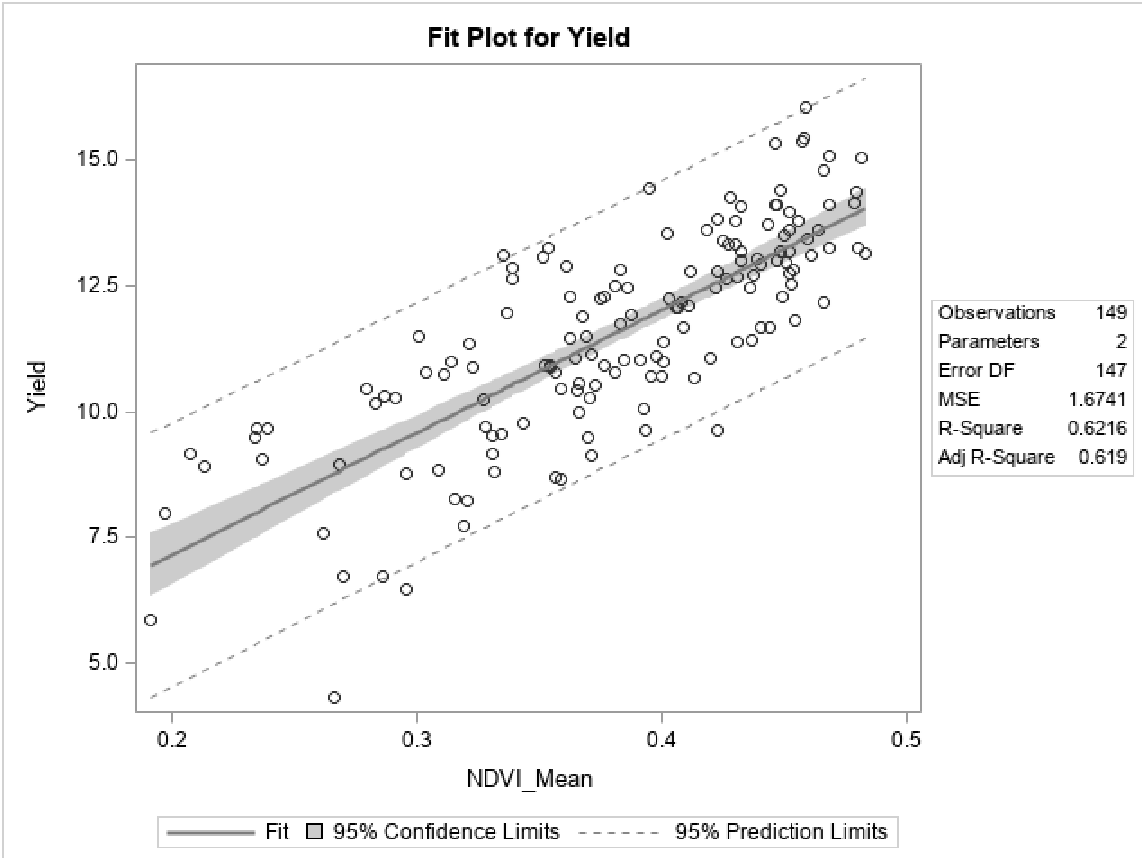


Figure A2.11. Regression analysis of NDVI average versus yield on 9/23/2019 (McCaull Research Farm, n=180, α=0.05).

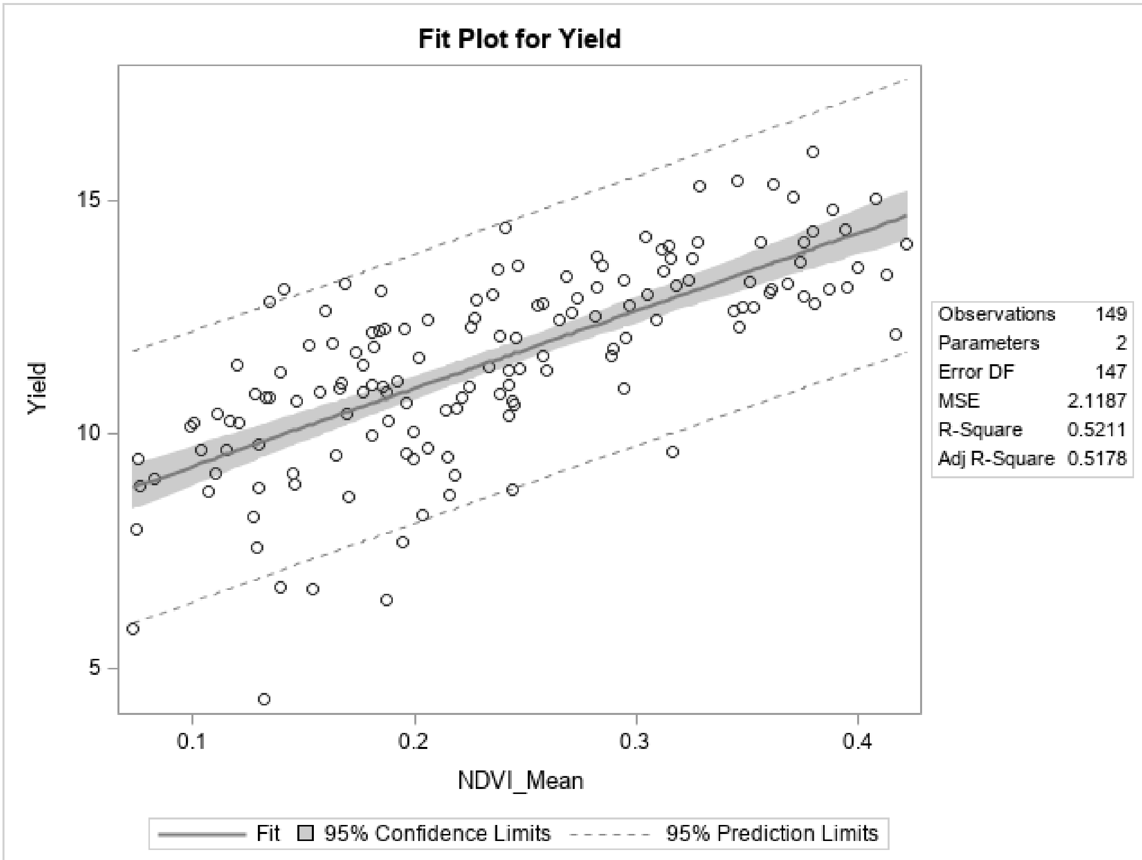


Figure A2.12. Regression analysis of CV versus yield on 7/11/2019 (McCaull Research Farm, n=180, α=0.05).

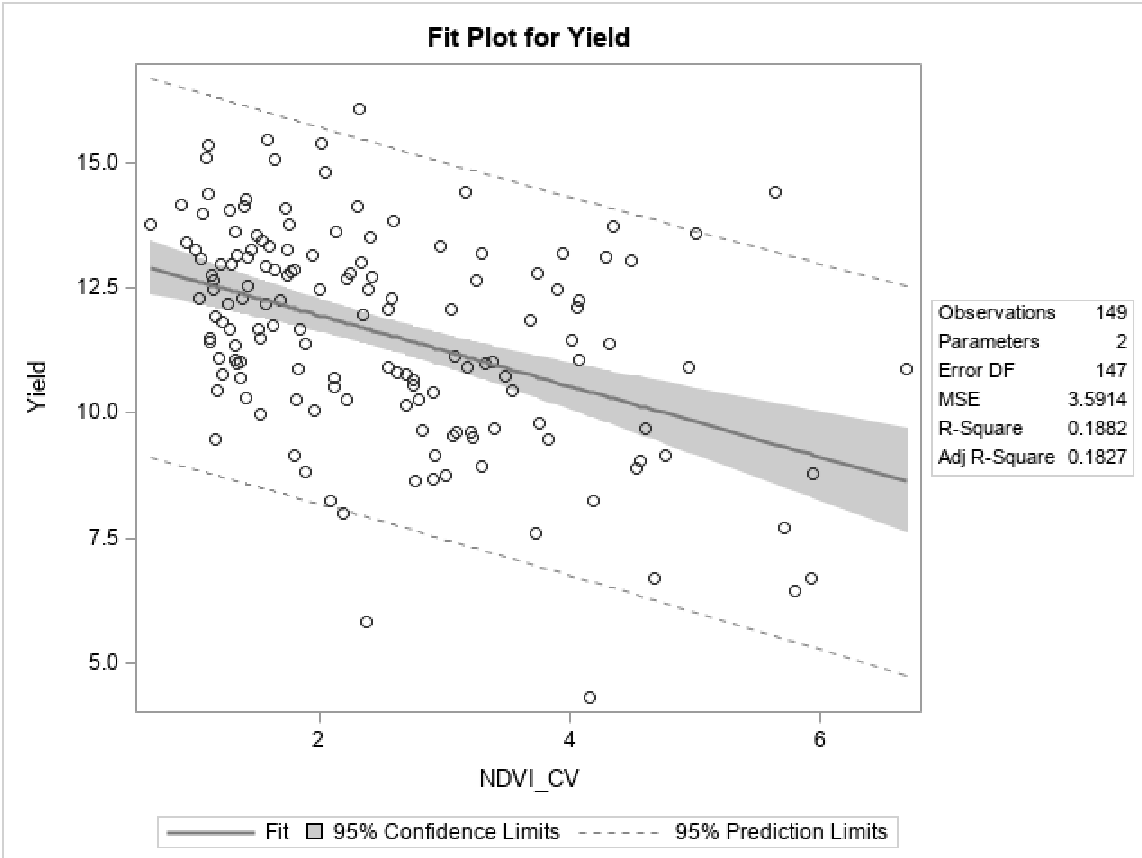


Figure A2.13. Regression analysis of CV versus yield on 7/25/2019 (McCaull Research Farm, n=180, α=0.05).

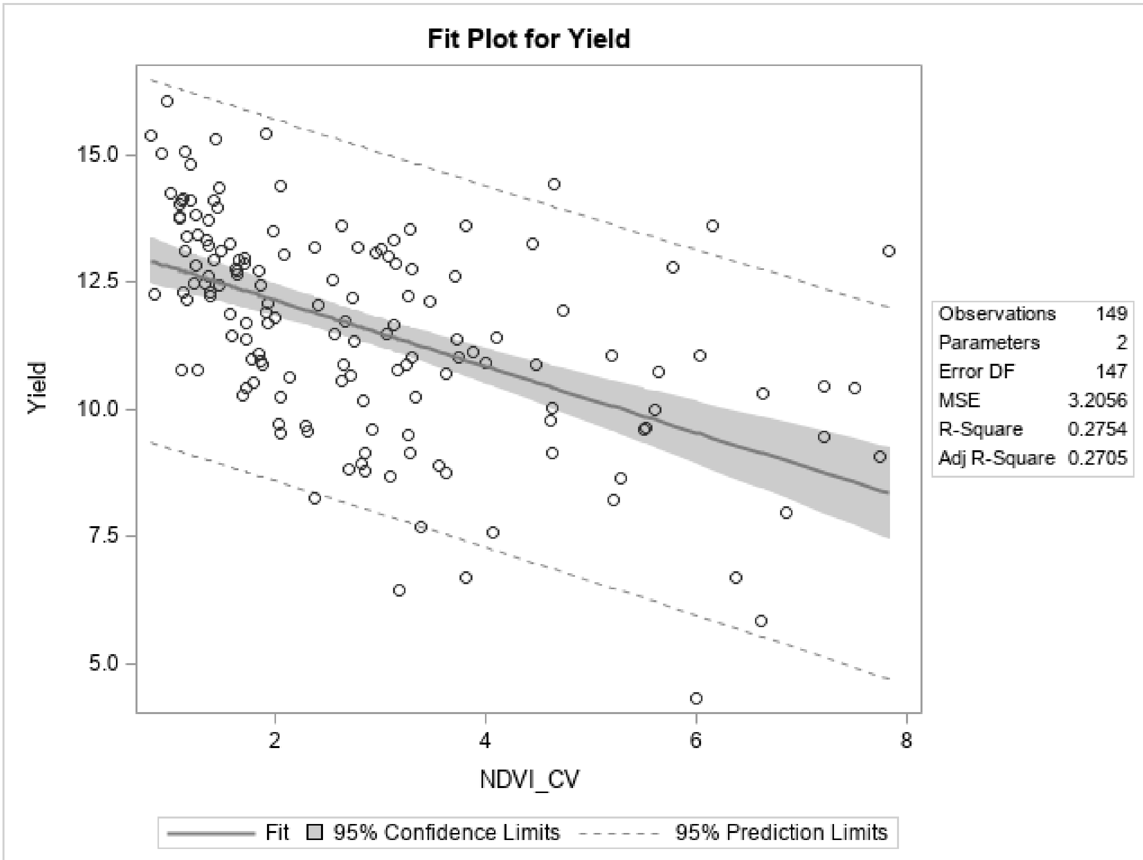


Figure A2.14. Regression analysis of CV versus yield on 7/29/2019 (McCaull Research Farm, n=180, α=0.05).

