YIELD EFFICIENCY USING A STOCHASTIC FRONTIER APPROACH FOR CORN, SOYBEANS, AND HARD RED SPRING WHEAT IN NORTH DAKOTA

A Thesis
Submitted to the Graduate Faculty
of the
North Dakota State University
of Agriculture and Applied Science

By

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In Partial Fulfillment of the Requirements
for the Degree of
MASTER OF SCIENCE

Major Department:
Agribusiness and Applied Economics

March 2017

Fargo, North Dakota

North Dakota State University
Graduate School

Title

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The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

MASTER OF SCIENCE

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ABSTRACT

Agriculture is a keystone for the North Dakota economy. The research focused on three selected crops' yield: corn, soybeans and HRS wheat. The research provides a direct and indirect cumulative elasticity measure for North Dakota for each of the three crops' yields using stochastic yield frontier models. In addition, the research provides the technical efficiency frontiers for nine different regions in North Dakota as well as across the 22 years (1994 to 2015).

The results revealed that each of the three crops' yields have a stronger relationship with weather variables than input cost and quantity variables. The mean level of corn, soybeans, and HRS wheat technical efficiency were 73 percent, 80 percent, and 72 percent, respectively. This research proposes that each of the three crops' operations could potentially improve efficiency without adding extra expense of input costs. Overall, North Dakota farmers were relatively efficient in each of the crops' operations.

ACKNOWLEDGEMENTS

I would like to thank my entire committees, Dr. David Roberts, Dr. Frayne Olson, and Dr. Jack Norland, for their knowledge about the topic and advisements throughout the completion of my thesis. I appreciate the many efforts you spent helping me through the numerous economic analysis questions with which I struggled. I would like to express further gratitude to my main academic advisor, Dr. David Roberts, for two years of mentoring, guidance and friendship. I would also like to thank Laura Trude and Tammi Heville for their knowledge of technical writing and great sources for important literature for my thesis. To the Department Chair Dr. William Nganje, thank you for the encouragement and support for the graduate students. In addition, I would like to thank the North Dakota Trade Office for providing the export assistantship for graduate students and enabling me to pursue a higher level academic degree.

I want to thank my American Family, Paul Goulding and Laurel Goulding for helping me since I came to the United States in 2007; without their warm help and wonderful support, surviving the country would be difficult. Special appreciation to my uncles, Lawson Jones and Lee Jones and their farm “L&L Jones farm partnership” for letting me be involved in farm operations and giving me the great opportunity to learn how modern farm production works.

Sincere thanks to my parents who have believed in me and let me start my own journey in the United States of America: Father Badarch Chultem, Mother Enkhbayar Sunduijav Father in Law Badral Bold and Mother in Law Gerelchimeg Nyamaa. Special gratitude to my loving wife, Oyumaa Badral, who has helped me to be open minded, stood by me every step, and encouraged me throughout the entire time. Thank you for always being there for me and being a great role model for teamwork and best friend. Finally, I am proud to be one of the bison herd at North Dakota State University.

DEDICATION

Very special dedication to older brother Batbayar Badarch and younger brother Bat-Enkh Badarch, you are my best brothers and most treasured people to me. I am very thankful of being loved and being the middle brother for you two. Nine years ago, I left my brothers behind me to pursue education in the United States of America. I missed our formative years of brotherhood, however, I hope this achievement would replace the moments we were not together and satisfy the quality of our brotherhood. Moreover, I expect more successes and achievements from all of us, which would positively affect our life in the many years ahead. To my father Badarch and my mother Enkhbayar, they give us the inspiration to pursue higher education, endless support, and selfless effort in caring and loving us.

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LIST OF ABBREVIATIONS

AcCoYie……………………………….actual corn yield (page 65, 67)

AcSoyYie…………………………….....actual soybean yield (page 70, 72)

AcWheYie…………………………….....actual HRS wheat yield (page 75, 77)

CoYieTE………………………………..corn yield technical efficiency (page 64, 66)

DEA…………………………………….Data Envelopment Analysis (page 26, 27, 28, 29)

EC……………………………………….east central (page 66, 67, 71, 72, 76, 77)

MeanTE……………………………….mean of technical efficiency (page 64, 66, 69, 71, 72, 74, 76)

MedianTE…………………………….median of technical efficiency (page 64, 66, 69, 71, 72, 74, 76)

NC……………………………………….north central (page 66, 67, 71, 72, 76, 77)

NE……………………………………….northeast (page 66, 67, 71, 72, 76, 77)

NV……………………………………….north valley (page 66, 67, 71, 72, 76, 77)

NW……………………………………….northwest (page 66, 67, 71, 72, 76, 77)

PreCoYie…………………………….....predicted corn yield (page 65, 67)

PreSoyYie…………………………….predicted soybean yield (page 70, 72)

PreWheYie…………………………….predicted HRS wheat yield (page 75, 77)

SC………………………………………..south central (page 66, 67, 71, 72, 76, 77)

SFA……………………………………...Stochastic Frontier Analysis (page 5-7, 9, 26-30, 35, 36, 53, 58, 60, 79, 86)

SE………………………………………..southeast (page 66, 67, 71, 72, 76, 77)

SoyYieTE……………………………..soybean yield technical efficiency (page 69, 71)

SV………………………………………..south valley (page 66, 67, 71, 72, 76, 77)

SW……………………………………….southwest (page 66, 67, 71, 72, 76, 77)

WheYieTE…………………………….HRS wheat yield technical efficiency (page 74, 76)

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CHAPTER I. INTRODUCTION

Background

In the late 1860s land was being offered for farmers in the northern Dakota Territory when the region was first open to homesteading. Small grains and row crops were planted; this was how farmland started taking over North Dakota.

North Dakota farmers have been growing a variety of crops over the past ten decades, averaging over 26 million acres of land for farming. The economy of North Dakota is heavily dependent upon agricultural production activities, with Census of Agriculture records identifying 30,961 farms in the state in 2012 (USDA/NASS, 2016). Farms in the state planted 23.72 million acres of field crops in 2015, which is approximately 41.78 percent of North Dakota's total land area (USDA/NASS, 2016). Total field crop production was worth $6.69 billion, generating 12.46 percent of North Dakota's total gross domestic product (GDP) in 2015 (USDA/NASS, 2016).

A strong bullish market in agriculture existed between 2005 and 2013 and a burgeoning oil and gas industry during the period 1995 to 2014, lead to rapid economic growth for the state of North Dakota. However, a recent price rout for both crude oil and agricultural commodity prices have caused economic growth to stall, decreasing the state's GDP and causing a one billion dollar shortfall in the state's budget (Nowatzki, 2016). Moreover, agriculture in North Dakota is dominated by few commercial crops besides livestock. Due to minimal diversification in crops, commodity price volatility has a big impact on the state's economy. North Dakota is already operating almost all of its farmland, over 90 percent of the total land is used for farming and livestock, thus no additional farmland is available for expansion. Since demand is ever-increasing for food and energy, farming the land efficiently with limited farmland supply is necessary for meeting this demand.

The essential role of technical efficiency in farm profit maximization has been acknowledged for many years (Bravo-Ureta and Pinheiro, 1993). Utilizing innovative technologies and new varieties of inputs dedicated to improving crop yield and farm productivity has been commonly contemplated. However, technically efficient farming is another important part of farm output improvement, which is directly associated with farm income and economic efficiency. Farmers can save input costs by increasing the efficient use of inputs from their production. For instance, $234.6 million could be saved by merely increasing efficiency one percent in the use of nitrogen fertilizer in small grain production globally (Raun and Johnson, 1999). This is one of the many inputs that has an unexpectedly high value for only increasing efficiency one percent. Estimating yield efficiency using inputs and technical efficiency for individual farmers could contribute to increased farm profitability, a stable state economy, and benefit the environment as well as public health.

United State Department of Agriculture statistics indicate that in 2015 North Dakota was the nation's top producer of barley, dry edible beans, canola, flaxseed, hard red spring (HRS) wheat, and durum wheat (USDA/NASS, 2016). Furthermore, the state's top three crops by economic value of total production in 2015 were HRS wheat, corn grain, and soybean. The three economically dominant crops also ranked as the top three crops by acreage planted in 2015 (USDA/NASS, 2016). The research by Holmes and Lee (2012) explored the top five land uses in the Red River region for 1997 to 2006 and their top five crops included the current three dominant crops in addition to sugar beets, and potato.

