DEVELOPMENT OF A YIELD PREDICTION MODEL AND SENSOR BASED NITROGEN RATE CALCULATOR FOR WINTER CANOLA (BRASSICA NAPUS) GROWN IN OKLAHOMA

By

LINDA SHAWNTEL ERVIN

Bachelor of Science in Plant and Soil Science

Oklahoma State University

Stillwater, Oklahoma

2011

Submitted to the Faculty of the
Graduate College of the
Oklahoma State University
in partial fulfillment of
the requirements for
the Degree of
MASTER OF SCIENCE
July, 2015

DEVELOPMENT OF A YIELD PREDICTION MODEL AND SENSOR BASED NITROGEN RATE CALCULATOR FOR WINTER CANOLA (BRASSICA NAPUS) GROWN IN OKLAHOMA

Thesis Approved:

D. Brian Arnall

William Raun

Jason Warren

ACKNOWLEDGEMENTS

I would like to take this opportunity to thank the many people who have helped, supported, and guided me through graduate school. First, I would like to say thank you to my advisor and committee members, Dr. Brian Arnall, Dr. Bill Raun, and Dr. Jason Warren. Dr. Arnall, you have given me unwavering support and encouragement for the past two years. Thank you for giving me this opportunity and for guiding me along the way. You have been a great advisor, mentor, and friend and are truly appreciated. Dr. Raun, thank you for always being there when I needed help or advice and being an awesome professor, it was an honor having you on my committee. Dr. Warren, thank you for your encouragement and always listening when it was needed, "just do it" will forever be ingrained in me. It has been a privilege to work with all three of you. Second, I would like to say thank you to all the interns, undergraduates, and graduate students that have helped me over the past two years with my project. I also would like to thank the Oklahoma Oilseed Commission and the fertilizer checkoff for funding this project. Lastly, I would like to say thank you to my family and friends for being a sounding board and supporting me through everything. Most importantly, I want to say thank you to my husband who is my biggest supporter and pushes me to be better every day. You all make up an outstanding group of people and I consider myself lucky to have you.

Name: LINDA SHAWNTEL ERVIN

Date of Degree: JULY, 2015

Title of Study: DEVELOPMENT OF A YIELD PREDICTION MODEL AND SENSOR BASED NITROGEN RATE CALCULATOR FOR WINTER CANOLA (BRASSICA NAPUS) GROWN IN OKLAHOMA

Major Field: PLANT AND SOIL SCIENCE

Abstract:
As the area under winter canola (Brassica napus) production increase and producers gain more experience with the crop many want to improve their nitrogen management practices. Oklahoma State University research and extension personnel have been developing and promoting the use of N-Rich strips and sensor based nitrogen rate calculator (SBNRC) in winter wheat since the late 90's. This study was conducted to determine if final grain yield of canola can be predicted with the use of normalized difference vegetative index (NDVI) and incorporate the yield prediction into a nitrogen fertilization optimization algorithm (NFOA) which would be used for an online SBNRC. In the fall of 2013 and 2014 trials were established at three locations. Trials consisted of twelve treatments in a RCBD with three replications in 2013 and 6 replications in 2014. Treatments 1-7 included a range of pre-plant N rates, these treatments were used to develop the yield prediction model. Treatments 8-12 consisted of a range of top-dress N rates, these treatments were used to validate the algorithms being developed. In 2013-2014 growing season, no data was able to be collected due to complete crop failure. In 2015, all data was combined and showed a high correlation between final grain yield and NDVI. When the data was narrowed to only sensor readings taken after growing degree days (GDD) reached 90, the relationship improved. Unlike previous algorithms developed, normalizing data with GDD or heat units did not improve upon the model. A low correlation was found between $RI_{HARVEST}$ and RI_{NDVI} which allowed the use of a $RI_{ADJUSTED}$ value to be used in the NFOA. Utilization of the YP_0 model and $RI_{ADJUSTED}$ along with percent grain N (3.76%) and a NUE of 70%, the NFOA was developed. Using NFOA, top-dress N rates were calculated for both locations. The resulting recommendations were within 0 and 2 kg N ha^{-1} of the optimum N rate documented by the curve developed from the top-dress treatments. While much more work is needed this work documents that the use NDVI measurement and the N-Rich strip utilized in a yield prediction and RI model can be used to produce an accurate top-dress N rate.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

REVIEW OF LITERATURE

Canola Management

Canola (*Brassica napus*) has many uses from oil production for human consumption to biodiesel production. Canola production continues to increase in popularity with Oklahoma producers. According to the National Agriculture Statistics Service, canola production in Oklahoma has risen from 925 ha in 2007 to over 101,000 ha in 2013 (NASS). Rotating winter wheat (Triticum aestivum) with canola has many benefits including decreased pest pressure and increased economic return. Canola requires more nitrogen (N) than the cereals it's usually rotated with (Rathke et al. 2005). The use of N-rich strips, optical sensors, and N rate calculators have been proven successful in production systems in Oklahoma (Butchee et al. 2011). These technologies could be applicable to winter canola systems as well. Research regarding N requirements of canola varies greatly. The N requirement for winter canola is approximately 60 g kg^{-1} (Conley et al. 2004). Timing and amount of N applied strongly affects winter canola productivity. Growth and yield of canola is significantly increased as N rates increase, but studies have shown that oil per unit seed weight decreases with the increasing N rate (Barłóg and Grzebisz, 2004).

Applied N fertilizer has shown an increase in pods per plant with no increase in seeds per pod (Hocking et al. 1997). Less than 50% of applied N is recovered by the seed at harvest, and if the plant is drought stressed, that number can be significantly reduced (Schjoerring et al. 1995). Early planting and high rates of N result in stem elongation and higher biomass which will make canola more susceptible to winter kill (Rathke et al. 2006). The nitrogen use efficiency (NUE) of canola tends to decrease with increasing N rates (Chamorro et al. 2002). Since canola has a low NUE, it is important to use all methods of N management that is available to producers (Rathke et al. 2006).

Current N Rate Recommendations

Stanford (1973) outlined the components of nitrogen rate removal based on yield and percent N, soil contribution, and NUE. The major land grant N rates have been based on these components. During Stanford's work in corn, he noted that it is important to know the internal requirement of N for an attainable yield. Using an efficiency factor between 50-70% can account for most of those factors (Stanford 1973). Historically, producers have been using yield goals to determine N rates by subtracting the soil test N from an average of highest yields for the given field for the past five years (Raun et al 2001). Yield goals have been used to determine the N uptake portion of the Stanford equation. Residual soil N and mineralized soil N serve as N sources for succeeding crops. To account for soil N, soil testing procedures were developed and were available for use by producers. The yield goal method of N application has some downsides including not accounting for how much N will mineralize or immobilize in the soil for the season. This could lead to over or under application of N. Over application of N can result in environmental pollution and under application can result in economic losses for the producer. Lory and Scharf (2003) further showed that yield goals lack validity.

In this study, recommended N rates in corn exceeded economically optimum N rate (EONR) on average by 90 kg ha-1 and were not correlated with EONR. Yield goals also do not include how efficient the plant is at using applied N. Efficiency of applied N is influenced by many factors including rate, time, climate, and soil conditions.

Nitrogen Fertilization Optimization Algorithm

The use of in-season measurements to create a N rate recommendation have been increasing in use and have been shown by many to both increase productivity and nitrogen use efficiency. One such approach utilized in winter wheat corn (*Zea mays*) and sorghum (*Sorghum bicolor*) is the nitrogen fertilization optimization algorithm (NFOA) first proposed by Lukina et al. (2001). Lukina describes the four components for calculating N rate based upon a series of in-season measurements and calculations. The factors utilized in the NFOA can be directly correlated with the inputs utilized in the equation Stanford produced in 1973. The components of the NFOA are as follows.