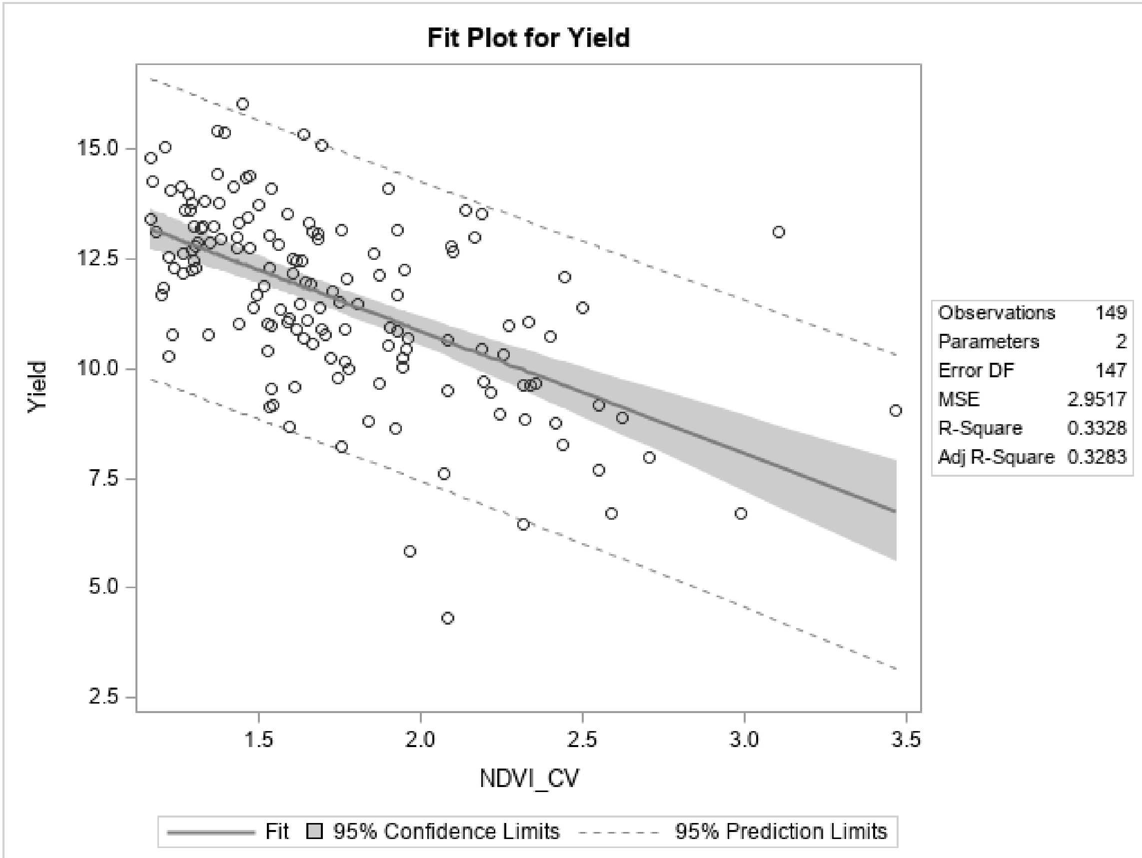


Figure A2.15. Regression analysis of CV versus yield on 8/05/2019 (McCaull Research Farm, n=180, α=0.05).

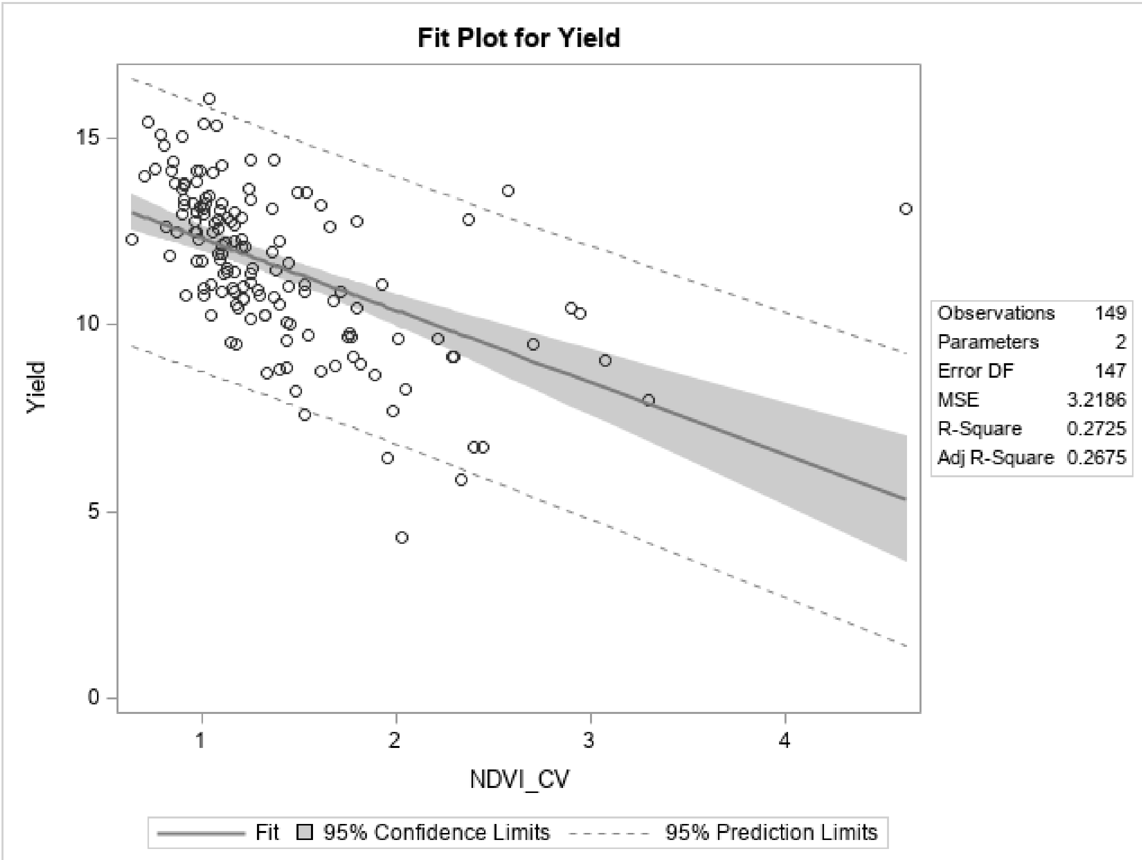


Figure A2.16. Regression analysis of CV versus yield on 8/13/2019 (McCaull Research Farm, n=180, α=0.05).

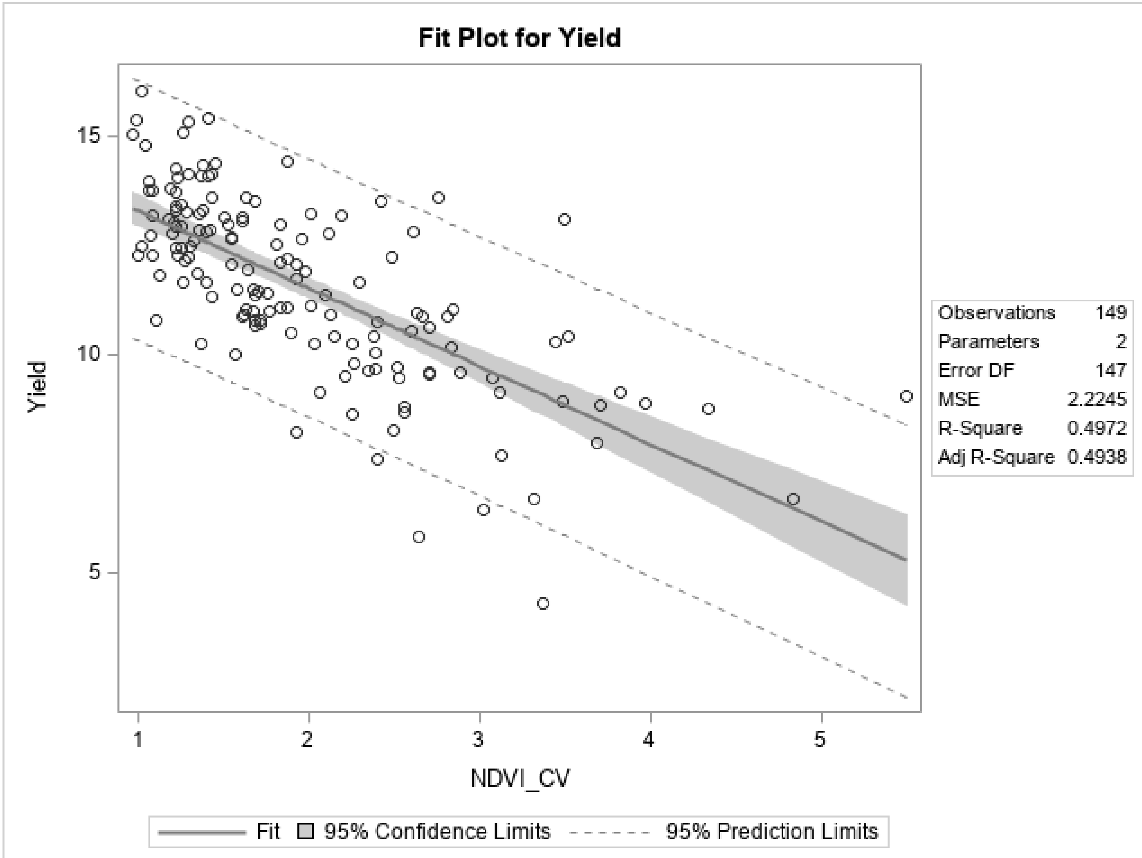


Figure A2.17. Regression analysis of CV versus yield on 8/19/2019 (McCaull Research Farm, n=180, α=0.05).

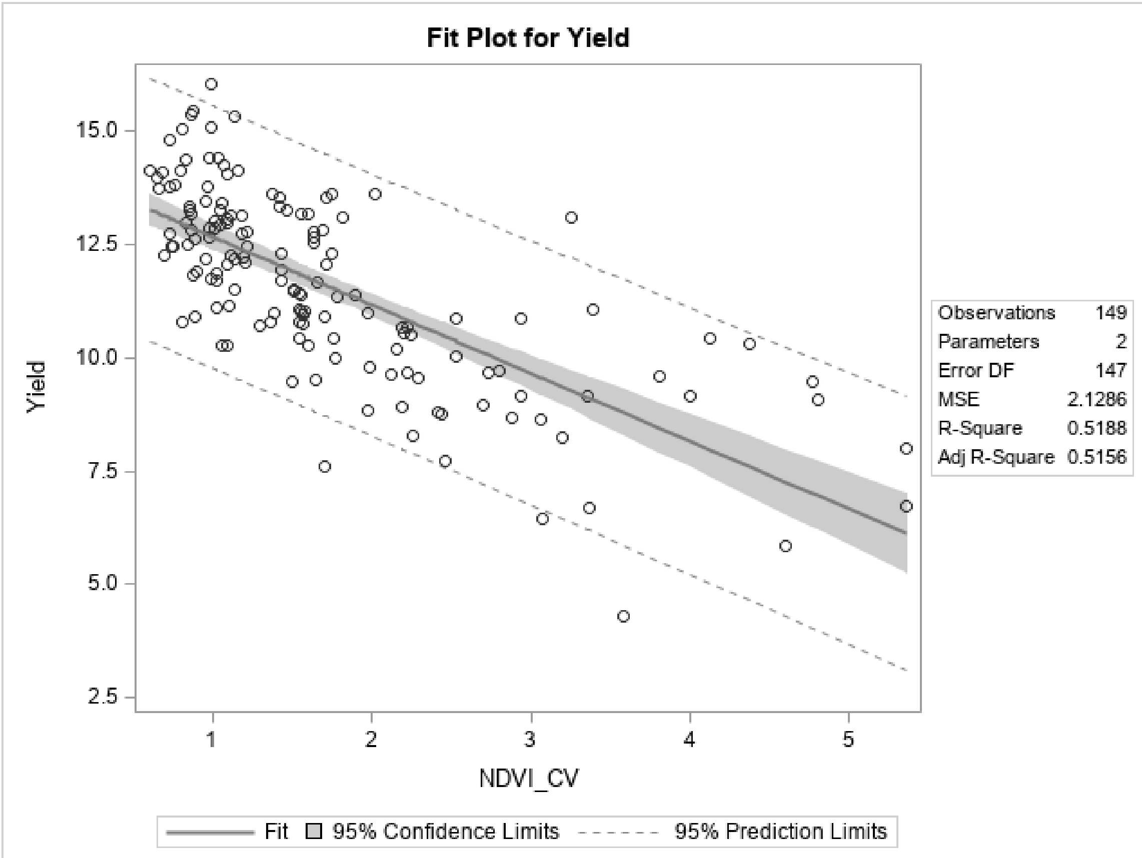


Figure A2.18. Regression analysis of CV versus yield on 8/29/2019 (McCaull Research Farm, n=180, α=0.05).