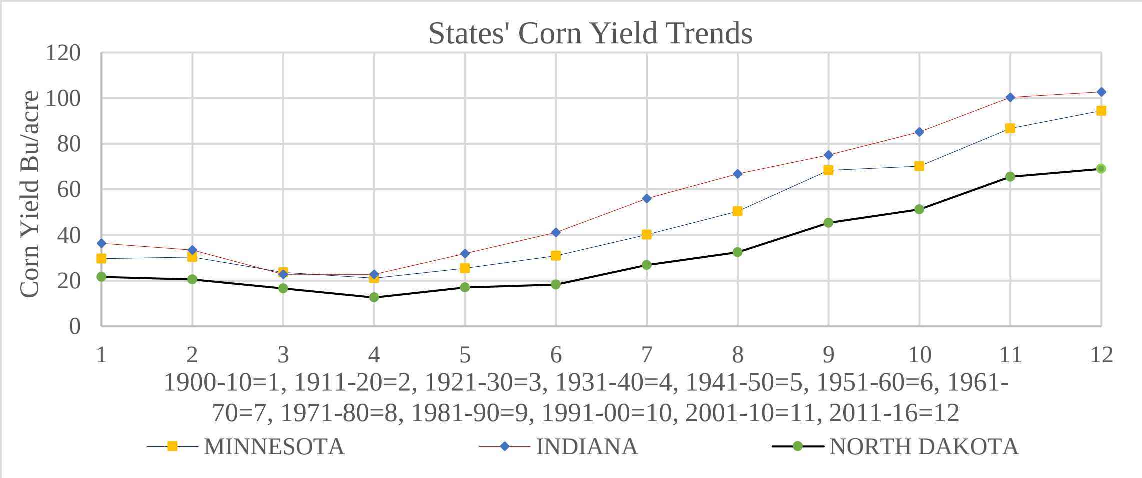

Figure 1. Corn Yield Improvement by Ten-Year-Average in 20th and 21th Century. Source: USDA NASS Surveys.

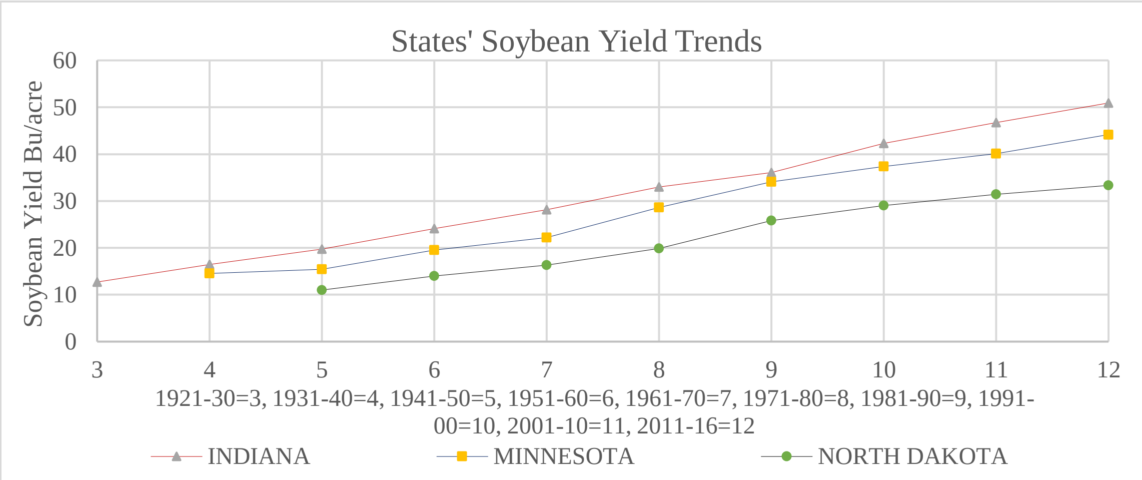

Figure 2. Soybean Yield Improvement by Ten-Year-Average in 20th and 21th Century. Source: USDA NASS Surveys.

In order to show clear indication for corn, soybean, and HRS wheat yield improvements in North Dakota, Figure 1, Figure 2, and Figure 3 indicate the Ten-Year-Average trend line for their yield in 20th and 21st centuries. Moreover, the comparison in Figure 1 between two states' corn yields and North Dakota corn yield has a couple of purposes: (1) General information about corn yield trend over time and (2) Illustration of almost identical rate in improvement for corn yield trends from 1940s to 2010s.

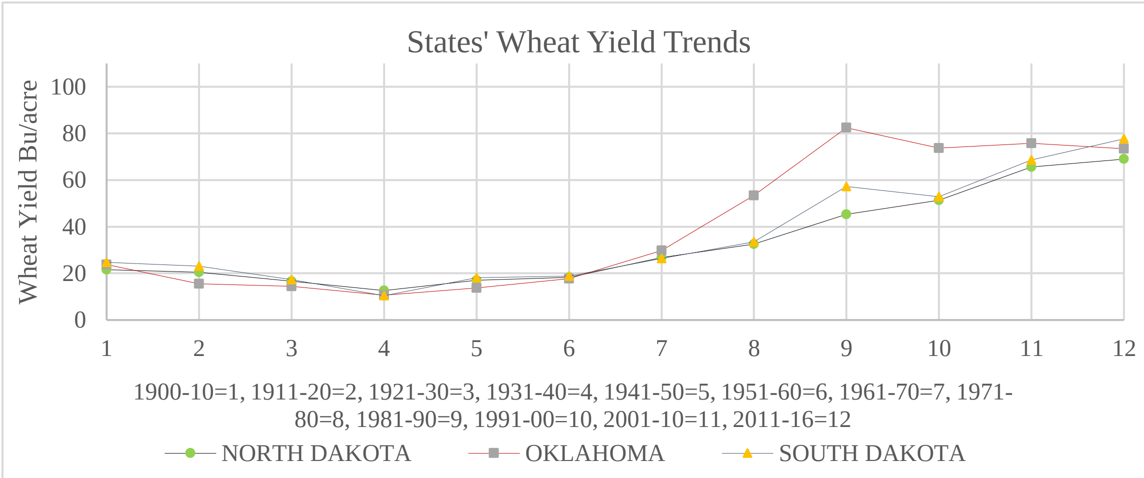

Figure 3. Wheat Yield Improvement by Ten-Year-Average in 20th and 21st Century. Source: USDA NASS Surveys.

The comparison in Figure 2 between two states' soybean yields and North Dakota soybean yield has a couple of purposes: (1) General information about soybean yield trend over time and (2) Illustration of all states shows a linear growth rate with a similar slope in the trend line from the 1930s to 2010s.

Lastly, Figure 3 indicates the Ten-Year-Average trend line for wheat yield in the last and current centuries. Figure 3 serves a couple of purposes: (1) Providing general information about wheat yield trend over time and (2) Illustrating for all three states that wheat yields were almost the same from the early 1900s to 1960s, then Oklahoma and South Dakota states' wheat yield jumped from 1960s to 1990s. However, most of the yield trend lines converge and stay in the same range after the 2000s until present.

The evaluation of the effectiveness of farm production inputs and weather variables for yield efficiency of the three dominant crops in North Dakota could provide a strong insight into what we may expect nationally in these three crops' yield variations. The research expectation is that the results and findings could be used by policy makers to explore new opportunities for productivity and production efficiency of farms in order to maintain a stable farm income as well as farm economic contribution to the state's economy. More importantly, the results and findings can lead to an evaluation of the impact of changes in farm policies on North Dakota farmers within different regions of North Dakota over the past couple decades.