1. Yield Potential (YP)
2. % Grain N Removal
3. Response Index (RI)
4. Efficiency Factor (NUE)

Yield Potential

Research around the world has developed tools to allow for the ability to estimate final yield in season to improve upon the yield component in the Stanford equation. One of the technologies with the greatest potential for in-season use is optical reflectance sensors. Photosynthetic pigments in leaves, such as chlorophyll and carotenoid, have relatively low reflectance in the visible spectrum (400-700nm) because of the high absorption at these wavelengths. Plants reflect high amounts in the near-infrared (NIR) part of the spectrum (700-1300nm). Chlorophyll has the highest reflectance in the red-edge portion of the spectrum (680-730nm) which is described as the abrupt change from visible light to NIR. Normalized difference vegetative index (NDVI) is widely used as a green biomass predictor (Penuelas and Filella, 1998). NDVI is calculated as follows:

$$\boldsymbol{NDVI = \frac{(NIR - Red)}{(NIR + Red)}}$$

Optical sensors have been widely used to capture reflected light at specific wavelengths from the crop canopy to calculate vegetative indices such as NDVI (Holzapfel et al. 2009). In wheat, Raun (2004) showed NDVI to be highly correlated with biomass at Feekes 4 and 6. By Feekes 10, NDVI began to decrease in correlation. NDVI was correlated with forage N uptake, grain yield, and final grain yield. Multiple studies in wheat (Raun et al. 2004, Labus et al. 2002, Raun et al. 2001), bermudagrass (*Cynodon dactylon*) (Taylor et al. 1998), rangeland (Todd et al. 1998), and in canola (Osborne 2007, Holzapfel et al. 2009, Mkhabela et al. 2011) have shown NDVI to be highly correlated to biomass and that biomass is correlated to yield. It is important to note that NDVI cannot capture post sensing stresses which can lower yield potential. For example, high temperatures during flowering can result in decreased yields which NDVI cannot capture (Mkhabela et al. 2011). In season estimated yield (INSEY) is calculated by dividing NDVI by growing degree days (GDD) greater than zero. This estimates biomass produced per day (Raun 1999). By dividing NDVI by GDD, Lukina et al. (2001) was able to normalize NDVI throughout the growing season which allows for sensing throughout the season. Teal et al. (2006) showed no improvement in yield prediction by dividing NDVI by GDD in corn but showed that this normalized values and allowed it to be used various climates. To predict yield early to apply a top-dress fertilizer based on predicted needs, the NFOA was developed (Lukina et al. 2001). The ability to predict yield in-season with NDVI is essential to the NFOA model. Yield potential is calculated as one standard deviation above the line that describes the relationship between measured grain yield and INSEY (Raun et al. 2005, Teal et al. 2006). Mkhabela et al. (2011) has shown that with the use of MODIS-NDVI crops yields can be successfully predicted up to two months before harvest. The study showed that the predicted yields were within 10% of actual yield. Combining atmospheric and soil data to the MODIS-NDVI has shown an improvement over NDVI alone (Mkhabela et al. 2011).

N Removal

There is approximately 33kg of N in one metric ton of canola seed. The straw may contain up to 10kg of N per metric ton (Brennan 2006, Kansas State University Extension 2007). Percent grain N must be calculated to use in the NFOA.

Responsiveness

Response Index is the response additional N fertilizer has on final yield. Response index ($RI_{HARVEST}$) is determined at harvest by dividing the yield of the N rich plot (non-limiting N plots) by the yield of the check plot (Farmer practice, YP_0). Response index shows how responsive the crop is to applied N fertilizer. The NUE should be expected increase as RI increases (Raun and Johnson 2003). The $RI_{HARVEST}$ is calculated at harvest as a final measure of response. For this reason RI_{NDVI} should be used in season to adjust N rate. The RI_{NDVI} is the NDVI of the N rich plot (non-limiting N plots) divided by the NDVI of the check plot. Mullen et al. (2003) showed that RI_{NDVI} could be used to predict $RI_{HARVEST}$ and that RI_{NDVI} is a viable method to accurately predict in-season the potential for a response to additional N fertilizer. However, Hodgen et. al. (2005) noted that the relationship between RI NDVI and RI HARVEST did not have a slope of 1.0.

Sensor Based Nitrogen Rate Calculation

Oklahoma State University has developed algorithms that utilize optical sensors to collect NDVI and predict yield. The goal in using the SBNRC is to be able to give accurate top-dress and variable rates. Using optical sensors to give N rates have shown to increase nitrogen used efficiencies (NUE) in wheat (Raun et al. 2005, Lukina et al. 2001), corn (Raun et al. 2002), and canola (Holzapfel et al. 2009). Basing mid-season nitrogen recommendations on these algorithms have shown an increase of 15% NUE (Raun et al. 2005). By multiplying the predicted yield of the farmer practice (YP_0) by RI_{NDVI}, you get the attainable yield if you fertilized (YP_N). Nitrogen rate is the difference in YP_N and YP_0, multiplied by the percent grain N, and divided by a common efficiency factor between 0.5 and 0.7 (Raun et al. 2005, Raun et al. 2013).

The calculation used to calculate top-dress N rate is:

$$\boldsymbol{N\ rate = \frac{[(YP0\ x\ RI) - YP0]\ x\ \%N}{NUE}}$$

On-line Sensor Based Nitrogen Rate Calculator

The final product for this study would be an on-line SBNRC. This would allow producers that are currently utilizing optical sensors and N-rich strips in wheat to continue with this technology in their canola rotation. This is a user friendly website that uses the NFOA to calculate top-dress N rates. Butchee et al. (2011) using the SBNRC recommendation on large scale producer fields showed a decrease of applied N by 23 kg ha^{-1} on average when compared to farmer practice. This study also showed that while using the decreased N rates, final grain yield and protein levels stayed the same (Butchee et al. 2011). Implementations of technologies such as the SBNRC have the potential to save producers a significant amount of money.

Objectives

The objectives of this study were to develop a yield prediction model using in season NDVI, develop a nitrogen fertilization optimization algorithm for winter canola grown in Oklahoma, and evaluate the NFOA using treatments 8-12, and develop a sensor-based nitrogen rate calculator using the NFOA for winter canola in Oklahoma.