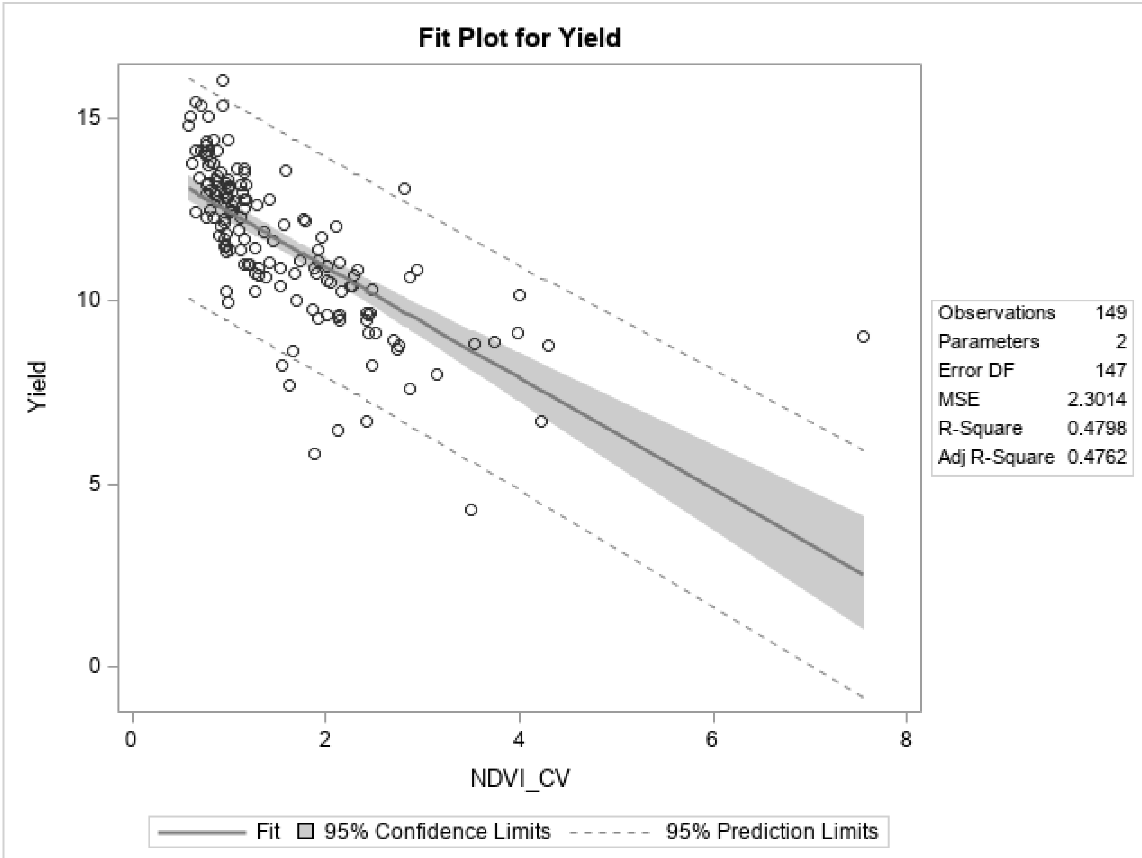


Figure A2.19. Regression analysis of CV versus yield on 9/05/2019 (McCaull Research Farm, n=180, α=0.05).

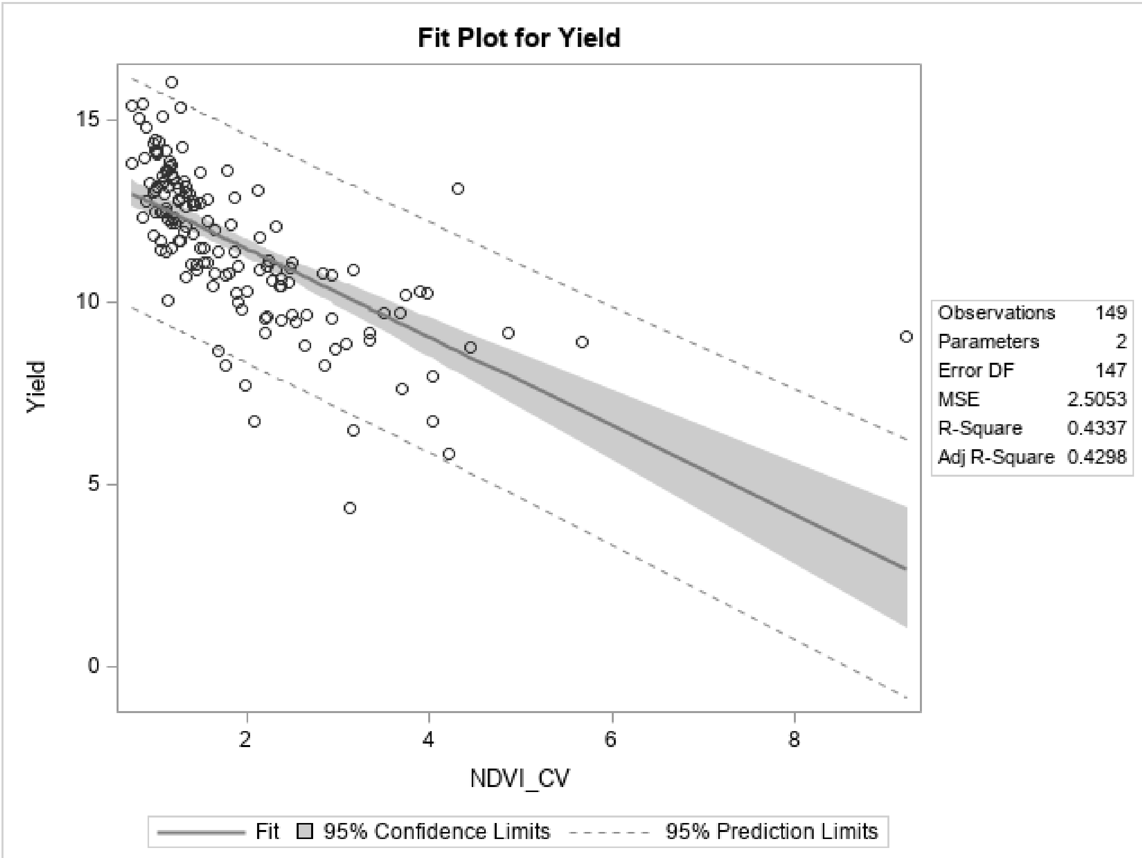


Figure A2.20. Regression analysis of CV versus yield on 9/10/2019 (McCaull Research Farm, n=180, α=0.05).

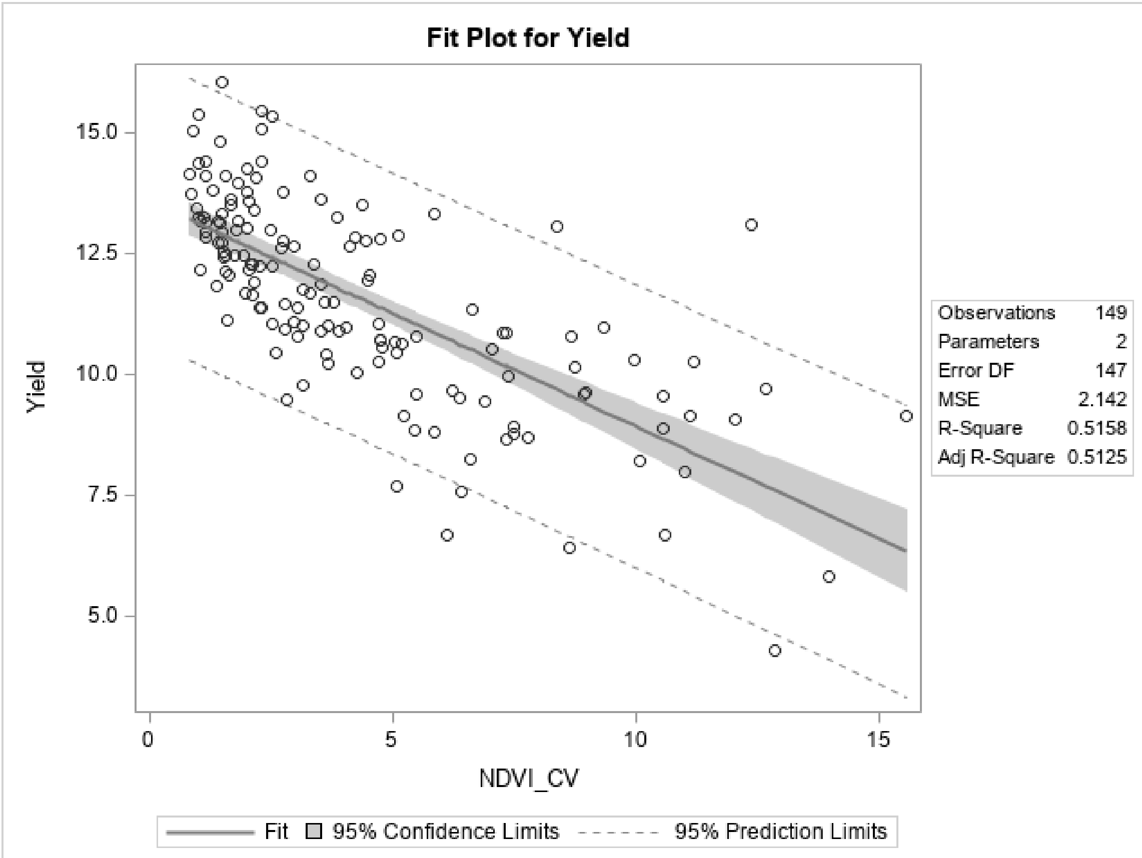


Figure A2.21. Regression analysis of CV versus yield on 9/17/2019 (McCaull Research Farm, n=180, α=0.05).

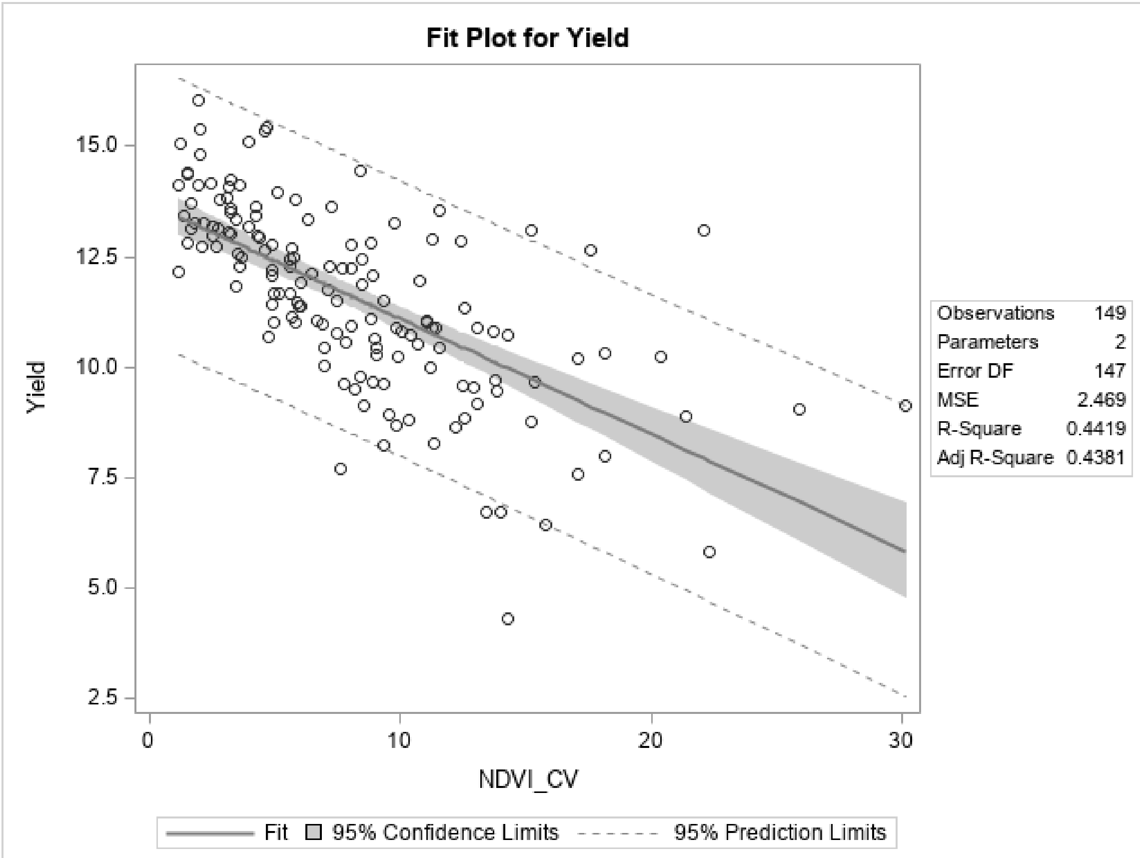


Figure A2.22. Regression analysis of CV versus yield on 9/23/2019 (McCaull Research Farm, n=180, α=0.05).