The research analyses of efficient use of inputs for the three dominant crops has been developed in many different research studies and different regions (Roberts, Brorsen, Solie, & Raun, 2011; Blum, 2009; William & Gordon, 1999), although our research is the only study to include all three crops in one paper. Furthermore, the marginal benefit of our research is to evaluate the efficient yield improvement from direct and indirect inputs such as seed, fertilizer, chemical, crop insurance, and energy costs and average temperature and total rainfall in crop growing season. For instance, farmers have no control over the temperature and rainfall variables however, they can control how much nitrogen fertilizer they should apply for their crop. Therefore, it is important to evaluate the elasticity of these inputs on yield improvements for the three dominant crops.

The research utilized Stochastic Frontier Analysis (SFA) for a sample of North Dakota farms using a panel data set of 1,778 observations for the corn yield model, 2,070 observations for the soybean yield model, and 3,640 observations for the HRS Wheat yield model over a 22-year time period, from 1994 to 2015. Technical efficiency score for individual observations was estimated based on models for each crop on an annual basis as well as a regional basis. In addition, predicted versus actual technical efficiency frontiers for each time period and region are illustrated by this research as well.

Objectives

The main objective of the research is to first develop a crop yield frontier model to evaluate the yield efficiency of the three economically dominant crops grown in North Dakota: corn, soybeans, and HRS wheat. Secondly, the research is going to evaluate the elasticity effects from critical farm production inputs as well as weather variables for the three selected crops' yields in order to detect potential improvement in yield. Thirdly, the research will compare the distinction between the predicted and actual technical efficiency frontiers by time periods as well as for different regions. The research will also apply a similar comparison between the predicted and actual crop yields for each of the three crops by time periods and for different regions. Lastly, to determine the efficiency performance by time period and region, the research will use and categorize technical efficiency scores of individual farms to identify the consistency of efficient farming for each of the three crops.

These are the specific objectives:

1. To develop the crop yield efficiency model for each of the three crops based on the SFA to enhance crop yield efficiency predictions and to evaluate the input elasticity effects on each of the three crops' yield.
2. To determine and illustrate graphically the three crops' yield efficiency frontier based on average technical efficiency score to demonstrate the differences by year and region.
3. To compare the three crops' predicted frontier based on the yield efficiency frontier model versus the crop's actual yields to illustrate graphically.
4. To distribute technical efficiency scores of each crop's yield by categorizing into three groups and to determine the consistency of efficient farming percentile from each of the three crops' yield efficiency scores.

Hypotheses

We will test the following hypotheses:

1. The yield frontiers for each of the three crops have increased during the study period.
2. Weather variables such as temperature and rainfall shift the production frontier every year.

3. Each region has a comparative advantage for different crops as represented by spatially varied yield frontiers.

The evaluation of crop yield efficiency and efficient use of input sources are extremely important in order to maximize farm profit, to utilize input sources effectively and efficiently, and to become better farm managers by making better decisions. Sustainability of farm income in a highly volatile market and with strong climate variation would be very difficult without contemplation of crop yield efficiency and managing input sources efficiently. According to Tilman et al (2002), most of the best quality farmland is already used for agriculture, which implies that increasing farmland would be expensive. As a matter of fact, growing crops in newly expanded farmland would have a difficult time satisfying the crop yield expectation. Thus, a better option for sustaining farm income is to reduce the potential for inefficiency from input sources, while improving the crop yield efficiency and maintaining the crop's yield.

Procedures and Methodology

The methodology of the research is going to utilize the SFA with Maximum Likelihood estimation to develop the crop yield efficiency frontier models for each of the selected three crops. Furthermore, the research is going to utilize technical efficiency scores to generate the percent difference relative to nine selected regions as well as over 22 years. Most of the data for output and input were gathered from the North Dakota Farm Business Education Management program (NDFBMEP). The sample data consists of information from 7,488 observations in 1994 to 2015 and is an unbalanced panel data set. In addition to this data, the research adds weather data gathered from the North Dakota Agricultural Weather Network (NDAWN). Overall, the data set is restricted to 1994 to 2015, due to a limitation in weather data availability. The theoretical models, empirical models, and testing procedures are provided in detail in the methodology chapter.

Organization

Chapter II reviews the prevailing literatures on improvement for the selected three crops' yield and yield efficiency, effective statistical methods used, and analyses of efficient use of direct and indirect inputs from different studies done internationally and domestically. Chapter III presents and describes the theoretical and empirical models used in the thesis to achieve an analysis of crop yield efficiency frontier and technical efficiency changes over time by year and region for each of the three selected crops in North Dakota. In addition, Chapter III contains the description of the data used in the research and details the features of the dataset and data sources. Chapter IV presents the regression results and discussions. Finally, Chapter V presents the summary and conclusions. Furthermore, Chapter V includes important findings for policy implication and summarizes the limitations of the thesis and further research needs.

CHAPTER II. LITERATURE REVIEW

Introduction

The literature review emphasizes the three selected crops' yield improvement over time for the United States of America and other countries, and explores the impacts of climate variation in these crops' yield. It also emphasizes the yield efficiency improvement from efficient input uses and explores important inputs for efficiency in farm production. Finally, it emphasizes the alternative approach to measuring the technical efficiency and agricultural research by SFA.

History of Agriculture and Crops in North Dakota

North Dakota was home to many different Indian tribes such as Sioux, Mandan, Arikara, Chippewa, and Hidatsa. Most of the tribes were nomads and hunters, a few tribes were farmers, in fact the Mandan tribe farmed along the Missouri River and grew corn, squash, pumpkin, and sunflower. The North Territory has been used for agricultural purposes for over 200 years; starting with the Indian tribes Mandan and Arikara. The state of North Dakota has a very successful and rich history in agriculture. The trade for agriculture commodities started between Native American tribes and Canada prior to the 1800s. This trade was called the Fur Trade. Trading took place along the Missouri River and reaching to the south western portion of the state to include trade with the Mandan and Arikara tribes. Additionally, early settlers came from Canada to the Dakota Territory and more and more settlers found their way down the Red River to Henry's fur trading post. Based on the education of Henry's vegetable crops, many of the settlers farmed and survived in the new land of the North Territory. This encouraged more Scottish settlers and others to come and farm in the Dakota Territory (North Dakota Agriculture History, 2007).

Doebley et al (2002) enhanced corn genetics research, based on the theory and research from Dr. Beadle, and discovered that all corn was most genetically similar to a teosinte type from the tropical Central Balsas River Valley of southern Mexico. Based on their calculation of genetic distance between the ancient corn (Balsas teosinte) and the modern corn, corn was initially domesticated by local farmers about nine thousand years ago (Doebley et al 2002). Corn was introduced in North America about seven thousand years ago and Native Americans transformed corn through special cultivation techniques (Native Tech, 1994). The corn production and productivity was sufficient to supply the diet for a whole family year around (Native Tech, 1994).

Recently, corn has become an important crop in North Dakota and is used mainly in fuel ethanol and food processing (High Fructose Corn Syrup). Cropland share of corn production was about two percent of total cropland in the 1970's and now corn production takes more than ten percent of total cropland (Taylor and Koo, 2013). Corn production has become one of the fastest growing crops in the state, because of the many benefits associated with its economic value. For instance, total revenue of corn production had tripled in the past 15 years ($454 million to 1.42 billion; Taylor and Koo, 2013). Corn prices increased $3.74 to $6.85 per bushel from 2008 to 2012, the economic contribution from corn production and corn processing for North Dakota also increased to $9.7 billion (USDA/NASS, 2015). Corn is definitely one of the major economic contributors for the state. In 2015, corn was ranked as the third crop in North Dakota and the economic contribution was $1.05 billion at an average price of $3.20 per bushel (approximately 12 percent of total state crop sale; USDA/NASS, 2015).

According to History of Soybeans (2014), soybeans were initially domesticated by Chinese farmers around 1100 BC in Southeastern Asia. Around the middle of the 1850's, soybean seeds were distributed to farmers in Illinois and the Corn Belt states. Soybean seeds were a gift from people rescued from a Japanese fishing boat in the Pacific Ocean in 1850. In the early 1900's, American chemist George Washington Carver discovered that soybeans have high protein and oil content. The USDA and the American Soybean Association (ASA) brought additional varieties of soybeans from China and encouraged U.S. Farmers to grow soybeans for animal feed and other purposes (History of Soybeans, 2014).