CHAPTER II

MATERIALS AND METHODS

Three locations were established in the 2013-2015 growing seasons in Oklahoma. Location one was at the North Central Research Station (NRC) near Lahoma, Oklahoma using a conventional tillage system. Location two was located at the Lake Carl Blackwell Research Station (LCB) near Stillwater, Oklahoma in a no-till system. Location three was located at the South Central Research Station (CHK) near Chickasha, Oklahoma in a no-till system. Soil series descriptions can be seen in Table 1. The treatment structure consisted of a randomized complete block design with 12 treatments replicated three times. The 2014-2015 study had the same treatment structure, but replicated 6 times. For all site years plot size was three meters by six meters. Treatments 1-7 had a range of pre-plant N rates from 0-134 kg ha^{-1} in 22 kg increments and no top-dress N. These treatments were used in the yield prediction and response index models. Treatments 8-12 received a pre-plant N rate of 22 kg ha^{-1} and a range of top-dress N rates from 22-112 kg N ha^{-1} in 22 kg increments (Table 2). These treatments were used for algorithm validation. Soil samples were collected randomly throughout each study location to a depth of 15 cm. Samples were sent to the Oklahoma State University Soil, Water, and Forage Analytical Laboratory (SWFAL) for complete analysis consisting of routine, secondary, and micronutrient concentrations, soil test results shown in Table 3. Canola was planted with a seeding rate of 5.6 kg ha^{-1} on 38 cm rows. In 2014, the Chickasha location was planted using 18 cm rows. Herbicide and insecticide was applied on an as needed basis. Weeds were controlled pre-plant and post emergence prior to dormancy using 2.5 L ha^{-1} glyphosate. Pyrethroid was used to control insects at a rate of 146 mL ha^{-1}. The fertilizer source was ammonium nitrate (34-0-0) broadcasted onto the soil surface. Greenseeker® reflectance data is collected every 14 days from rosette to flowering from the center two rows of each plot. The Greenseeker® is held approximately 60 cm above the crop canopy. Indices collected included: NDVI, Red 660nm, Red 710nm, Red 735nm, and near infrared (NIR). NDVI will be calculated by the sensor using (NIR-Red 660nm)/(NIR+Red 660nm). At maturity the center 1.5m of each plot were direct harvested with a Massey Ferguson 8XP plot combine. Sub samples of grain were collected from each plot and analyzed to determine grain quality. After harvest, SAS and linear regression will be used to model data.

CHAPTER III

RESULTS

In the 2013-2014 growing season, CHK had stand loss due to winter kill during flowering temperatures dropped below freezing for a week which resulted in a complete loss at this location. The soil crusted after planting LCB which caused replanting. This pushed planting date back to far for the plants to survive winter. At NRC there was not sufficient soil moisture at planting which resulted in small plants going into winter and ultimately a complete stand loss at this location. Due to the fact that all locations during the 2013-2014 year were lost to environmental impacts the remainder of the results section will focus on the 2014-2015 crop year for the LCB and CHK locations. The trial at NRC during the 2014-2015 crop year was lost again due to winter kill and dry, cold fall weather conditions.

N Rate

At CHK a wide range in treatments yields was observed, for example, the check plot (treatment 1) had a range in yield from 1552.8 kg ha^{-1} to 888.7 kg ha^{-1} (data not shown). The highest yielding treatment was 1596.75 kg ha^{-1} and the lowest yielding treatment was 1071.82 kg ha^{-1} (Table 4). Across all 72 plots the highest yielding plot was 1962.98 kg ha^{-1} and the lowest had a yield of 712.92 kg ha^{-1}. However analysis of the yield data showed no significant impact of treatment. The wide range in yields can be attributed to a varied stand establishment. While nearly 100% stand was achieved in some plots others had diminished stands, in some cases as poor as 25%. This variation was likely due to a varied planting environment, residue from the previous wheat crop was poorly distributed and in areas in which residue was the most dense, crop establishment was the poorest. When the data was analyzed separately as pre-plant treatments (1-7) or top-dress treatments (2, 8-12) there was no significant impact of treatment on yield. Therefore it was concluded that the site was non-responsive to nitrogen fertilization and the optimum pre-plant and top-dress rates for 0 kg N ha^{-1}.

At LCB the individual plot grain yields ranged from 478.5 kg ha^{-1} to 2270.6 kg ha^{-1}. At this location there was a significant treatment response (Table 4). Treatment 7 (134.4 kg N pre) had numerically the highest yield at 2010.17 kg ha^{-1}, treatments 11 (22kg N pre 89 kg N top-dress), 12 (22kg N pre 112 kg N top-dress), and 6 (112 kg N pre) were not statistically different with yields of 2006.9, 1926.35, 1811.6 kg ha^{-1} respectively. The non-fertilized check (trt 1) had the lowest recorded yield at 718.6 kg ha^{-1}. When the data was analyzed separately as pre-plant treatments (1-7) or top-dress treatments (2, 8-12) treatment was significant in both cases. As would be expected yield increased with increasing nitrogen rates. On analysis of pre-plant treatments 6 and 7 were statistically higher than all other treatments with yields of 1811.6 and 2010.2 kg ha^{-1} respectively, but were not statistically different from each other. Treatment 2 was included in the analysis of the top-dress treatments to represent the un-fertilized check as all top-dress treatments received 22 kg N pre-plant, the same as treatment 2. In analysis of top-dress treatments the 89 and 112 kg N ha^{-1} (trt 11 and 12) were not statistically different with yields of 2006.9 and 1926.35 kg ha^{-1} respectively. The yield of treatment 11 was statistically greater than all other treatments. Based on these results it was concluded that the optimum pre-plant rate in this environment was 112 kg N ha^{-1} and the optimum top-dress rate was 89.6 kg N ha^{-1} with a 22 kg N ha^{-1} pre-plant application. The data presented suggests that the optimum rate for the LCB location was 112 kg N ha^{-1} regardless of application timing.

YP

To evaluate the ability of NDVI to predict final grain yield individual plot data, i.e. NDVI and grain yield, was used in the correlation not treatment averages. When NDVI from all sensing dates was evaluated for its correlation with final grain yield a polynomial equation best fit the data with a r^2 of 0.64 (Figure 1.). Unlike Teal et. al. (2006) observed in corn, the predictive nature of NDVI was not improved with the incorporation of a growing degree days greater that zero, $INSEY_{GDD}$. In this experiment the correlation between $INSEY_{GDD}$ and final grain yield resulted in a r^2 of 0.46 (Figure 2). However when $INSEY_{HU}$ was evaluated it showed improvement over using $INSEY_{GDD}$ by increasing the r^2 from 0.46 to 0.52 (Figure 3). The incorporation of an environmental component did not improve the ability to predict yield better than as the use of NDVI alone. The accuracy of the YP_0 model was improved when the NDVI data was limited to sensor readings that were collected on or after 90 GDD. Using this data the relationship between NDVI and final grain yield improved and showed a stronger correlation with an r^2 of .73 (Figure 4). Again the incorporation of INSEY (GDD) did not improve the correlation with an r^2 of 0.69 (Figure 5) and in this case the use of INSEY (HU) (r^2 of .70) was a better fit than $INSEY_{GDD}$ yet not a strong as NDVI alone (Figure 6). Partitioning the data out further only evaluating the last sensor reading taken at the initiation of bolt resulted in correlation between NDVI and final grain yield to be higher than when using all data yet lower than the >90GDD data set, with an r^2 of .71 (Figure 7). This indicates that the optimal time of sensing to accurately predict final grain yield for this experiment was the time period between GDD 90 and pre-bolt. However it was still possible to predict yield at all sampling points in this study.

While Freeman et. al. (2003), Raun et. al. (2001), and Teal et. al. (2006) used an exponential equation to best fit the relationship between INSEY and final grain yield the exponential model had a lower r^2 in all cases. For all data NDVI and grain yield the exponential and polynomial models has respective r^2 of 0.64 and 0.54. The >90 day NDVI data had exponential and polynomial models has respective r^2 of 0.73 and 0.65 and the pre bolt NDVI data exponential and polynomial models has respective r^2 of 0.71 and 0.59 (data not shown).