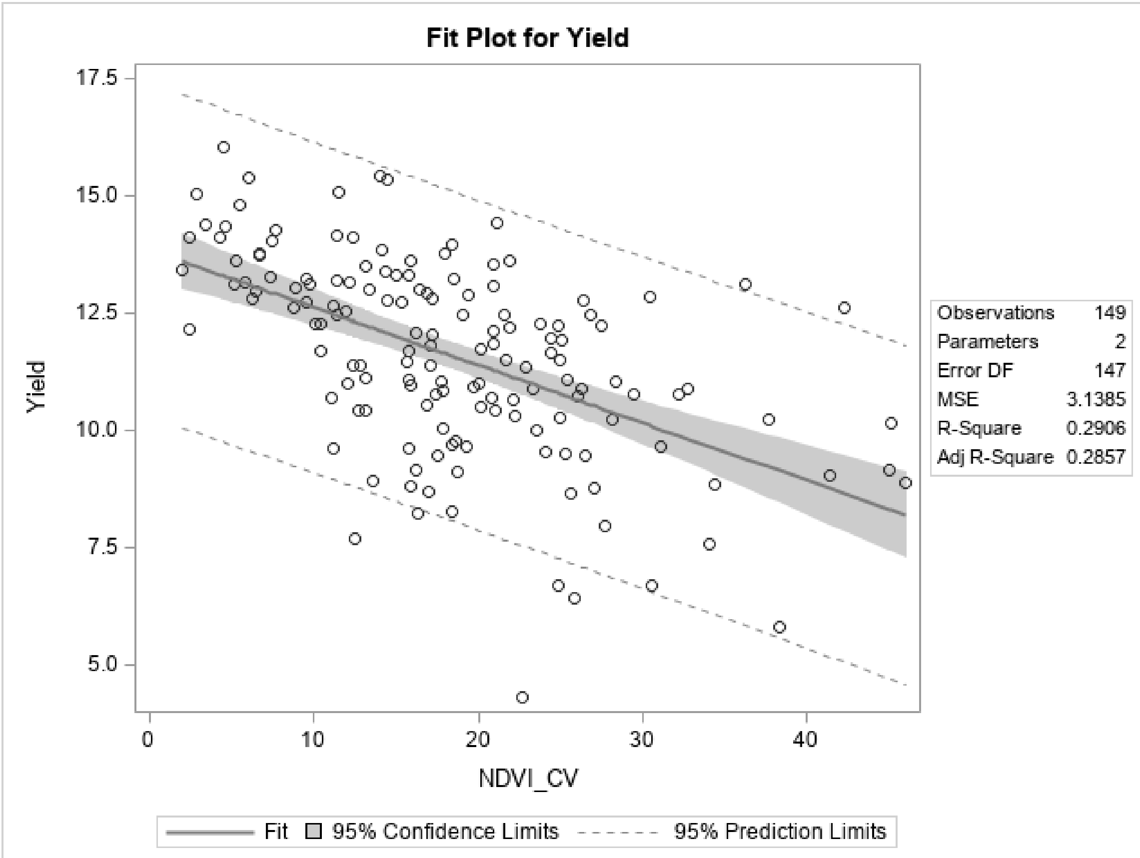


Figure A2.23. Regression analysis of NDVI average versus yield on 4/23/2020 (McCaull Research Farm, n=180, α=0.05).

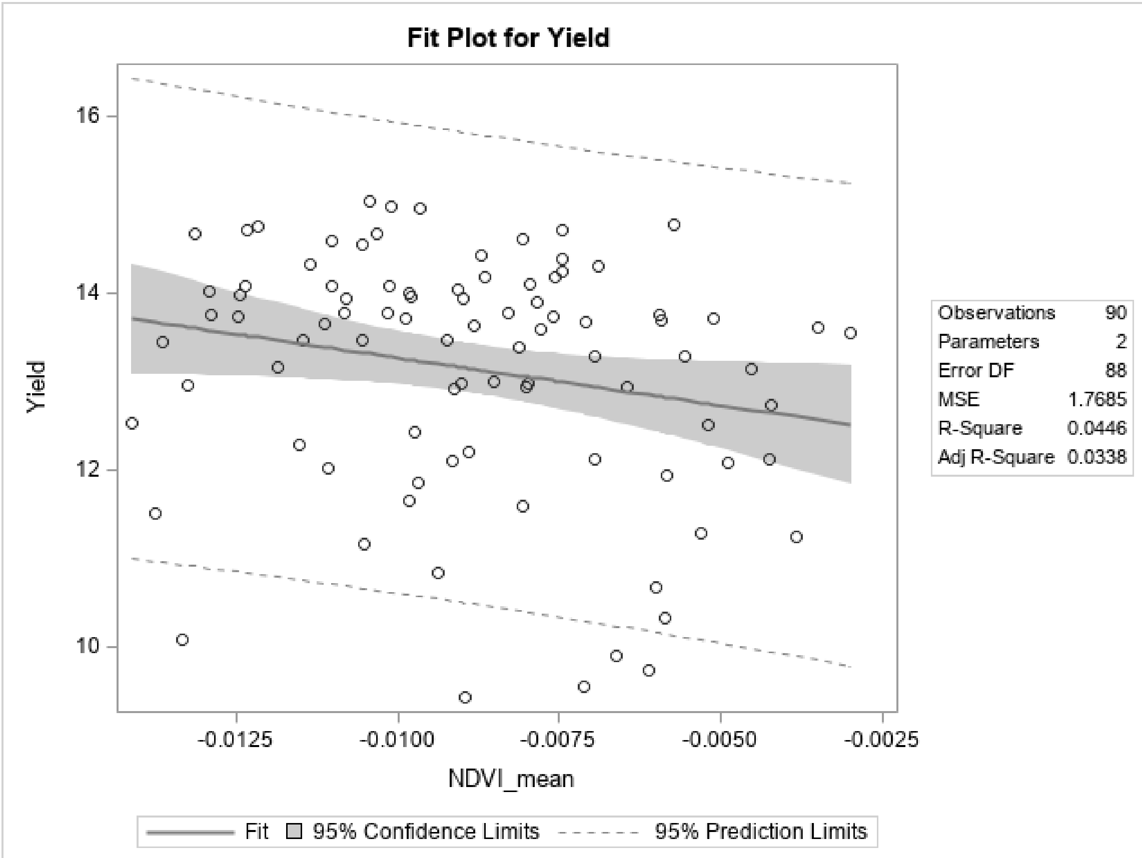


Figure A2.24. Regression analysis of NDVI average versus yield on 6/01/2020 (McCaull Research Farm, n=180, α=0.05).

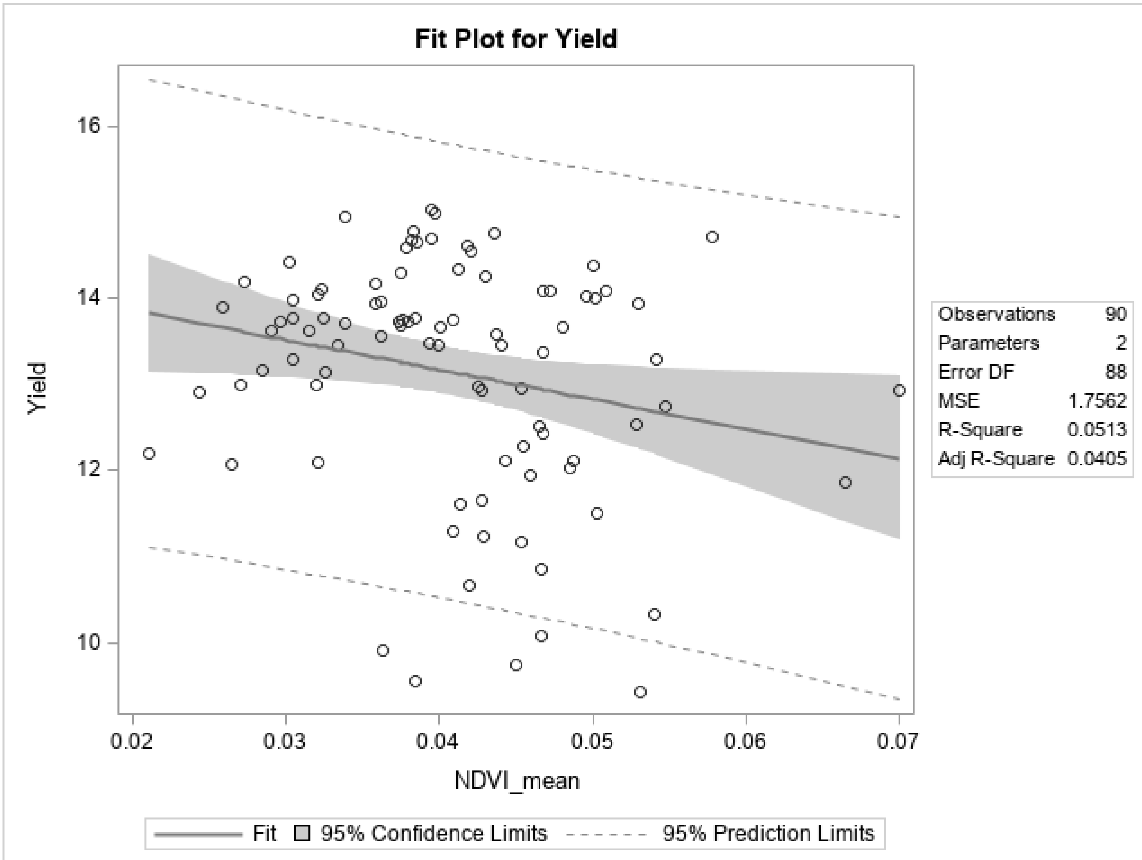


Figure A2.25. Regression analysis of NDVI average versus yield on 6/15/2020 (McCaull Research Farm, n=180, α=0.05).

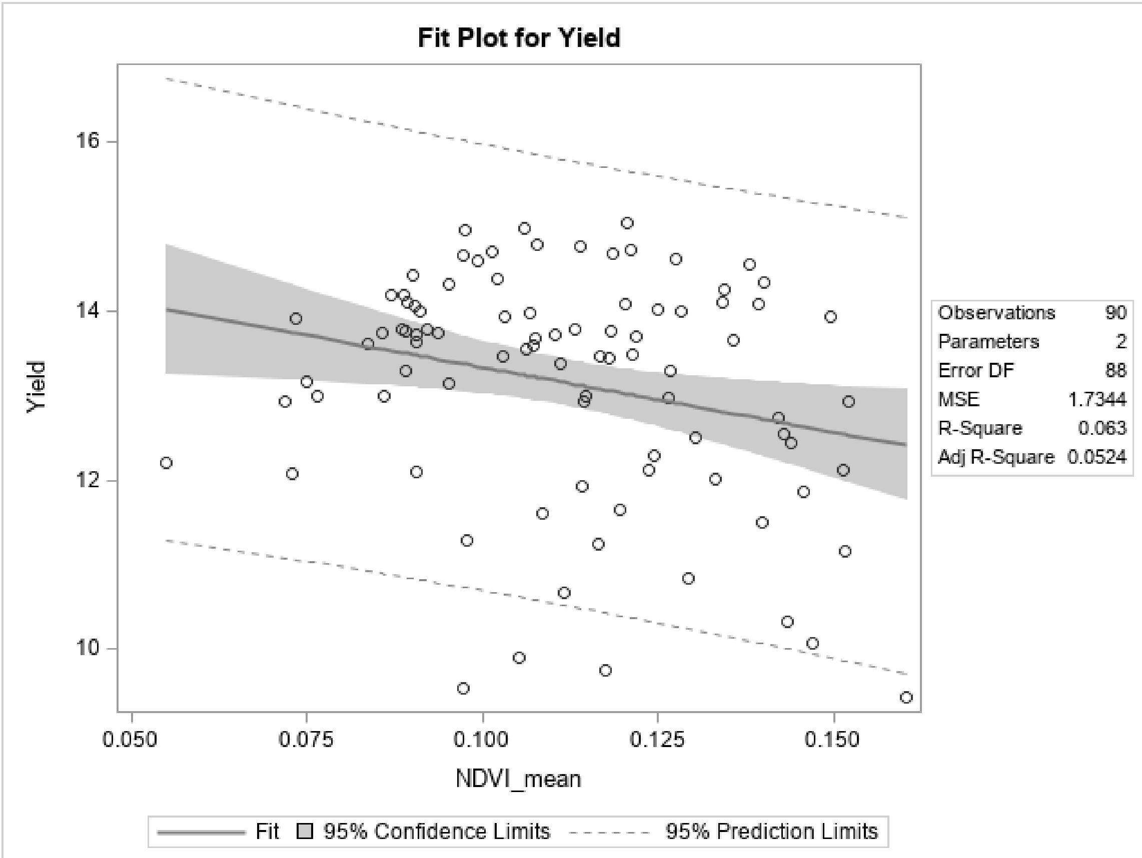


Figure A2.26. Regression analysis of NDVI average versus yield on 6/25/2020 (McCaull Research Farm, n=180, α=0.05).