According to the USDA, North Dakota ranked tenth for soybean production in 2014, however, North Dakota exports most of its soybeans overseas. Moreover, soybean production was economically valued $1.56 billion in 2015 at an average price of $8.5 per bushels and it is approximately 17 percent of total crop sales (USDA/NASS, 2015). North Dakota has an excellent performance in the past 20 years of exporting soybeans all around the world. In fact, North Dakota soybean exports were valued at $1.8 billion (at an average price of $9.50 per bushel) in the period of 2014 through 2015 (International Marketing, 2016).

One of the first adopted crops was wheat in North Dakota. Wheat has been one of the main cereal crops grown in North Dakota. Historically, Volga Germans introduced Hardy New wheat varieties into the Great Plains in the late 19th century. Since then, the United States Department of Agriculture (USDA) and state experimental stations have developed many new varieties of wheat and taught farmers how to grow them (Moon, 2008).

Today, HRS wheat and durum wheat are North Dakota's leading agricultural cereal crops and the state has been a leading producer of durum wheat and one of the top producers for HRS wheat nationwide. According to the North Dakota Wheat Commission, North Dakota's HRS wheat production provides almost half of the nation's HRS wheat (250 million bushels) and durum wheat production supplies two-thirds of the nation's durum wheat (50 million bushels) on the average. Approximately 62 percent of North Dakota farmers grow wheat. Statistically, 45 percent of farmers grow HRS wheat, 15 percent of farmers grow durum wheat and 2 percent of farmers grow Hard Red Winter (HRW) wheat. Wheat production uses about nine million acres of land, one-fourth of North Dakota's total land. The farmers in North Dakota have been exporting wheat all around the world; close to 100 countries imported wheat from the state in the past five years.

Leistritz and Coon (2010), categorized ND's economic activities into five basic sectors: (1) Agriculture, (2) Manufacturing, (3) Energy extraction and conversion, (4) Tourism, and (5) Federal Government operations. These five economic activities were developed by the North Dakota Input-Output Model. These five sectors changed some in response to recent economic activities and market prices, however, agriculture is still the major driving force in the state's economy. Moreover, North Dakota still leads in production of HRS wheat, barley, oats, edible beans, durum wheat, canola, flaxseed, lentils and honey (Leistritz and Coon, 2010). Therefore, the state's economy has been and still is dependent upon agricultural activities and their economic contribution. Agricultural variability contributes to weaknesses and strengths in the state's economy. Crops grown in North Dakota provide the potential to enhance employment as well as the state's economy through new processing facilities and value-added production (Leistritz and Coon, 2010).

Agriculture in the United States of America

In the 20th century, U.S. agriculture and farming operation changed dramatically. Labor intensive farm operation required a large number of farmers. Almost half of the U.S. population was diversified farmers in rural areas. This changed to a small number of farmers with a lot of land, equipped with highly productive machinery and equipment, whose specialized farms were located in rural areas where less than a fourth of the U.S. population lives. As a consequence of this transformation, U.S. agriculture became tremendously productive and efficient and has contributed to the overall growth of the U.S economy throughout the 20th century (Dimitri et al, 2005). Shortly after World War II, revolution in technology, mechanical power, advanced farming operation, and development of chemical inputs influenced production of agriculture in the U.S. and increased productivity by an average of 1.9 percent annually from 1948 to 1999. At the same time, productivity in other industries grew an average of 1.3 percent annually (William, 1995). Another influential factor for U.S. agricultural production was demand shift. Consumers' began preferring products that were convenient, traditional, and healthy, such as low-calorie, low-sodium, and gluten free products. Thus, agricultural commodity contracts and vertical integration for supply of high-valued commodities changed the traditional agricultural market as a result of demand force (Macdonald et al, 2004).

The United States of America has a major role in corn production as well as world corn trade. Some states grow more corn than others, depending upon the climate, soil productivities and other factors. For instance, Iowa, Illinois, Nebraska, Minnesota, and Indiana are the top five corn producers in the U.S. Today, corn is used in two main purposes: feed grain production (about 95 percent of total feed grain) and food and industrial products (starch, corn oil, fuel ethanol, and others) (ERS.USDA, 2016).

Research by Duvick and Cassman (1999) identified the corn yield increase in the post-Green Revolution era by estimating corn breeding efforts. Particularly, corn grain has an absence of published data for biomass that would help determine yield improvement. Duvich and Cassman, (1999) stated that historically, corn yield improvement was explained by rain-feeding and irrigation. The research supported contests among irrigated farmers, and reports of record rain-fed corn are more likely to determine the yield levels; those effects can be the best estimator for corn yield potential. However, corn yields in the rain-fed time-series comparison are well below these yield levels, which makes it difficult to support this conclusion. The research finally concluded that no strong evidence was found for an increase in yield potential of corn hybrids adapted to the north-central U.S. during the past 25 years (Duvich and Cassman, 1999).

Figure 4 demonstrates corn yield trends from the 1960s to 2010s. These five countries lead world corn production. As Figure 4 shows, all five producers' corn yield improved in this period, however, corn yields for Ukraine, Brazil, and Argentina increased more quickly than for the USA and China after 2010. The corn yield trend for the USA was increased by an average of 80 bushels per acre almost linearly in the period 1960 to 2010 and leveled off after 2010. Duvich and Cassman (1999) concluded there was no strong evidence of corn yield improvement in the last 25 years.

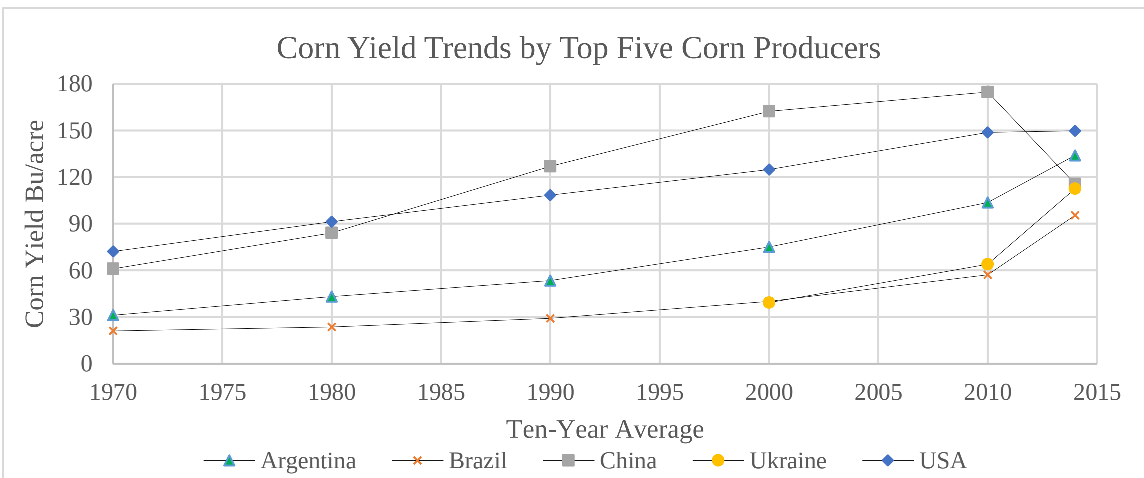

Figure 4. Corn Yield Trends by Ten-Year-Average, Periods from 1960s to 2010s. Source: FAOUNSD/STAT, 2016.

Perhaps yield improvement was much smaller, however it gradually increased over time as shown in Figure 4. The corn yield trend for China on the other hand shows that yield improvement was greater than others in the period from the early 1980s to 2010, and then dropped suddenly from 2010 to 2014. According to Erda et al (2005), climate change could reduce the corn yield by up to 37 percent in next 20 to 80 years based on their Regional Climate Change model (PRECIS). Thus, sudden corn yield reduction in China may be due to climate change in some degree.

Shortly after World War II, U.S. soybean production boomed because of the benefits of soybeans. U.S. consumer diets improved tremendously as well. As a result, soybean demand increased for numerous reasons such as: food consumption, export volume, feed livestock, and vegetable oil. Hence, one solution was to increase the soybean production in order to meet the demand need (History of Soybean, 2014). Ultimately, soybean meal has been one of the preferred options for feeding livestock at an affordable price. Soybeans have many different features than other crops; they have stronger tolerance to herbicides, require less cultivation and have stable consumer demand (History of Soybean, 2014). Current statistics indicate that U.S. soybean producers lead world soybean production (3.9 billion bushels = 106.9 million metric tons in 2015) (USDA/FAS, 2016).