For the development of the NFOA the polynomial model for NDVI and grain yield using sensor reading collected after 89 GDDs will be utilized. The equation is as follows (Figure 8):

$$\mathbf{YP_0 = 13977 * (NDVI)^2 - 5226.9 * (NDVI) + 1907.2}$$

Where NDVI is: the average NDVI value collected from the Farmer Practice

RI

Hodgen et. al. (2005) and Mullen et. al. (2003) noted that in winter wheat, the relationship between $RI_{HARVEST}$ and RI_{NDVI} did not result in an equation with an intercept of zero and a slope of one. Therefore there was a need to create an adjusted RI ($RI_{ADJUSTED}$) for accurate prediction of crop responsiveness in the NFOA model. As in the YP_0 evaluation individual plots are utilized not treatment averages. To calculate a RI_{NDVI} value the NDVI of any given plot, within the treatment range of 2 to 7, was divided by the NDVI value obtained the 0N plot in its corresponding replication. For this work when all data was combined and the relationship between $RI_{HARVEST}$ and RI_{NDVI} was examined at both LCB and CHK, a low correlation with an r^2 of .22 was found (Figure 9). When the relationship between $RI_{HARVEST}$ and RI_{NDVI} was explored by location, the data from LCB resulted in a slightly better correlation with an r^2 of 0.32 (Figure 10). However at CHK a negative but poor relationship between $RI_{HARVEST}$ and RI_{NDVI} was observed, $r^2 = 0.11$ (Figure 11). As previously discussed, CHK had no response to added N and variability in yield was determined by plant stand. We hypnotizes that this lack of response to fertilizer nitrogen explains the lack of or negative correlation between RI_{NDVI} and $RI_{HARVEST}$ at this location. For the development of the NFOA the linear model for the relationship between RI_{NDVI} and $RI_{HARVEST}$ utilizing only data collected from LCB will be used. The equation for the $RI_{ADJUSTED}$ is as follows:

$$\mathbf{y = 3.13x - 1.73}$$

Where: $y = RI_{ADJUSTED}$
$x = RI_{NDVI}$

NFOA

A NFOA utilizing the YP_0 model and the $RI_{ADJUSTED}$ model previously recommended, a percent grain N content of 3.76%, and NUE of 70% was used to calculate a top-dress N rate recommendation for both sites. For the NFOA calculation, the NDVI values for treatment 2 and 7 were used in the YP_0 and $RI_{ADJUSTED}$ calculations. The NFOA for CHK recommended the need for no additional fertilizer. The NFOA when calculated for LCB produced a recommended topdress rate of 98.6 kg N ha-1. The response curve developed from treatments 8-12 can now be used to validate these values. At CHK the optimum N rate was determined to be 0.0 kg N ha-1, which the NFOA accurately predicted. At LCB the top-dress response curve identified the optimum N rate for that location to be 89.6 kg N ha-1. This value is 9 kg N ha-1 less than the NFOA predicted rate. All the components of a NFOA have been discussed and the winter canola NFOA is as follows:

$$\mathbf{[(YP_0 * RI_{ADJUSTED}) - YP_0] * \%\ Grain\ N / NUE}$$

Where: $YP_0 = 13977x^2 - 5226.9x + 1907.2$
$RI = RI_{ADJUSTED} = 3.13(RI_{NDVI}) - 1.73$
$\%\ Grain\ N = 0.0376$
$NUE = 0.70$

CHAPTER IV

DISCUSSION

The development of a NFOA will allow for accurate top-dress N rate recommendations to provide an alternative to applying all N pre-plant and ultimately reducing the risk of applying too much or too little N. Yield prediction is the most important component of the NFOA. Winter canola grain yield was highly correlated with NDVI within all YP_0 models. However, when utilizing sensor readings collected after GDD reached 90 or more, the r^2 increased from 0.64 to 0.73. The r^2 slightly decreased when only using the last sensor readings, taken at the initiation of bolting, to 0.71. These two models produced the highest r^2 and are an indication that the best time to sense to get an accurate prediction of yield is after GDD reach 90 and prior to bolting. Unlike the algorithm developed for other grains, normalizing NDVI with the use of GDD and cumulative heat units did not improve the yield prediction. Utilizing heat units was an improvement over GDD, but still not as good as NDVI alone. It is also important to note that at least in this data set row space did not impact the correlation between NDVI and yield. A correlation between $RI_{HARVEST}$ and RI_{NDVI} was not a one to one relationship so therefore to properly estimate the responsiveness to added N an adjusted RI equation was used. The yield model and $RI_{ADJUSTED}$ equation presented represent one year of data collection. The robustness of the models will have to be improved with the addition of additional data collected over a series of years and locations.. It is important to continually update these algorithms to allow them to become accurate in multiple environments and account or changes in crop genetics. Canola NUE is not discussed often within literature, but the overall opinion is that it is highly dependent on variety and environments. Additional research would be needed to look into a more accurate NUE for winter canola. For this experiment, the NUE was set at 70% which may need to be refined in the future. This research is a good start to producing an online sensor based nitrogen rate calculator for use by producers. The data presented shows that canola yield can be accurately predicted using NDVI and the Greenseeker® sensor. It also shows that we are able to predict an accurate mid-season N rate for winter canola grown in Oklahoma. As previously discussed, the amount of N needed at CHK and LCB were vastly different with 0.0 N needed at CHK to 89.6 kg N ha^{-1} needed at LCB. This demonstrates the importance of technologies such as the SBNRC in the pursuit of a cropping system which is both economical and environmentally sound.

REFERENCES

Barłóg, P. and W. Grzebisz. 2004. Effect of timing and nitrogen fertilizer application on winter oilseed rape (Brassica napus) growth dynamics and seed yield. J. Agron. Crop Sci. 190:305-313.

Brennan, R. 2006. Nutrients in canola: maintaining the balance in your rotation. Department of Agriculture and Food. Farmnote 203.

Butchee, K. S., J. May, and B. Arnall. 2011. Sensor based nitrogen management reduced nitrogen and maintained yield. Online. Crop Manage. doi:10.1094/cm-2011-0725-01-RS.

Chamorro, A. M., L.N. Tamagno, R. Bezus, and S.J. Sarandón. 2002. Nitrogen accumulation, partition, and nitrogen-use efficiency in canola under different nitrogen availabilities. Commun. Soil Sci. Plant Anal. 33:493-504.

Conley, S. P., D. Bordovsky, C. Rife, and W.J. Wiebold. 2004. Winter Canola Survival and Yield Response to Nitrogen and Fall Phosphorus. Crop Manage. doi: 10.1094/cm-2004-0901-01-RS.

Hocking, P.J., P.J. Randall, and D. DeMarco. 1997. The response of dryland canola to nitrogen fertilizer: portioning and mobilization of dry matter and nitrogen, and nitrogen effects on yield components. Field Crops Research. 54:201-220.

Holzapfel, C.B., G.P. Lafond, S.A. Brandt, P.R. Bullock, R.B. Irvine, M.J. Morrison, W.E. May, and D.C. James. 2009. Estimating canola (Brassica napus L.) yield potential using an active optical sensor. Can. J. Plant Sci. 89:1149-1160.

Johnson, G.V., and W.R. Raun. 2003. Nitrogen response index as a guide to fertilizer management. J. Plant Nutr. 26:249-262.

Labus, M.P., G.A. Nielsen, R.L. Lawrence, R. Engel, and D.S. Long. 2002. Wheat yield estimates using multi-temporal NDVI satellite imagery. Int. J. of Remote Sens. 23: 4169-4180.

Lory, J.A. and P.C. Scharf. 2003. Yield gaol versus delta yield for predicting fertilizer nitrogen need in corn. Agron. J. 95:994-999.

Mkhabela, M.S., P. Bullock, S. Raj, S. Wang, and Y. Yang. 2011. Crop yield forecasting on the Canadian prairies using MODIS NDVI data. Agric. For. Meteorol. 151:385-393.

Mullen, R.W., K.W. Freeman, W.R. Raun, G.V. Johnson, M.L. Stone, and J.B. Solie. 2003. Identifying an in-season response index and the potential to increase wheat yield with nitrogen. Agron. J. 95:347-351.