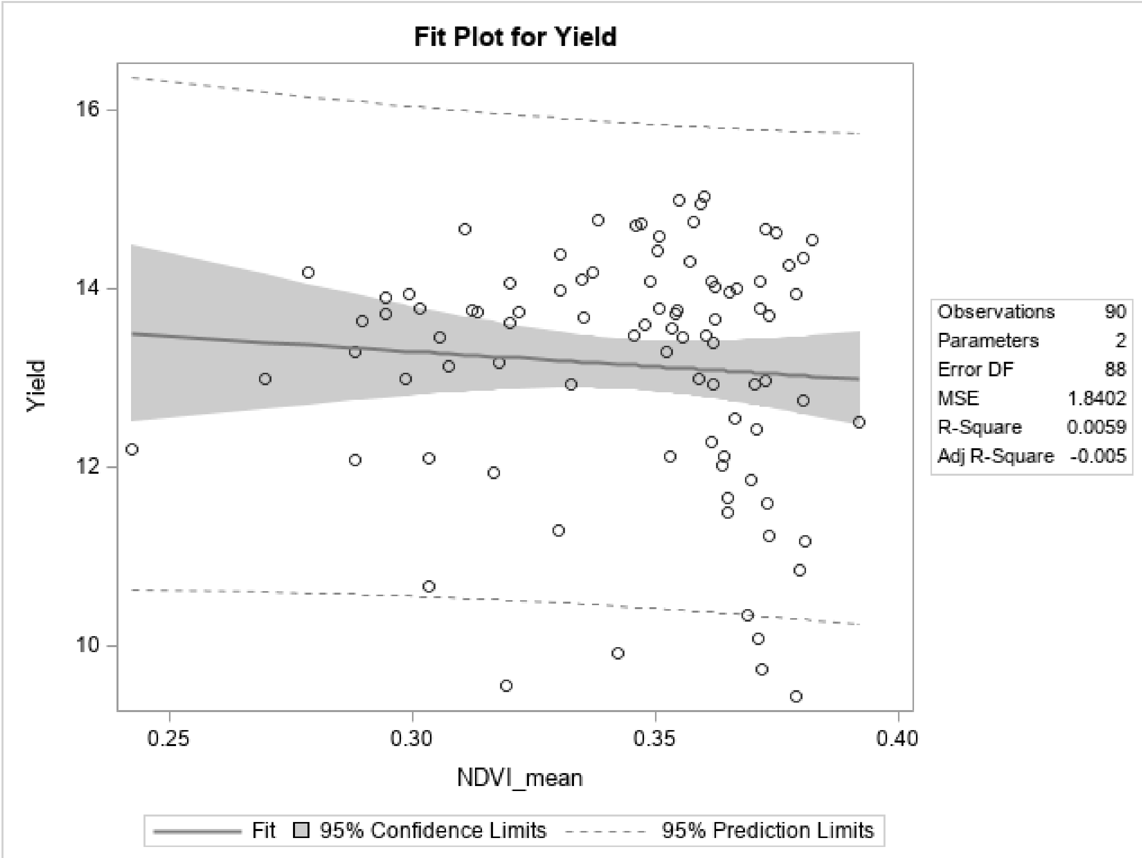


Figure A2.27. Regression analysis of NDVI average versus yield on 7/08/2020 (McCaull Research Farm, n=180, α=0.05).

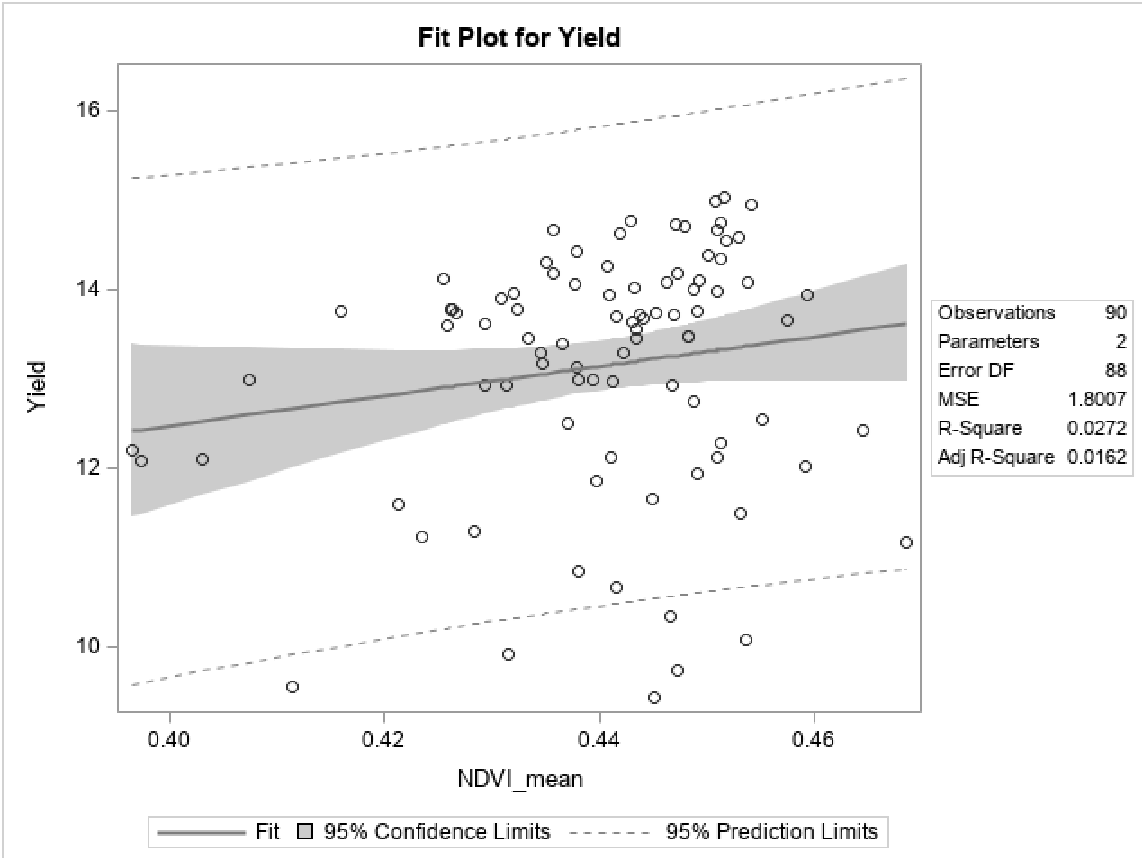


Figure A2.28. Regression analysis of NDVI average versus yield on 7/20/2020 (McCaull Research Farm, n=180, α=0.05).

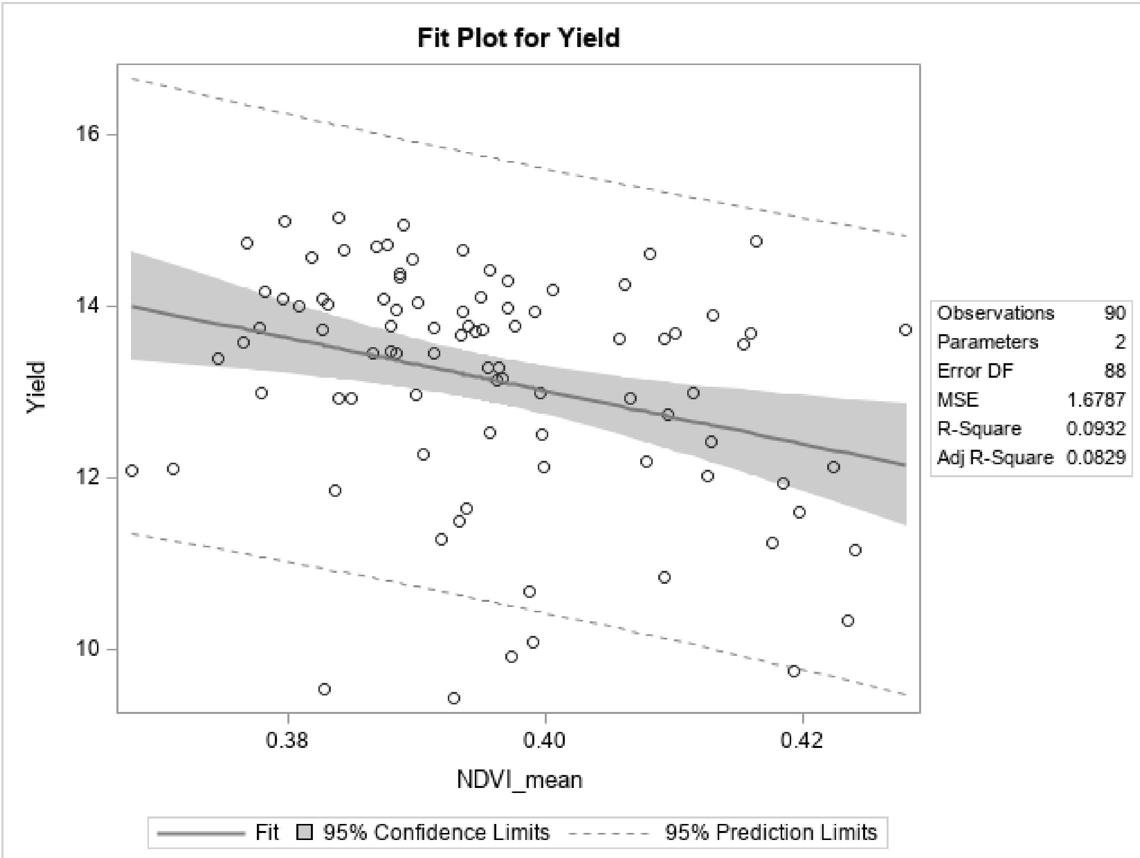


Figure A2.29. Regression analysis of NDVI average versus yield on 8/04/2020 (McCaull Research Farm, n=180, α=0.05).