Based on the research from Specht et al (1999), soybean yield improvement increased by 54.0 kg ha-1 yr-1 in last century, which is attributed to technology adopted by farmers. Moreover, soybean yields linearly improved at a rate of 22.6 kg ha-1 and at 31.2 kg ha-1 during the period from 1924 to 1998 and the period from 1972 to 1998 respectively. However, soybean yield variation increased in the last 25 years more than in the prior 25 years. The increasing yield variation could imply that yield variation may have a close relationship to climate variation. A following section, yield improvement and climate variation, will review this in detail.

Figure 5 demonstrates soybean yield trends from the 1960s to 2010s. These five countries lead world soybean production. Based on the 10-year-average yield trends, almost all yield trends show a similar rate of improvement over time, except China. China has a much greater yield than the other countries, but yield started dropping from the 2000s and dropped even more steeply after 2010.

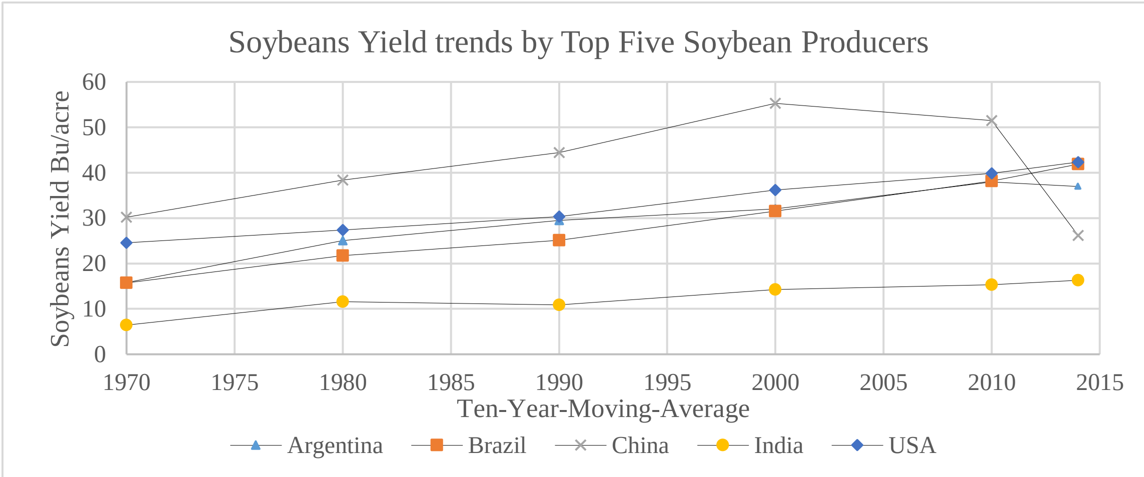

Figure 5. Soybeans Yield Trends by Ten-Year-Average, Periods from 1960s to 2010s. Source: FAOUNSD/STAT, 2016.

The yield trend for U.S. soybean steadily improved from the 1960s until 2014 and this has been mentioned in other research (see Specht et al, 1999; Ustun et al, 2001).

The United States of America is ranked as the third leading wheat producer in the world. North Dakota, Kansas, Montana, Washington, and Texas are the top five wheat producers in the U.S. In general, U.S. wheat is classified into five varieties: HRS Wheat, HRW Wheat, Soft Red Winter (SRW) Wheat, White Wheat, and Durum Wheat. HRS and HRW Wheat make up almost 60 percent of total wheat production. According to the USDA, world wheat production produced the highest amount of wheat in 2011: 25.5 billion bushels. U.S. wheat production contributed to about 4 percent of total wheat in 2011 (2 billion bushels) in the world. The U.S. is the world's largest wheat exporter, even though world wheat exports decreased dramatically over the past 20 years. The U.S. exported 975 million bushels of wheat overseas in 2011 (Wheat, 2016).

Wheat is the one of the highest valued cereals produced and approximately 215.5 million hectares of farmland is used for wheat production in the world. Research by Calderini and Slafer (1998) showed the wheat yield trend of 21 countries throughout the 20th century. The study stated the wheat yield improvements were not strong in beginning of the century. As matter a fact, 15 out the 21 countries showed no yield improvement at all. The main conclusion of the study was supported by other researchers (Fisher, 1998; Dalrymple, 1998), as well as other researchers from different countries (Riggs et al, 1981; Duvick, 1984; Evans, 1993). However, almost all countries revealed strong upward trend for yield improvements during the second half of the century according to figure 6 below.

Figure 6 demonstrates wheat yield trends from the 1960s to 2010s. These five countries lead world wheat production. Based on the Ten-Year-Average yield trends, there is fairly large yield distinction between countries. For instance, yield for China and France have a much higher increase than the other three countries.

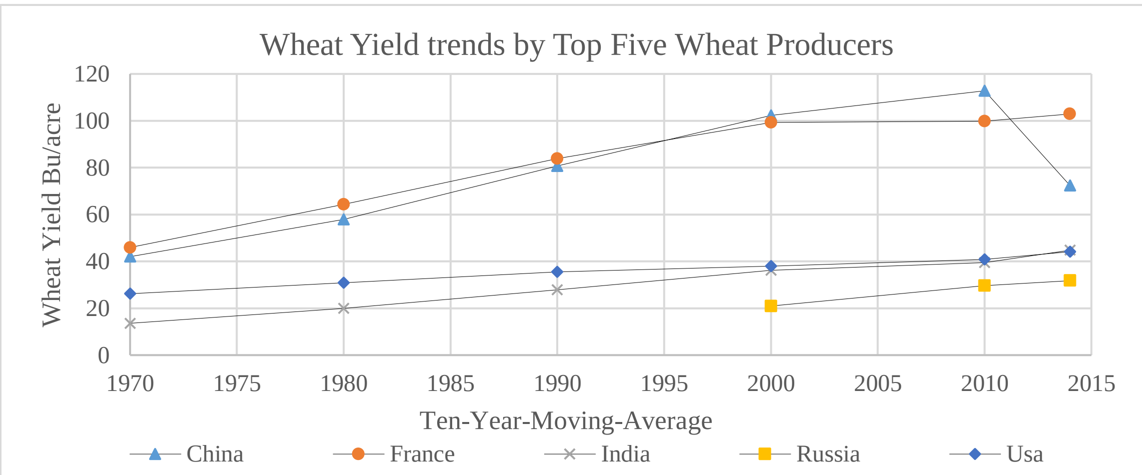

Figure 6. Wheat Yield Trends by Ten-Year-Average, Periods from 1960s to 2010s. Source: FAOUNSD/STAT, 2016.

Recent research by Ray and others (2012) evaluated the yield trend for four major crops (maize, rice, wheat and soybean) grown all over the world. They commented about improvement of wheat yield from 1999 to 2008; 64 percent of wheat land indicated yield improvement at significantly different rates depending on their region and 34 percent of wheat land did not indicate yield improvement. Their analysis was based on a high-resolution geospatial dataset. Their analysis of yield improvement was measured in percentages of harvested land, in such that, global wheat yield improved in over 61 percent of wheat land harvested area corresponding to 130 million hectares and 37 percent of wheat land harvested areas were in yield stagnation and the rest of the 2 percent of wheat land areas harvested showed yield collapse. In general, Figure 4, 5, and 6 attempt to illustrate overall yield improvements for the three selected crops. In addition to that, selected countries for each crop were logically chosen by the performance of the three crops' production. The Ten-Year-Average was employed in time-series data of countries' yield performance in order to illustrate the selected three crops' yield trends in available periods (from 1960 to 2014). The Ten-Year- Average provides a wide range of movements, thus it may not capture every piece of the yield improvements in detail, which was not the mission to illustrate.

Most farmers are able to manage their inputs for production activities based on their experience, knowledge, education, and estimates, however, some factors are not controllable such weather conditions, although farmers know that weather conditions have an important influence on farming operations.