Osborne, S. 2007. Determining nitrogen nutrition and yield of canola through existing remote sensing technology. Agric. J. 2(2):180-184.

Penuelas, J and I. Filella. 1998. Visible and near-infrared reflectance techniques for diagnosing plant physiological status. Trends in Plant Sci. 3:151-156.

Rathke, G. W., O. Christen, and W. Diepenbrock. 2005. Effects of nitrogen source and rate on productivity and quality of winter oilseed rape (Brassica napus L.) grown in different crop rotations. Field Crops Research. 94:103-113.

Rathke, G. W., T. Behrens, and W. Diepenbrock. 2006. Integrated nitrogen management strategies to improve seed yield, oil content and nitrogen efficiency of winter oilseed rape (Brassica napus): A review. Agric., Ecosyst. Environ. 117:80-108.

Raun, W. (2013, October 2). Outline for Generating New Crop Algorithms for N Fertilization. Retrieved October 7, 2014, from http://www.nue.okstate.edu/Algorithm/Algorithm_Outline.htm

Raun, W.R. 1999. In-season prediction of Yield Potential in winter wheat. Better Crops. 83:(2) 24-25.

Raun, W. R., K.W. Freeman, G.V. Johnson, S.M. Modges, R.W. Mullen, and J.B. Solie. 2004. Evaluation of green, red, and near infrared bands for predicting winter wheat biomass, nitrogen uptake, and final grain yield. J.Plant Nutr. 27:1431-1441.

Raun, W. R., K.W. Freeman, G.V. Johnson, S.M. Modges, R.W. Mullen, and J.B. Solie. 2004. Evaluation of green, red, and near infrared bands for predicting winter wheat biomass, nitrogen uptake, and final grain yield. J. Plant Nutr. 27(8):1431-1441.

Raun, W.R., J.B. Solie, M.L. Stone, K.L. Martin, K.W. Freeman, R.W. Mullen, H. Zhang, J.S. Schepers, and G.V. Johnson. 2005. Optical sensor based algorithm for crop nitrogen fertilization. Commun. Soil Sci. Plant Anal. 36:2759-2781.

Raun, W.R., J.B. Solie, G.V. Johnson, M.L. Stone, R.W. Mullen, K.W. Freeman, W.E. Thomason, and E.V. Lukina. 2002. Improving nitrogen use efficiency in cereal grain production with optical sensing and variable rate application. Agron. J. 94:815-820.

Raun, W.R., J.B. Solie, G.V. Johnson, M.L. Stone, E.V. Lukina, W.E. Thomason, and J.S. Schepers. 2001. In-season prediction of potential grain yield in winter wheat using canopy reflectance. Agron. J. 93:131–138.

Schjoerring, J. K., J.G.H. Bock, L. Gammelvind, C.R. Jensen, and V.O. Mogensen.1995. Nitrogen incorporation and remobilization in different shoot components of field-grown winter oilseed rape (Brassica napus L.) as affected by rate of nitrogen application and irrigation. Plant and Soil. 177:255-264. 25.

Stanford, G. 1973.Rationale for optimum nitrogen fertilization in corn production. J. Environ. Quality. 2(2):159-166.

Teal, R.K., B. Tubana, K. Girma, K.W. Freeman, D.B. Arnall, O. Walsh, and W.R. Raun. 2006. In-season prediction of corn yield potential using NDVI at various vegetative growth stages. Agron. J. 98:1488-1494.

Taylor, S.L. W.R. Raun, J.B. Solie, G.V. Johnson, M.L. Stone, and R.W. Whitney. 1998. Use of spectral radiance for collecting nitrogen deficiencies and estimating soil variability in an established bermudagrass pasture. J. Plant Nutr. 21(11):2287–2302.

Todd, S.W., R.M. Hoffer, and D.G. Milchunas. 1998. Biomass estimation on grazed and ungrazed rangelands using spectral indices. International Journal of Remote Sensing. 19(3):427-438.

TABLES AND FIGURES

Table 1. Soil series descriptions for dominate soil series at each location obtained from Web Soil Survey.

Location	Soil Series
2013-2014 Lake Carl Blackwell	Pulaski fine sandy loam (Coarse-loamy, mixed, superactive, nonacid, thermic Udic Ustifluvents)
2014-2015 Lake Carl Blackwell	Port silt loam (Fine-silty, mixed, superactive, thermic Cumulic Haplustolls)
2013-2015 Lahoma	Grant silt loam (Fine-silty, mixed, superactive, thermic Udic Arigustolls)
2013-2014 Chickasha	McLain silty clay loam (Fine, mixed, superactive, thermic Pachic Argiustolls)
2014-2015 Chickasha	Dale silt loam (Fine-silty, mixed, superactive, thermic Pachic Haplustolls)

Table 2. Treatment structure used for all locations including total nitrogen rate, pre-plant nitrogen rate, and top-dress nitrogen rate.

Treatment	Total N	Pre-Plant	Top-Dress
	kg ha^{-1}	kg ha^{-1}	kg ha^{-1}
1	0	0	0
2	22	22	0
3	44	44	0
4	68	68	0
5	90	90	0
6	112	112	0
7	134	134	0
8	44	22	22
9	68	22	44
10	90	22	68
11	112	22	90
12	134	22	112

Table 3. Soil test characteristics for the South Central Research Station (CHK) near Chickasha, Oklahoma and Lake Carl Blackwell Research Station (LCB) near Stillwater, Oklahoma.

Location	**pH**	**BI**	**NO3**	**P**	**K**	**SO4**	**Ca**	**Mg**	**Fe**	**Zn**	**B**	**Cu**
			ppm	ppm	ppm	ppm	ppm	ppm	ppm	ppm	ppm	ppm
LCB	6.1	7.1	9	33	153	6	1387	312	59	0.76	0.25	1.65
CHK	5.7	7	24	18	144	7	1645	513	36	0.48	0.35	1.08

Table 4. Treatment means showing t-grouping (LSD) for grain yield at the Lake Carl Blackwell Research Station (LCB) near Stillwater, OK, and South Central Research Station (CHK) near Chickasha, OK 2014-2015.

TRT	**Yield kg ha^{-1}**	
	CHK	**LCB**
1	1213	719 h
2	1201	802 gh
3	1436	1075 fg
4	1286	992 ef
5	1380	1285 de
6	1168	1811 ab
7	1597	2010 a
8	1130	1218 ef
9	1336	1527 cd
10	1072	1707 bc
11	1155	2007 a
12	1193	1926 ab
SED	43.24	135.74

* Means with the same are letter are not significantly different at 0.05 probability level.

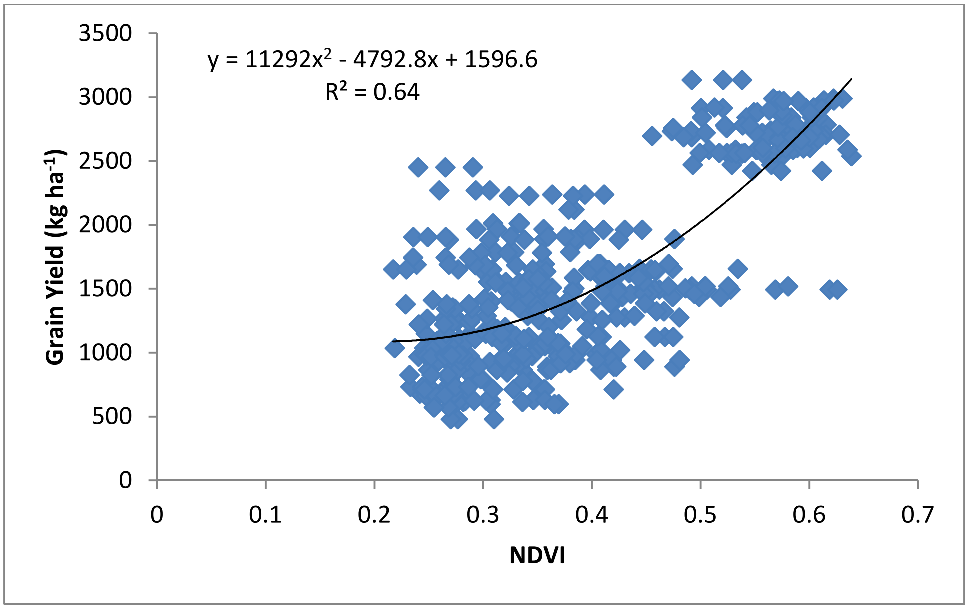

Figure 1. Polynomial relationship between final grain yield and NDVI for all sensor readings.