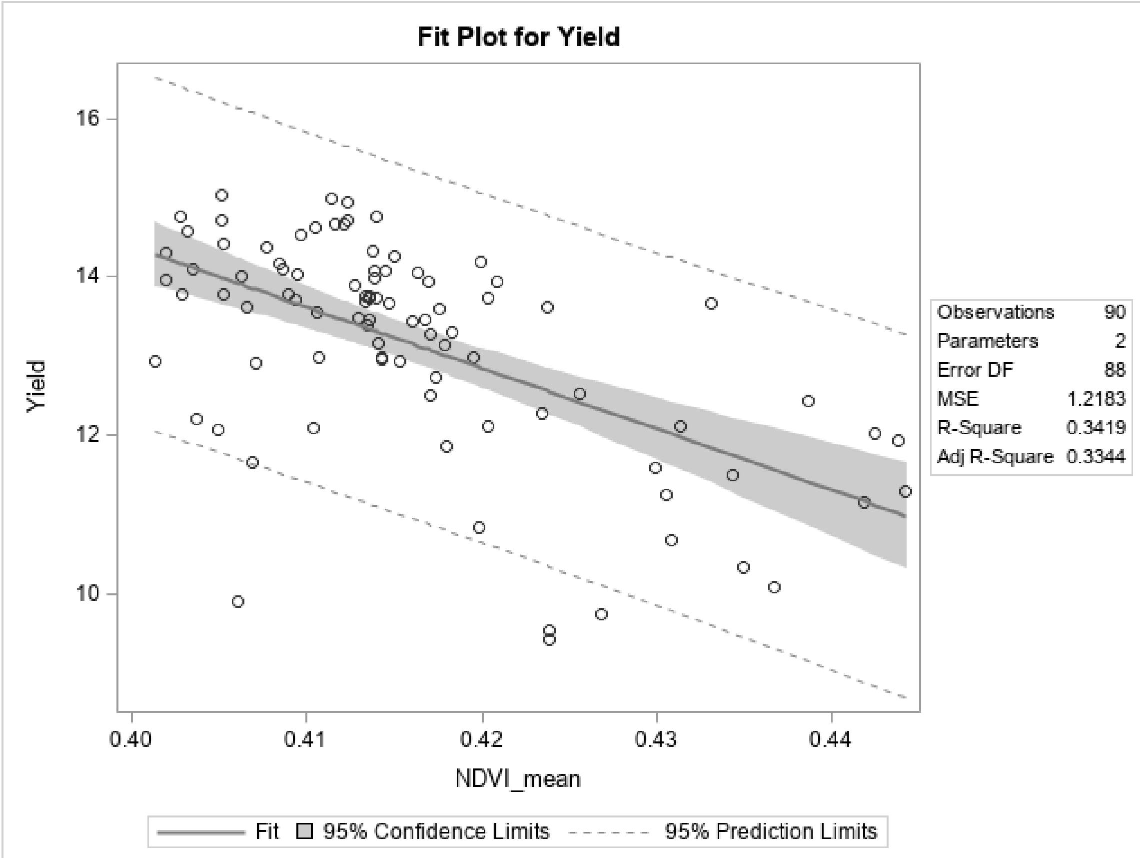


Figure A2.30. Regression analysis of NDVI average versus yield on 8/18/2020 (McCaull Research Farm, n=180, α=0.05).

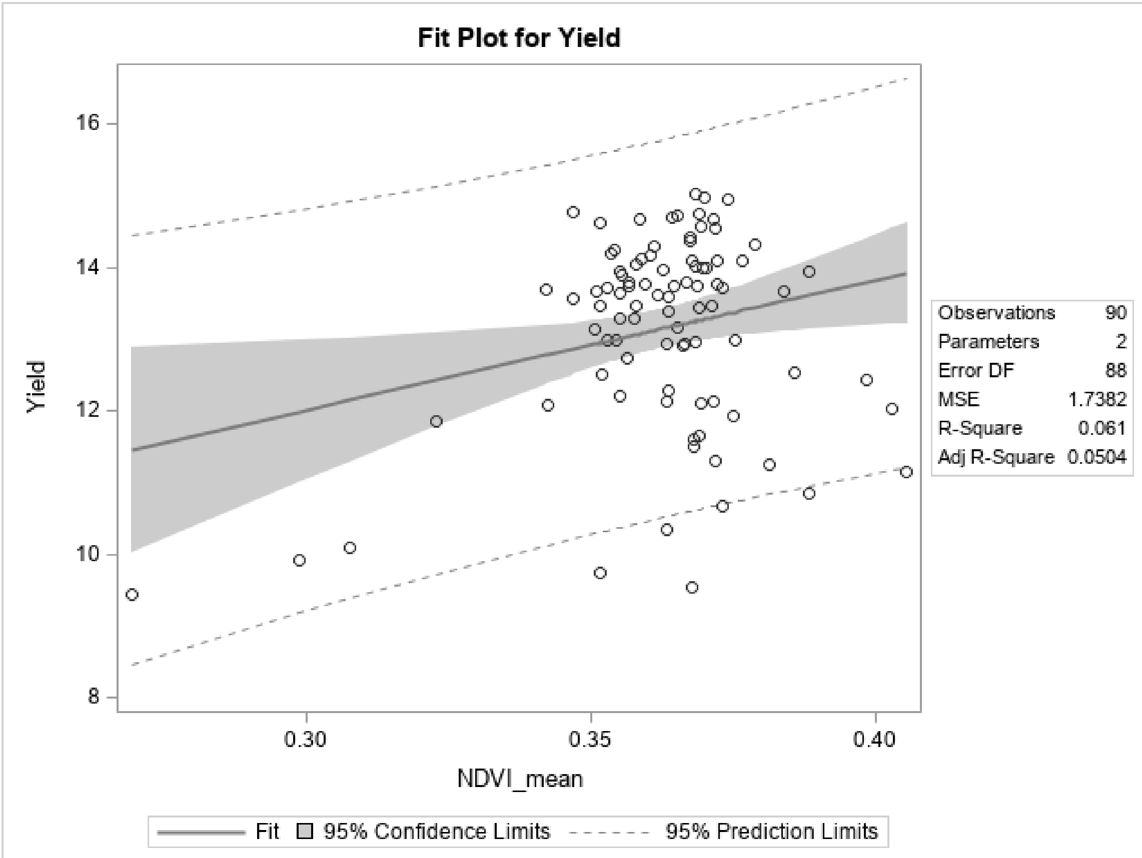


Figure A2.31. Regression analysis of NDVI average versus yield on 9/02/2020 (McCaull Research Farm, n=180, α=0.05).

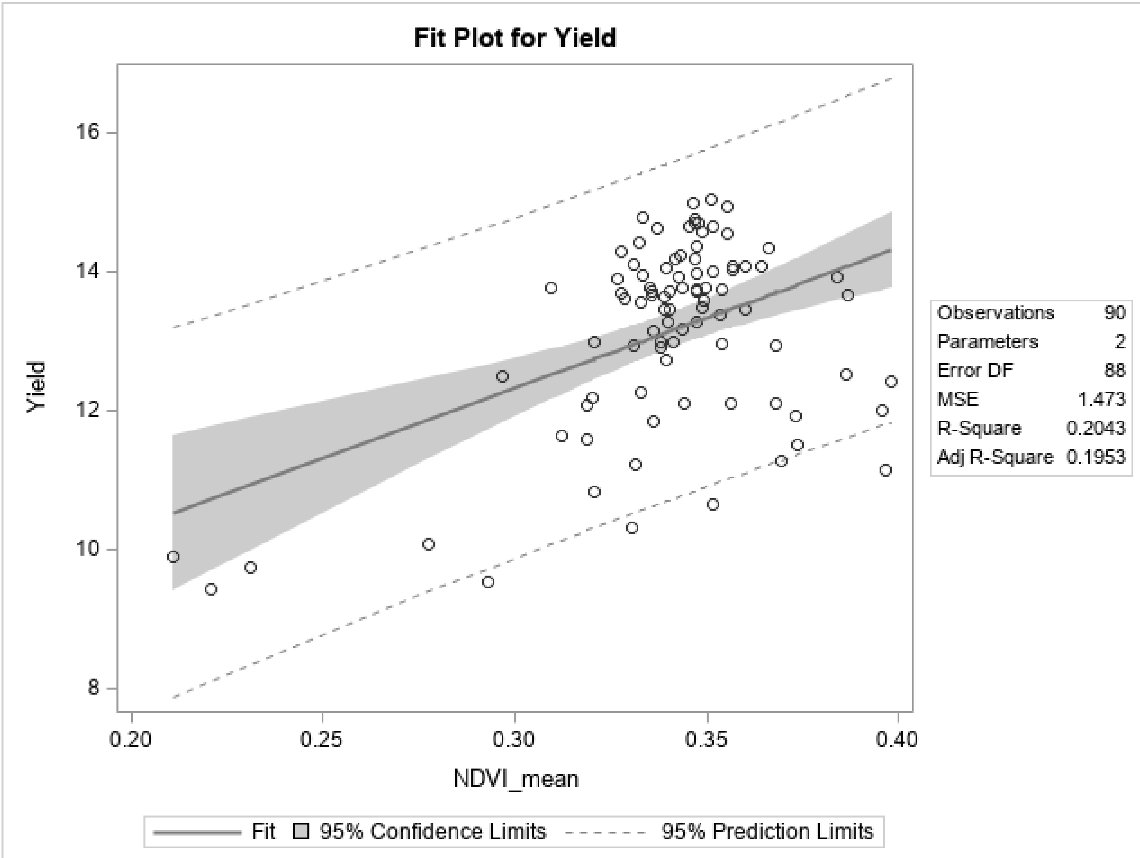


Figure A2.32. Regression analysis of CV versus yield on 4/23/2020 (McCaull Research Farm, n=180, α=0.05).

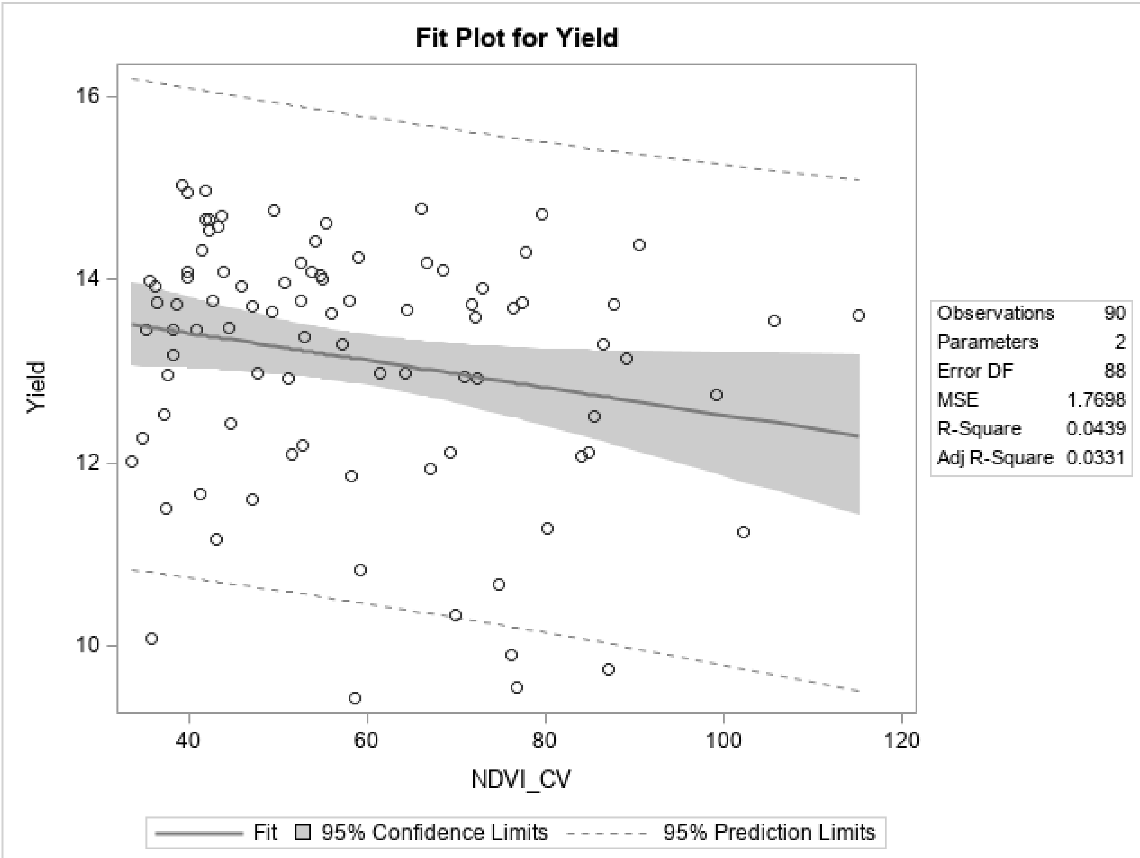


Figure A2.33. Regression analysis of CV versus yield on 6/01/2020 (McCaull Research Farm, n=180, α=0.05).