Impacts of Climate Variation in Selected Three Crops' Yields

Climate variability definitely influences the yield of each of the three dominant crops. Farmers monitor climate changes as they try to determine their expected yield. The climate variation could affect crops' yields negatively in one place and it could affect it positively in another place. There are numerous research articles that have been published evaluating the potential impacts of climate changes on U.S. agriculture (Beach et al, 2010; US Climate Change Science Program (CCSP), 2008; Greenstone and Deschenes, 2007; Mendelsohn et al 1994; Adam et al, 1990).

The research by Beach et al. (2015) tried to "quantify possible impacts of climate change upon agricultural three major crops' yields and forests based on the stabilization scenarios created under U.S. Environmental Protection Agency's Climate Change Impacts and Risk Analysis (CIRA) project." For more information on CIRA, see Waldhoff et al. (2015). The research projected the three selected crops' yields from 2010 to 2100 based on the two CIRA emission scenarios, the Reference Scenario and the Policy or Stabilization Scenario. See Paltsev et al., 2015 and Waldhoff et al., 2015 for each scenario explained in detail. Each crop yield differed depending on the United States region. For instance, the southern U.S. regions' crop yield benefited the least, while the northeast benefited the most from unabated climate changes in the referenced scenario. Moreover, irrigated and dry-land conditions' crop yield projected by IGSM-CAM (see Monier et al 2015) found that each of the three crops' national average yield increased under both scenarios. Finally, the research concludes with critical points for crop yield in response to climate changes. First, most crops' yields increased after the second half of the 21st century. Second, most of the irrigated crops tended to gain more yield than dryland crops, and lastly, crops' yields vary by U.S. region. While Beach et al. (2015) projected future crops' yields in terms of climate varation, other researchers addressed additional important impacts of weather events on crop yield.

Wang, Bowling, and Cherkauer (2016) primarily focused on the Midwest for evaluating the effect of climate variation on the crop yield. They utilized the Soil and Water Assessment Tool (SWAT), which was developed by the USDA-ARS and is a common tool for evaluating crop production and the hydrologic process in response to climate variation. Their findings suggest reduced crop yield occurs due to individual stresses during their research period (1941-2010). Their findings are: (1) for most of the regions in the Midwest, annual corn yield is inversely correlated with drought stress, particularly in the early and middle reproductive stages, as these are sensitive stages, (2) there is no relationship between corn yield and aeration stress in most regions in the Midwest, however, this may not true if they reduced the scope for a particular field, as relationships could occur at the plot scale and (3) lastly, recent years have a larger percentage of yield variation compared to past years. Overall, drought stress is the strongest indicator of corn yield in the historical period, for instance, total yield reduction due to drought stress was 8.2, 17.5, 15.2, and 9.7 percent for selected regions: Boone, Woodbury, Madison and Mason, respectively.

Due to increases in the frequency and intensity of strange weather events, such as excessive rainfall (floods) and temperature (extreme heat or cold), farmers encounter many obstacles in their farming operations. For instance, excessive rainfall throughout the planting season or after planting can result in a negative crop yield. Two things could happen (1) an excessively rainy spring would result in crop planting delay, which puts pressure on the time for crop growth and harvesting, (2) excessive rain after the crops are planted creates saturated soil, leading to the loss of nitrogen, increasing disease infections and depleting the oxygen in the soil.

According to Butzen (n.d.), planted crop fields are often flooded by excessive spring rainfalls, which are damaging to crops. During the flood, crop yield becomes uncertain, because flooding causes soil nitrogen loss. Many different crops are grown in the U.S. and each crop reacts to flooding differently. For instance, potatoes and dry beans are vulnerable under water, succumbing in less than one day (Glogoza, 2005). Wheat is a little more tolerant and withstands at least two days under water. Corn and soybeans are more tolerant and withstand two to four days under water (Berglund, 2005; Iowa State Extension, 1998; Stanley, 1980). However tolerant crops are to surviving flooding, the flood will still reduce the potential crops' yields to a certain degree by taking nutrition from soil, depleting nitrogen from the soil and washing out nitrogen fertilizer above the soil.

On the other hand, global warming is another threat for agriculture, especially crop production. Global average temperature have risen an average of 0.13 C degree per decade since the second half of the 20th century and is expected to increase at an even faster rate in the next couple of decades. A research study done by Lobell et al. (2011) developed models for four major crops' yield responses to evaluate the impact of recent temperature and precipitation trends from 1980 to 2008. Globally, corn and wheat yield reduced by 3.8 percent and 5.5 percent respectively as a result of climate trends. However, the climate impact for soybean and rice production differed by region, resulting in yield gains in some countries balancing losses in other countries. Furthermore, temperature trends have a stronger impact than precipitation trends, and thus, changes in temperature explain more crops' yield than changes in precipitation as far as regional and national levels.

Many papers researched and developed models that illustrate the impact of climate changes on major crops grown in the world. Some results and findings are similar, such as individual crop yield reacted differently in extreme weather events depending on the crop characteristics and different regions or nations have different yield outcomes depending on climate events. However, most of the papers generally prove that climate changes effect agricultural outputs, and differ on whether those changes are positive or negative. Having covered literature on crop yield changes in response to climate changes, the next section focuses more on crop yield efficiency in relation to inputs.

Yield Efficiency from Efficient Inputs Use

The world's cereal and oilseed production consistent increase is attributed by substantial improvement of quantity and quality of the crop yields and that is fueled by applying the sufficient amount of inputs such as seed, fertilizer, pesticide, new technology, irrigation system, and farm energy management (Tilman et al., 2002). In next section, thesis aims to define the crop yield efficiency meaning from definitions and each of these inputs are discussed in terms of the crop yield improvement, consequences in excessive input use, and benefits of the efficient input use in general.

Crop yield is defined by: (1) agricultural output, (2) measurement of the planted seed generation, and (3) measurement of the amount harvested per unit of farmland (Crop Yield, 2016). Economic efficiency is defined as every inputs' source is optimally allocated or utilized to produce the same level of output in the best way while minimizing waste (inefficiency) from inputs (Economic Efficiency, 2016). From these basic definitions, yield efficiency is referred to as optimally utilizing one or more inputs (efficient inputs) to produce the same level of one or more outputs (efficient outputs) while minimizing waste from excessive inputs (inefficiency). For instance, if a farmer reduced the amount of herbicide applied while maintaining and/or increasing the output in a particular crop, this implies an improvement of efficient use of herbicide and directly refers to improvement of yield efficiency as well. This example holds true when other inputs stay the same.

Not a lot of literature discusses crop yield efficiency, because the term is not used commonly in formal language, but many research studies focus upon efficient use of inputs in terms of efficient output. Research articles are reviewed to analyze the importance of inputs used in order to be efficient in output, that is, to improve crop yield efficiency. Based on the 1990s global food balance sheet, wheat, rice, and corn grain are the top three major food sources and these crops provide an average of 45 percent of total calories and an average of 30 percent of total protein sources. These major crops' yield has improved tremendously and seed varieties contribute to crop yield improvements. Different varieties of seed have different characteristics. For instance, some varieties are more resistant to diseases, fungus, and pests. Others are more tolerant to weeds, diseases, and pathogens.

The report posted by McGuire (2014) stated agriculture is dependent upon many inputs and some inputs could be substituted by others. However, fertilizer is difficult to substitute, because of its benefits. One of the essential inputs for grain is a nitrogen fertilizer and it increased by sevenfold from 1960 to 1995. Current forecasts indicate that nitrogen fertilizer is expected to increase another threefold by 2050, unless producers consider fertilizer efficiency use (Cassman and Pingali, 1995). Similarly, phosphorus fertilizers and phosphorus fertilizer is expected to increase dramatically by 2050, unless producers improve fertilizer efficiency use (Tilman et al., 2002). William and Johnson (1999) calculated that increasing the input efficiency of nitrogen fertilizer by 20 percent would save $4.7 billion per year for farmers all around the world. This is a quantitative value for how much producers could save in production costs in order to maximize net profit. Thus, increasing efficiency in fertilizer use could have a large economic impact.