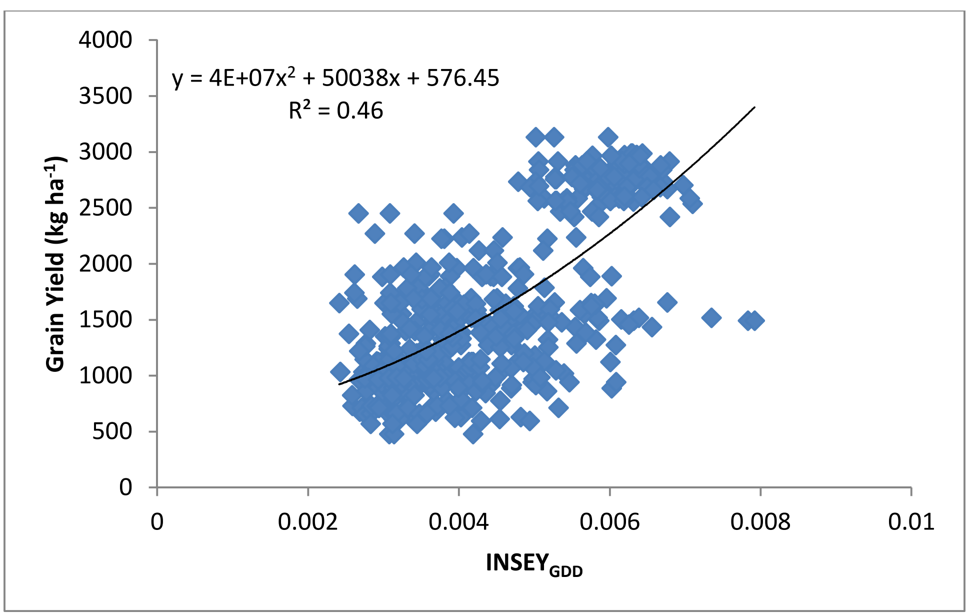

Figure 2. Polynomial relationship between final grain yield and $INSEY_{GDD}$ for all sensor readings

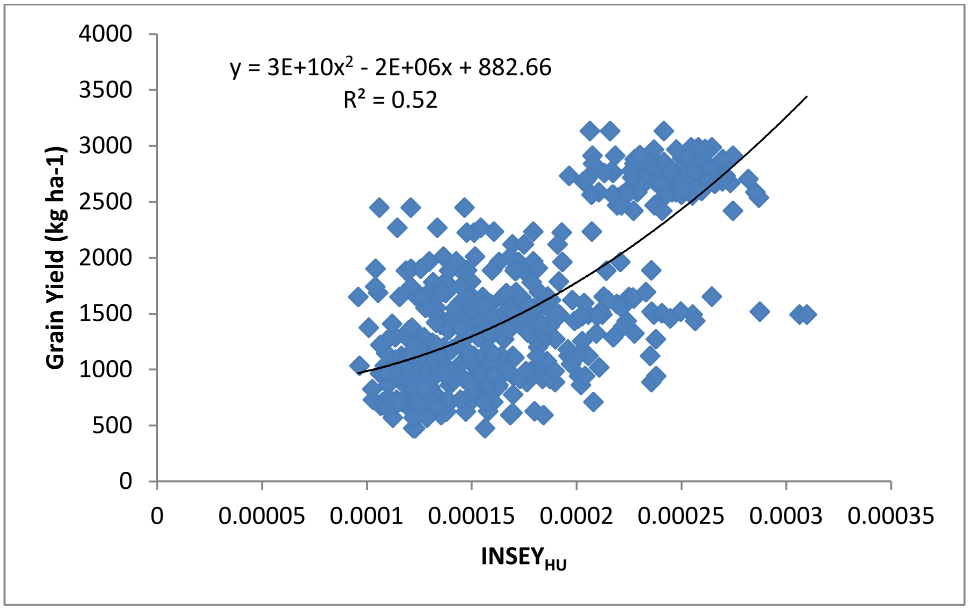

Figure 3. Polynomial relationship between final grain yield and $INSEY_{HU}$.

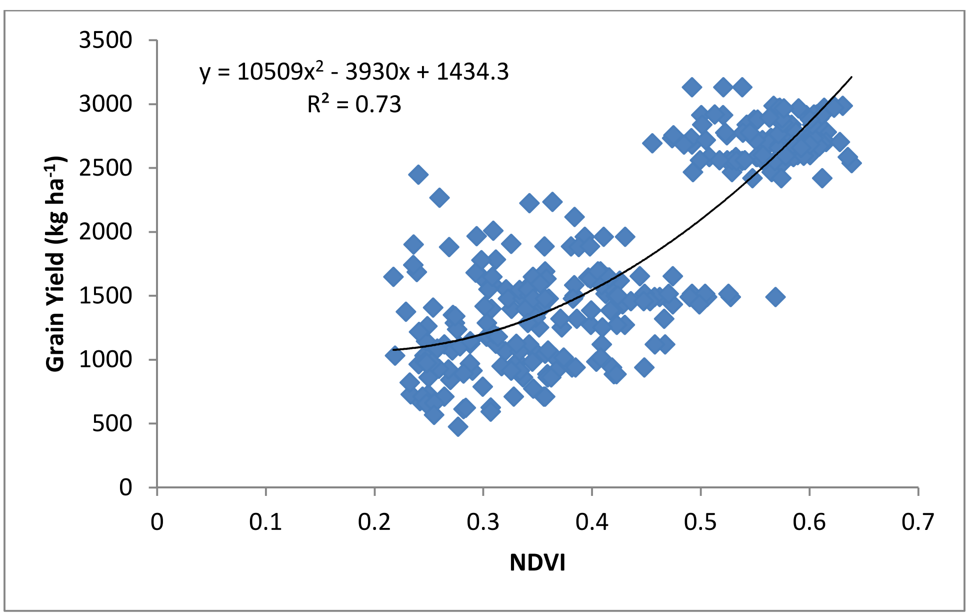

Figure 4. Polynomial relationship between final grain yield and NDVI using sensor readings taken after GDD reached 90 or more.