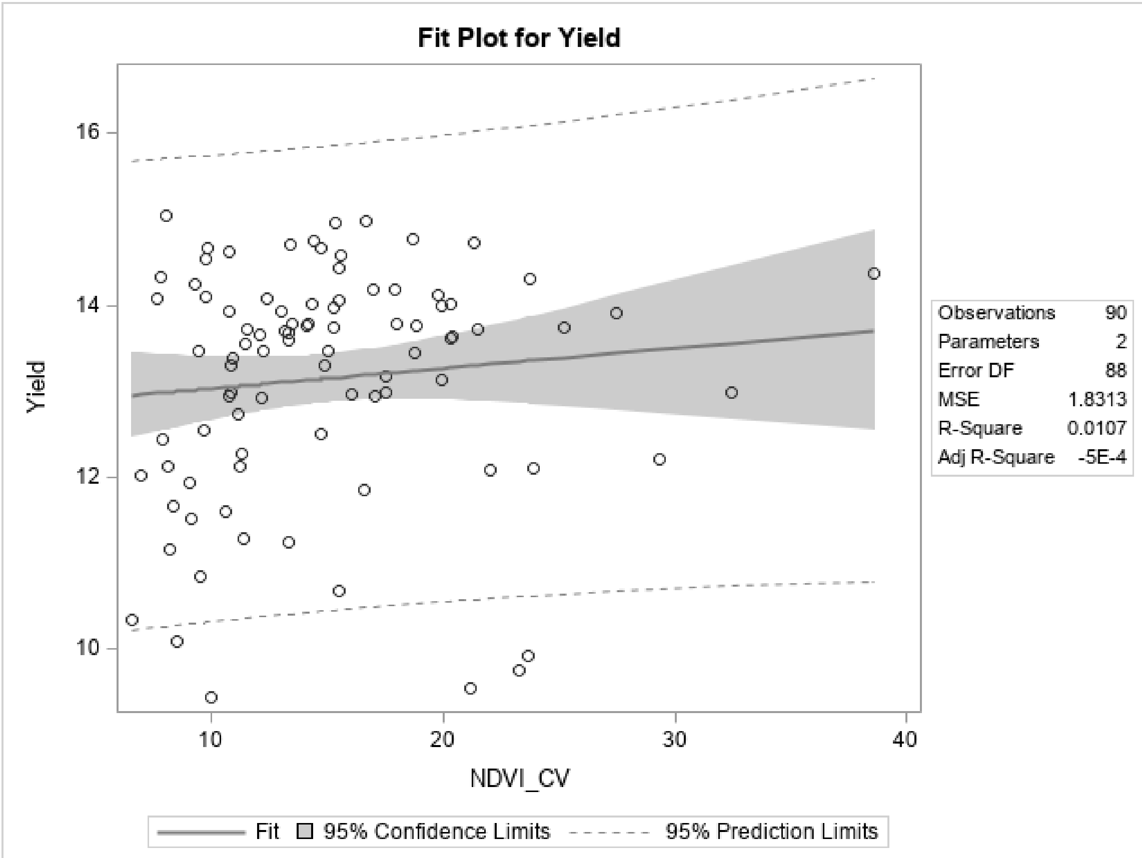


Figure A2.34. Regression analysis of CV versus yield on 6/15/2020 (McCaull Research Farm, n=180, α=0.05).

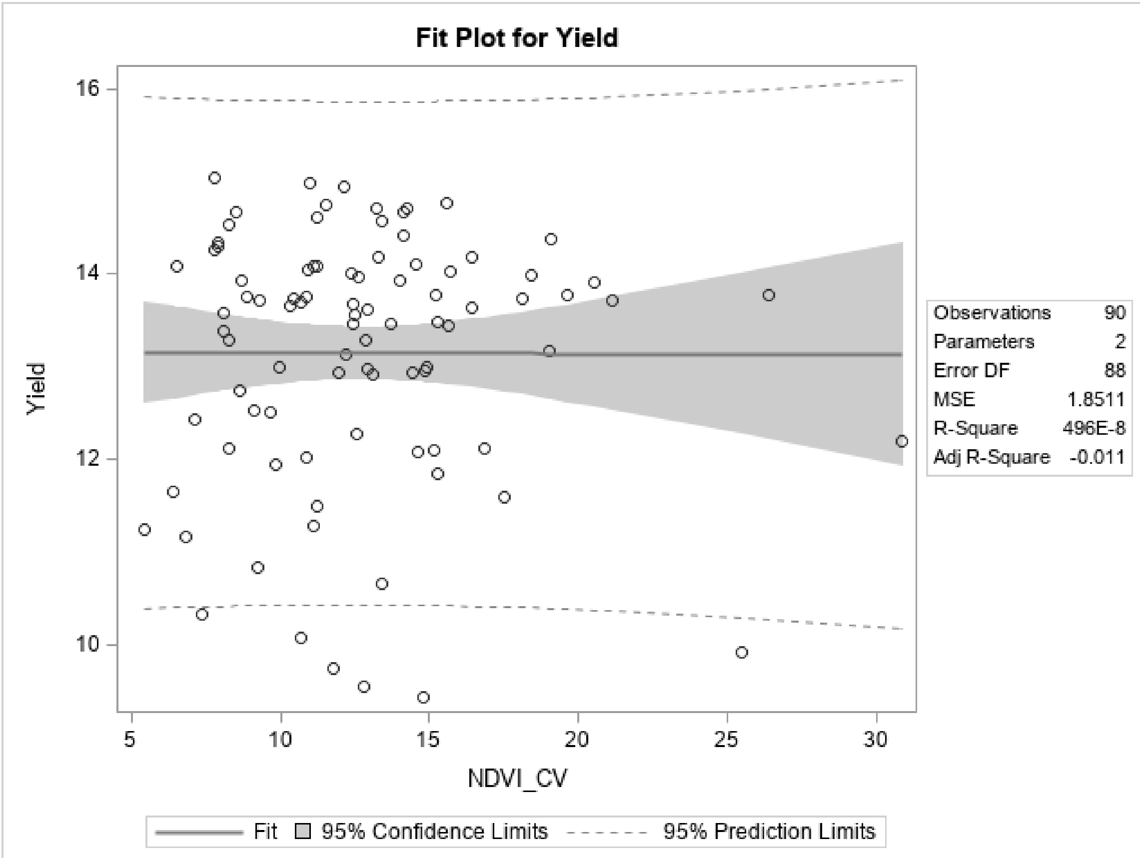


Figure A2.35. Regression analysis of CV versus yield on 6/25/2020 (McCaull Research Farm, n=180, α=0.05).

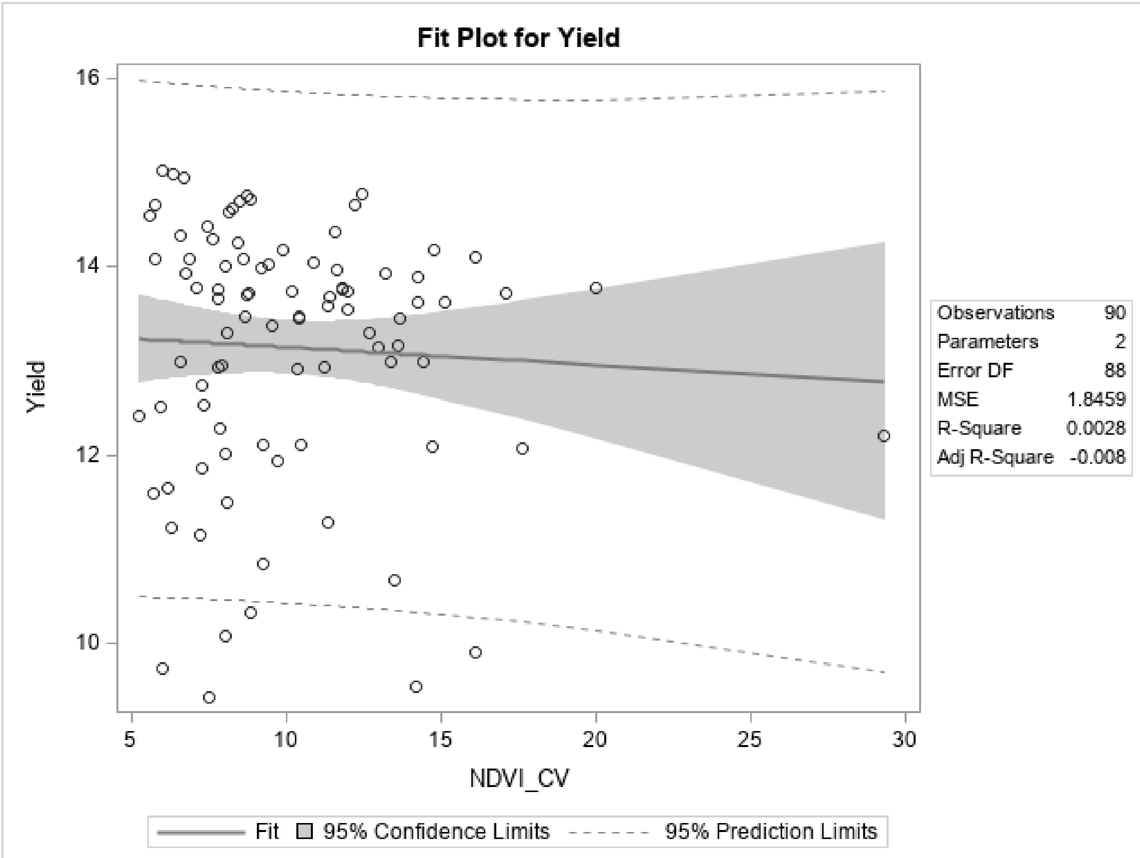


Figure A2.36. Regression analysis of CV versus yield on 7/08/2020 (McCaull Research Farm, n=180, α=0.05).

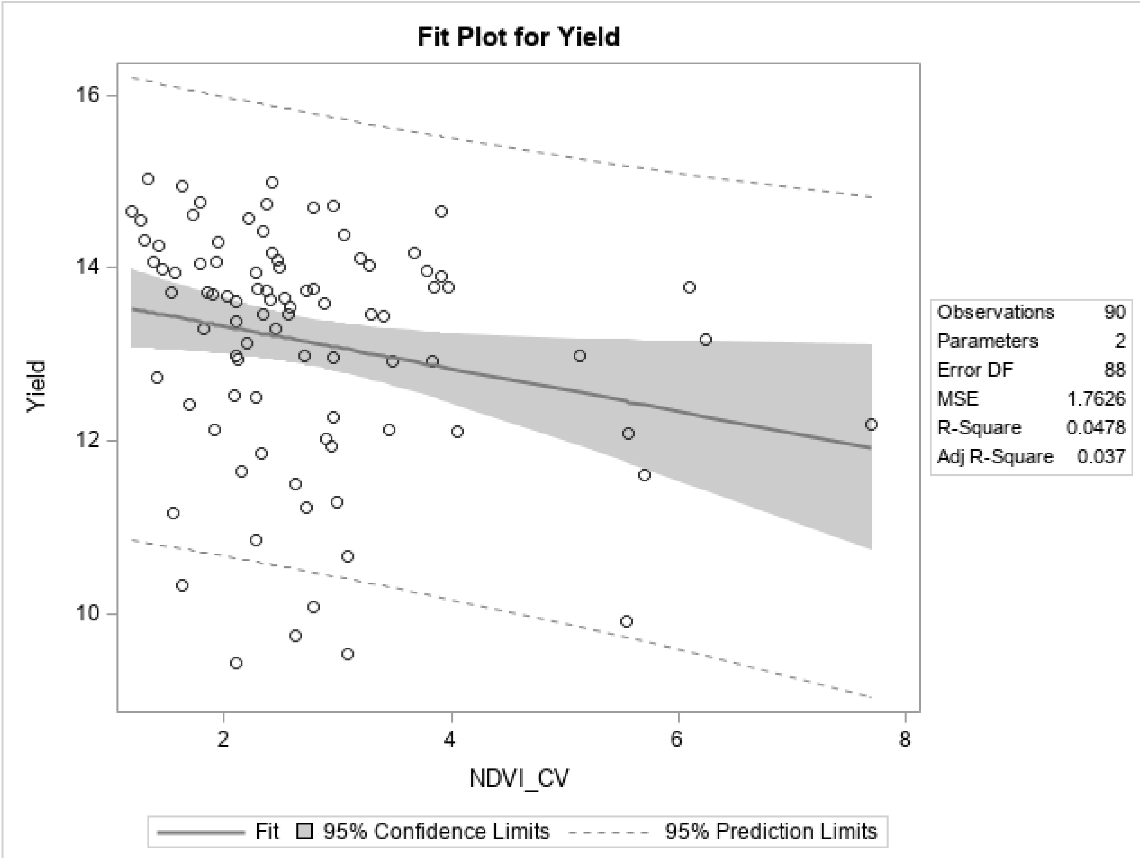


Figure A2.37. Regression analysis of CV versus yield on 7/20/2020 (McCaull Research Farm, n=180, α=0.05).