An article by Sylvester-Bradley (1993) reviews potential improvements for the efficient use of nitrogen fertilizer. Their article highlights three main challenges for increasing fertilizer efficiency. First of all, it is difficult to make a distinction between the effectiveness of normal nitrogen use between the first and second half of a crop's growing season. Thus, it is difficult to optimize the fertilizer applications as precisely as possible. Secondly, cheaper sources for nitrogen fertilizer encourage inefficient use of fertilizer. Lastly, crop yield reaches a ceiling where yield improvement can no longer increase. His suggestion for improving efficient use of nitrogen fertilizer was to improve an understanding of: when crops usually intake nutrients, when different parts of the plant require fertilizer differently, when crop quality changes when increasing yield, changes in the amount of fertilizer used in different types of crop, how different types of soil handle nitrogen residue differently, and lastly, how different crops require a different amount of fertilizer at different times. Finally, he concluded that nothing confirmed or recommended a reduction in the use of nitrogen fertilizer in farm operation.

In agriculture, one of the expensive inputs to sustain crop yield is pesticides. Pesticides are complex, containing herbicides, fungicides, insecticides, and plant growth regulators, among other things. Each pesticide is used for different purposes. For instance, herbicides are used for weed control, insecticides are used for insect control, and fungicides are used for fungus control. Initially, pesticides were produced in India and India is still the number one pesticide producer (Mathur, 1999). United States accounts for roughly 20 percent of total pesticide usage in 2007. The benefits associated with pesticides can be tremendous because they sustain crop yield improvement by controlling insects, weeds, and fungus. Pesticides play an important role in reducing yield losses from the weeds, disease and insect pests. The number of pesticide users increased dramatically in most countries, helping maintain crop: wheat yield in United Kingdom, corn yield in the United States and rice yield in India and China (Aktar et al. 2009).

The efficient use of pesticides has benefits not only for crop yield efficiency, but also a significant impact on human health and the aquatic ecosystem. The U.S. Geological Survey's (USGS's) National Water Quality Assessment (NAWQA) Program provided a national-scale view of pesticide occurrence in stream and groundwater. The key findings were that streams in each of the four areas (Agriculture, Urban, Undeveloped, and Mixed land) detected pesticides more frequently than in the ground water. Pesticide residues vary geographically and seasonally. In 8 of 83 agricultural streams and 2 of 30 urban streams, they exceeded 1 or more human-health benchmarks for annual mean concentration, which is explained as a low potential to impact human health. However, this has a high potential of adversely affecting aquatic life and fish-eating wildlife. The research clearly determined which chemicals were detected more often and illustrates the distribution of herbicides detected in streams in agricultural areas. The research suggested many ideas for understanding patterns of pesticide occurrence and the factors that influence them (Gilliom, 2007). However, the research never mentioned anything about how to prevent or stop herbicides from being drained into streams and groundwater.

The study by Alavanja et al (2002) evaluates the relationship between 45 pesticides and prostate cancer incidence in a prospective group study. The findings clearly indicate that most of the pesticides are safe to use based on the model estimation except one pesticide. The Methyl Bromide is an insecticide used commonly in agriculture and was highly significant with prostate cancer risk for both North Carolina and Iowa. Their study demonstrates that the exploitation of particular pesticide use in agriculture could also have a significant impact on prostate cancer, however, it is difficult to associate the cancer risks to agricultural exposures. In general, most of the pesticide could be harmful to human body and a significant impact of human health if lack of knowledge to use or accidents associated with dosage rate. Considering the efficiency of pesticide use can benefit human health.

In the past one hundred years, most technical changes in agriculture focused upon improvements in plant biology and technology innovation. New technology developed for efficient input use could result in crop yield improvement. For example, efficient water irrigation systems improved crop yield and also helped farmers to gain the knowledge of crops' water use.

Levidow et al (2014) researched case studies with two important objectives; (1) how to encourage the farmers to be concerned about water efficiency and (2) how to improve water use efficiency and effectiveness. Accordingly, the research reviewed numerous case studies, concluding that innovative irrigation technologies could improve water use efficiency in agriculture. Due to the improvement of irrigation technologies, efficient water use could reduce non-point pollution so as to minimize agrochemical runoff as well as fertilizer leaching issues.

Interesting research done by Blum (2009) concluded that efficient use of water helps, however, effective use of water is even more beneficial as it improves crops' moisture, which increases sustainability in the productive growth stage. The effective use of water is critical for water source management and to maintain and improve crop yield.

Approximately, 22 percent of the farmland uses a groundwater irrigation system in the U.S. According to USDA (2016), agricultural operation uses more than 80 percent of the ground and surface water annually. This implies the water has an important role in increasing crop yield and that innovation and research developments have an important role in improving the efficiency and effectiveness of water use. Thus, specialists should develop a model to evaluate the environmental benefits of effective and efficient water use.

Alternative Approaches to Technical Efficiency

Before exploring the definition of Technical Efficiency, one needs to understand the concept of production frontier. The production frontier defines the maximum output (crop yield) that a farmer can attain given the level of each input in production (see in detail Coelli et al, 1998). Thus, TE measures where the farmer operates in relation to the production frontier. For instance, if a farm is technically efficient, the farmer produces crop yield on the yield frontier, or if a farm is not technically efficient, the crop yield is beneath the frontier. According to Coelli et al (1998), there are four popular approaches often used to measure efficiency; (1) least-squares econometric production models, (2) total factor productivity indices, (3) Data Envelopment Analysis (DEA), and (4) SFA. The first two approaches assume that all farmers are technically efficient, which is inappropriate for this analysis. The last two approaches assume that all farmers are not technically efficient and can be used to evaluate technical efficiency. Moreover, DEA and SFA are also able to evaluate changes in efficiency, if using panel data. The following literature focuses more on the distinction between DEA and SFA approaches and aims to highlight the advantages and disadvantages associated with both approaches.

The main differences of these two approaches are that SFA is a parametric approach that hypothesizes a functional form and utilizes the data to econometrically estimate the parameters of that function using the entire set of decision making units (DMUs), whereas DEA is non-parametric approach, which means that it utilizes mathematical programming in order to evaluate the efficiency frontier. The table 1 demonstrates the distinctions in detail.

Table 1. Basic Distinction between SFA and DEA

Summary for distinction between DEA and SFA approaches	
SFA	DEA
Parametric	Non-parametric
Able to test hypothesis	Not able to test hypothesis
Utilizes Maximum Likelihood Econometric estimation	Utilizes Mathematical programming
Catches specific noises (separates noise from efficiency scores)	Cannot catch specific noise (noise is effectively part of the efficiency score)
Can only accommodate single output with multiple inputs	Can accommodate multiple outputs and multiple inputs
Functional form needs to be specified	Functional form is not specified

Table note: Power point presentation source by Cordeiro et al (2008).

A lot of the literature analyzes the distinction between SFA and DEA for many different research areas. Coelli (1995) concluded that any of the efficiency estimation approaches do not perfectly estimate efficiency. Depending on the application, researchers choose the approach to evaluate the efficiency. His recommendation is that SFA is more proper to use in agriculture application because not all deviations from the frontier are due to inefficiency, due to measurement error and missing variables. In addition, SFA has an advantage of being able to conduct some of the important econometric tests, however, DEA has an advantage of evaluating efficiency for a farm that has more than one output. Finally, he cautioned that technical efficiency measurement could be influenced by many different sources even though any of these estimation approaches are applied. For instance, omitted inputs or errors in inputs, poorly measured price variables, and uncaptured data from environmental factors could bias technical efficiency measurement.

Chebil et al (2014) developed an empirical study to measure the irrigation water efficiency parametrically and non-parametrically from sample data of Tunisian wheat farms and to compare the results between them. While both approaches revealed similar empirical results, SFA had a slightly higher technical efficiency score. Even though the Spearman rank test revealed a positive and statistically significant result at one percent level in the technical efficiency scores of parametric and non-parametric approaches for irrigation water use from, both approaches' technical efficiency scores relationship varied based on the data sets and research applications. (Amara and Romain, 2000).