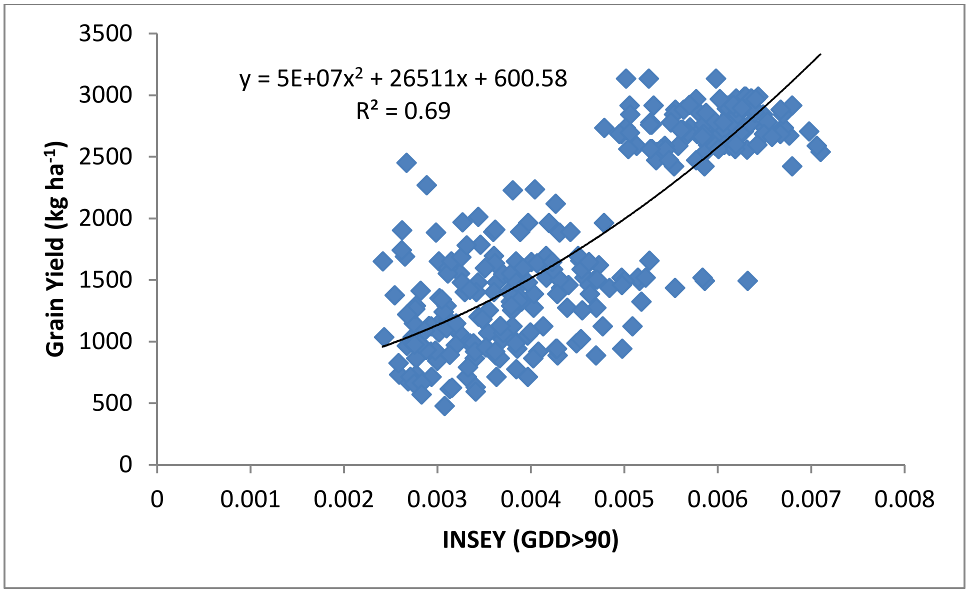

Figure 5. Polynomial relationship between final grain yield and $INSEY_{GDD}$ using sensor readings taken after GDD reached 90 or more.

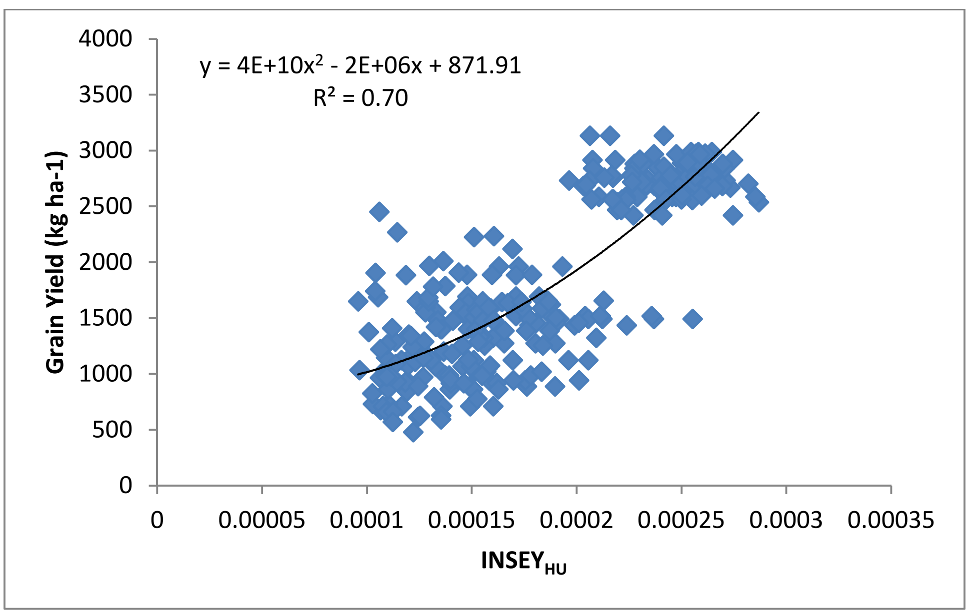

Figure 6. Polynomial relationship between final grain yield and $INSEY_{HU}$ using sensor readings taken after GDD reached 90 or more.

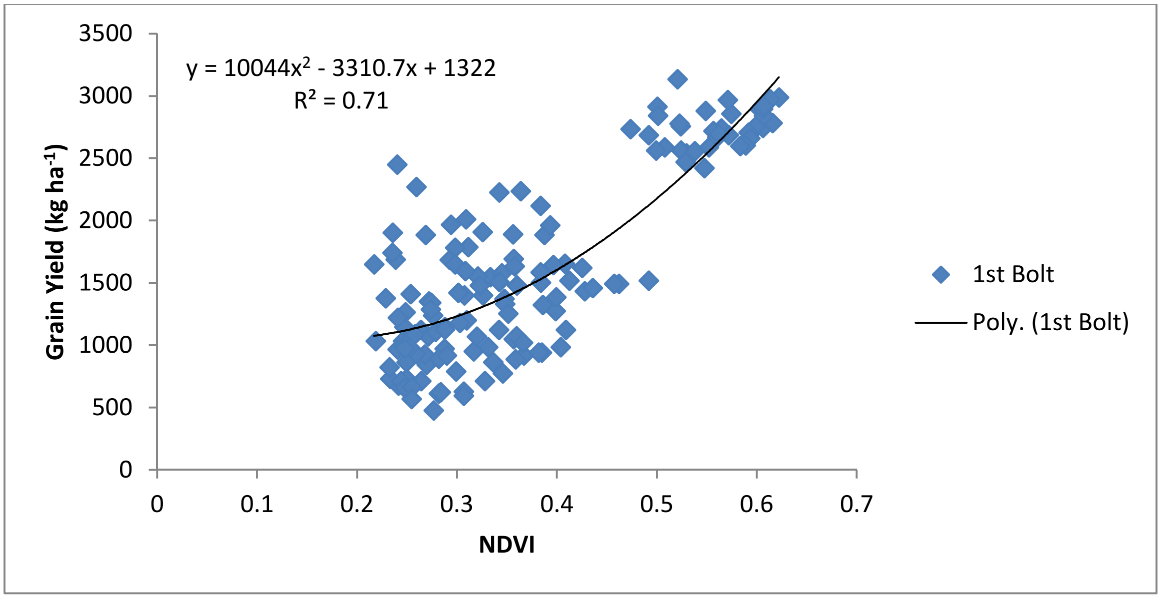

Figure 7. Polynomial relationship between final grain yield and NDVI using the last sensor readings at first bolt.

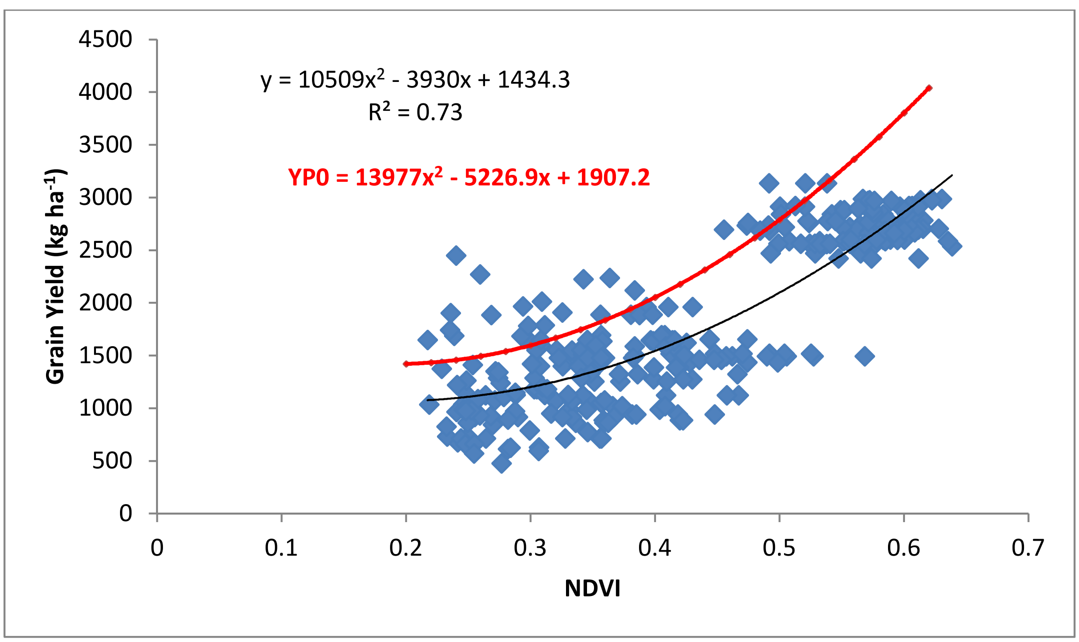

Figure 8. Polynomial relationship between final grain yield and NDVI using sensor readings taken after GDD reached or exceeded 90. Where YP = yield potential, mean + 1 standard deviation.