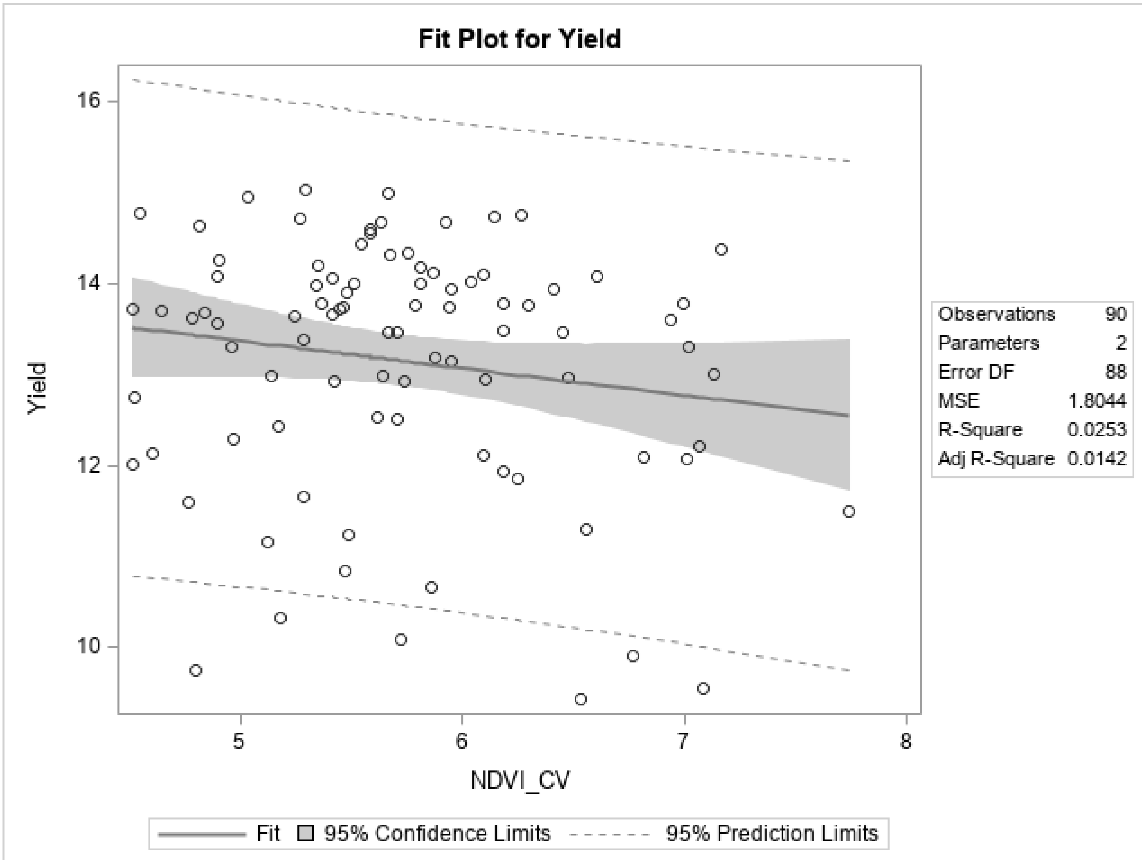


Figure A2.38. Regression analysis of CV versus yield on 8/04/2020 (McCaull Research Farm, n=180, α=0.05).

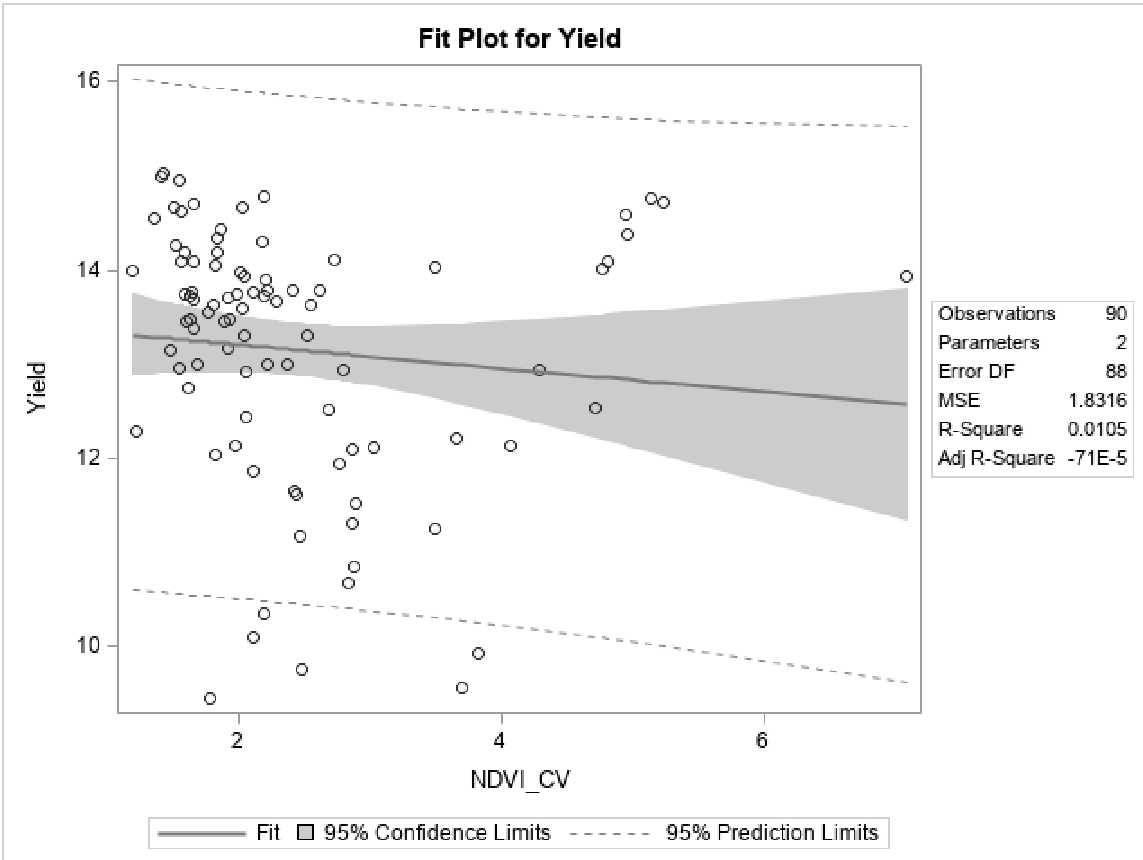


Figure A2.39. Regression analysis of CV versus yield on 8/18/2020 (McCaull Research Farm, n=180, α=0.05).

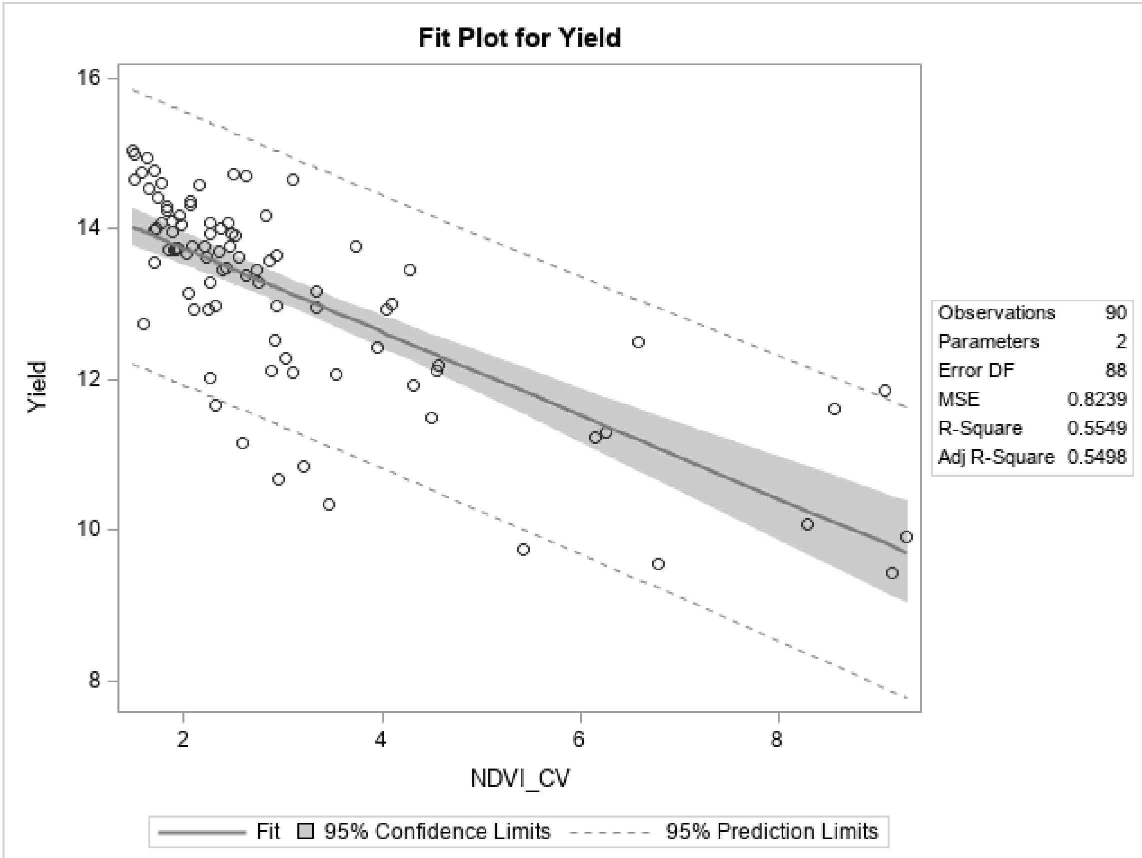
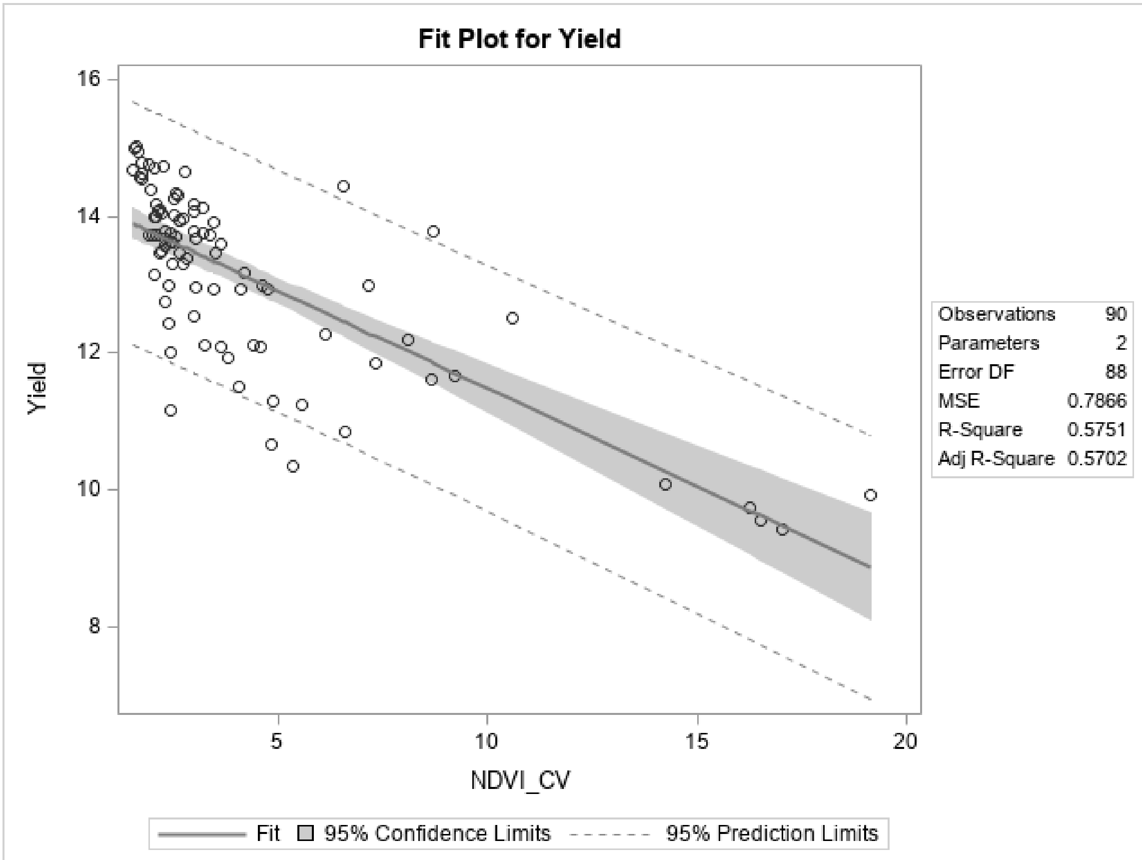


Figure A2.40. Regression analysis of CV versus yield on 9/02/2020 (McCaull Research Farm, n=180, α=0.05).



VITA

Kelsey Singleton

Candidate for the Degree of

Master of Science

Thesis: RESPONSE OF CORN YIELD TO IRRIGATION AND NITROGEN AND THE RELATIONSHIP BETWEEN YIELD AND NDVI MEASURED BY AERIAL IMAGERY

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Biographical:

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