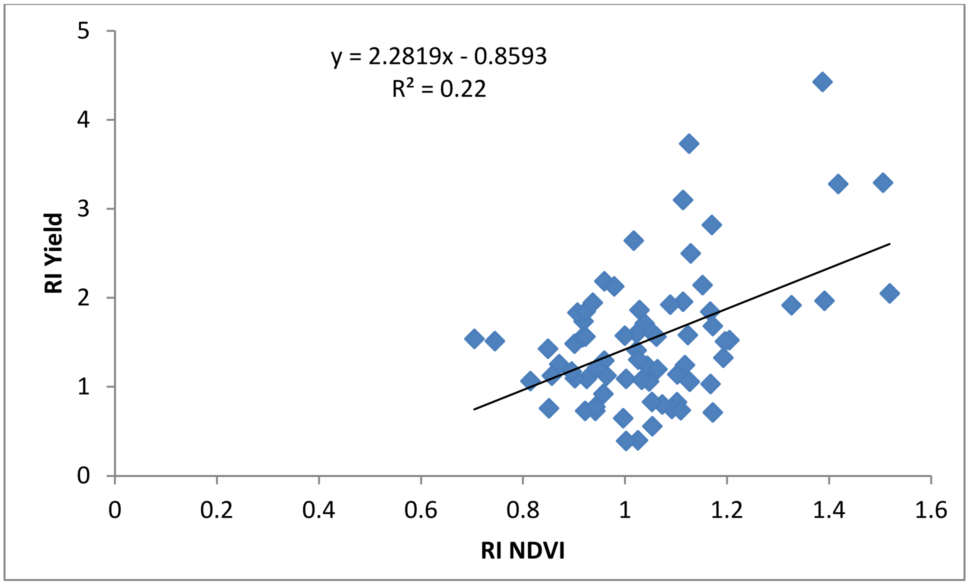

Figure 9. Linear relationship between the response index measured at harvest and the response index measured in-season for both locations.

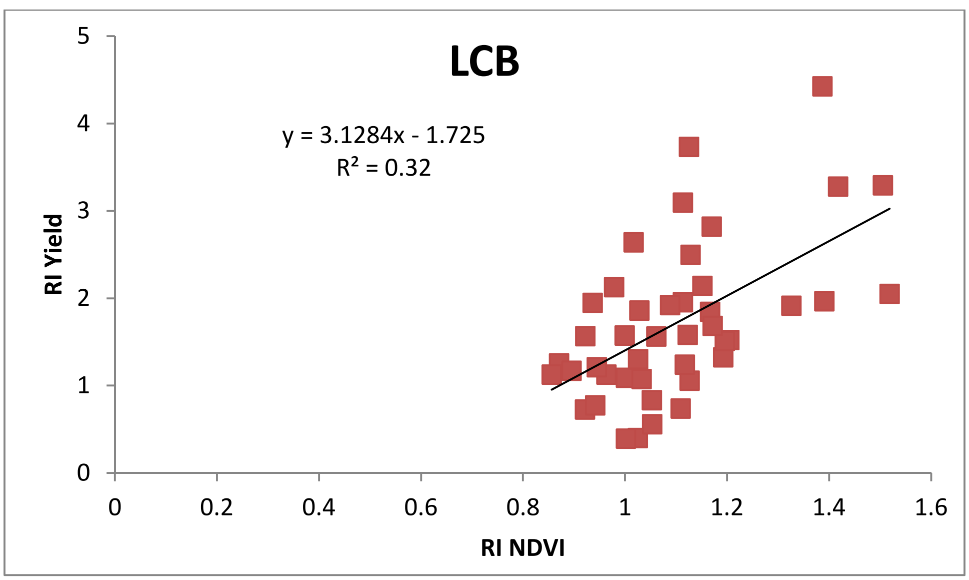

Figure 10. Linear relationship between the response index measured at harvest and the response index measured in-season for the Lake Carl Blackwell Research Station.

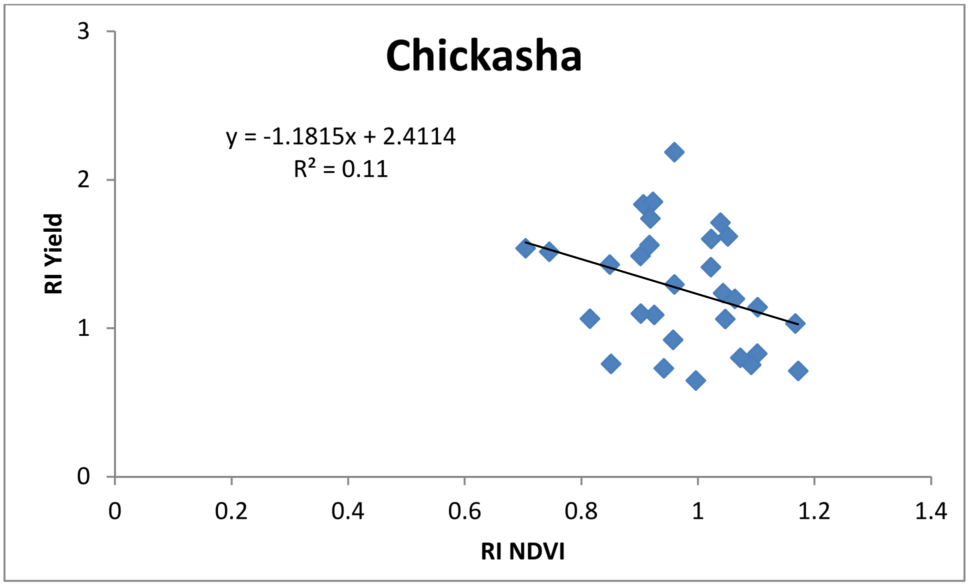

Figure 11. Linear relationship between the response index measured at harvest and the response index measured in-season for the South Central Research Station.

VITA

Linda Shawntel Ervin

Candidate for the Degree of

Master of Science

Thesis: DEVELOPMENT OF A YIELD PREDICTION MODEL AND SENSOR BASED NITROGEN RATE CALCULATOR FOR WINTER CANOLA (BRASSICA NAPUS) GROWN IN OKLAHOMA

Major Field: Plant and Soil Science

Biographical:

Education:

Completed the requirements for the Master of Science in Plant and Soil Science at Oklahoma State University, Stillwater, Oklahoma in July, 2015.

Completed the requirements for the Bachelor of Science in Plant and Soil Science at Oklahoma State University, Stillwater, Oklahoma in 2011.

Completed the requirements for the Associate of Science in Agronomy at Eastern Oklahoma State College, Wilburton, Oklahoma in 2009.

Experience:

Graduate Research Assistant
Plant and Soil Science
Oklahoma State University
August 2013 – July 2015

Professional Memberships:

American Society of Agronomy
Crop Science Society of America
Soil Science Society of America