Depending on the large data sample, applications for research areas, and researchers' preference, a large number of empirical studies are available for evaluating the SFA and DEA results. However, a number of studies imply that technical efficiency scores significantly differ by approaches used in agricultural applications. The meta-analysis developed by Iliyasu et al (2014) to compare SFA and DEA with data from 36 technical efficiency articles on aquaculture. 14 percent of total cases had used the DEA approach and 86 percent of total case used the SFA. Their model indicated that the technical efficiency mean of DEA tends to be greater than SFA. This may be due to DEA not accounting for random noise, which may affect the accuracy of technical efficiency scores, or this may be due to unequal number of DEA and SFA studies.

Wadud and White (2000) compared the SFA and DEA empirical research for agriculture applications. The research used farm level data to measure rice farmers' efficiency in Bangladesh and also compared the SFA and DEA efficiency measures to explore any significant differences in the estimates of efficiency. They developed a production frontier model under specification of the Translog Stochastic Frontier Production function model with inefficiency effect model and Linear Programming model for the DEA with Constant Return to Scale (CRS) and Variable Return to Scale (VRS). The technical efficiency of rice farmers in Bangladesh revealed small decreasing returns to scale under the production frontier model and increasing and sudden decreasing returns to scale under the setup to DEA approach. Both models' mean technical efficiencies were slightly different such that the mean of SFA was 0.791 and the mean of DEA CRS and VRS were 0.789 and 0.858, respectively. The coefficients of rank correlation between the rankings of the technical efficiency estimates are all positive and highly significant under the Spearman rank correlation test. Similar to the results of Chebil et al. (2014), the accuracy of the technical efficiencies from the SFA model was slightly greater than from the estimation of the DEA model.

Stochastic Frontier Approach in Agricultural Research

The Stochastic Frontier approach was empirically initiated and estimated for production efficiency by Farrell (1957). After a while, two SFA papers were initially published from two different places in the same year: Meeusen and Broeck (1977) and Aigner, Lovell, and Schmidt (1977). Shortly after, a third paper was published by Battese and Corra (1977). Each of the three papers initially developed stochastic frontier production models that include a collected error structure with a two-sided symmetric and a one-sided component model. Moreover, the one sided component captures inefficiency, while the two-sided error captures the random effects outside of the production unit, which includes errors and statistical noise. Recently, there are a large number of papers contributing to the development of this particular approach and more powerful estimators are being developed based on it, which the next chapter will explore in detail.

Currently, a literature search in Google Scholar for SFA results in over 3000 publications. This implies SFA has been around for a while and is one of the preferred econometric estimators for efficiency analyses. According to the CAB Abstracts database, SFA has been used for 853 articles from 1987 to present and all articles directly relate to agricultural research studies. Over 500 articles focused on economic efficiency in agriculture and the rest of the articles focused on crop production and productivity, exploring particular crops efficiency, farm profitability, farm input efficiency, and socioeconomics. The following literature are reviewed specifically in order to explore how SFA is used in efficiency research as well as other research of interest.

Many papers employed SFA to evaluate economic efficiency, especially technical efficiency in developing and developed countries. Due to capital constraint in many developing countries, the improvement of the production efficiency may be easier than improvement of new technology to increase productivity. Wassie (2014) uses SFA to evaluate the major crops' production efficiency in Ethiopia, specifically, wheat, maize, barely, sorghum, and white tiff. He observed many developing countries have difficulty improving production productivity, because of capital limitations, however, working towards improving production efficiency can realistically be done. He did not specifically mention any reason why SFA was chosen in his research, however, he was satisfied with the results from SFA and concluded that there is a high potential to increase the technical efficiency for major crops grown in Ethiopia.

As mentioned previously, major research areas focus on particular crop's production efficiency, for instance, Baten and Hossian (2014) attempted to use SFA for evaluating the technical efficiency for three varieties of rice production in Bangladesh. In addition, they observed farmers in developing countries were not able to explore all technological resources, therefore, the farmers often make inefficient decisions in their farming. They used SFA because of the characteristics of their research, that is, they considered rice production in Bangladesh as a single output and production as multiple inputs. The multiple functional forms used for evaluating the relationship between inputs and outputs and the research were evaluated by the Cobb-Douglas functional form, since this functional form is preferable when dealing with many independent variables. Moreover, the research compared the distinction between Half Normal and Truncated Normal Distribution in the Cobb-Douglas Stochastic Frontier Model and evaluated the technical efficiency in rice production. Their results confirmed that technical efficiency of rice production in Bangladesh has increased from 1980 to 2009. Each variety of rice has different technical efficiency scores in two different distributions; the mean of technical efficiency was 0.92 for the truncated normal distribution, whereas the mean was 0.81 for the half-normal distribution. However, the authors conclude that the half-normal distribution was preferable to the truncated normal distribution, because it was more accurate in graphing the technical inefficiency as well as mapping the increasing efficiency rate over time.

Naqvi and Ashfaq (2013) evaluate the technical efficiency for corn production in Pakistan by employing the Cobb-Douglas Stochastic Frontier model. They observed that the current level of hybrid corn yield has a high potential for improving by increasing the technical efficiency, despite some constraints that exist, such as: unfavorable weather, poor management of input use, inexperience in planting corn, and insufficient fertilizer and weed control. The results revealed the average technical efficiency given by the Cobb-Douglas Stochastic Frontier model was 0.8106, which reveals a surprisingly high technical efficiency despite all of the constraints mentioned above. Furthermore, mature farmers tend to be more technically efficient than younger farmers; this may due to their good management skills, as the authors commented. More interestingly, the authors conclude that functional forms such as the Cobb-Douglas and Translog models could have completely different results for technical efficiency, therefore, it is very important to specify the data and also to test the outcomes of each functional form.

Hormozi, Assodar, Abdeshahi, and Baruan (2013) evaluated the technical efficiency for rice production in Iran, hypothesizing high consumption of energy inputs for rice production, thus, irrigation energy was considered one of the important inputs for improving the technical efficiency of rice production. The feature of this study aimed to compare energy input use in terms of improving technical efficiency in five different regions, with each region displaying different characteristics. They used the Cobb-Douglas stochastic frontier model and their reasoning for choosing this approach and functional form is similar to previous studies. Their findings in this particular study were that the machinery, labor, seed variety and irrigation water have a strong impact on the technical efficiency of rice production. However, irrigation water energy use input has a small and positive coefficient with strong significance, which did not meet their hypothesis. Surprisingly, the equipment cost of the water pump has a strong impact on technical inefficiency. Overall, technical efficiency of rice production in Iran has averaged 0.64 and has a high potential to increase technical efficiency at some level from 0.00 to 0.37. Lastly, wet seeding with poor drainage has the highest positive impact upon the energy use efficiency in order to produce rice more efficiently.

Rahman (2003) evaluated the profit efficiency of modern rice farmers in Bangladesh and also determined the impact of different inputs on technical efficiency. The researcher was interested in how Bangladesh farm styles changed from traditional to modern varieties of rice farms in order to increase rice yield. Moreover, the modern farm income has declined despite exploring more farmland, as well as utilizing new variety of rice seeds. Thus, he analyzed farm profit as a dependent variable and used the Stochastic Frontier model with Translog profit frontier functional form to evaluate the profit efficiency in response to direct inputs: seed, fertilizers, and chemicals, and indirect inputs: education, experience, and extension contact. Although there were not many significant effects for inputs' cross multiplication and inputs squared terms in the profit frontier model, the highlight of this research was including those addition independent variables. The overall research findings were the mean technical efficiency score of 0.77, implying modern rice farmers in Bangladesh have the potential to increase profit by improving economic efficiency. In addition, modern rice farmers are able to operate more efficiently if they have more experience with new varieties of rice, easy access to input markets, own farmland with better soil quality, and are persistent in their farming operations.

Bravo-Ureta and Pinheiro (1993) reviewed 30 papers that analyzed the efficiency in farm level data with 14 different developing countries included in their analyses. The review categorized the articles by two main subjects: (1) Deterministic Production Frontiers and (2) Stochastic Production Frontiers. They divided the Stochastic Production Frontiers section using three data sample specifications: (a) cross-sectional data, (b) panel data, and (c) dual frontiers. The authors highlighted some interesting methodology considerations based on the overall review. First, choosing the variables in the model is an important process to arriving at an accurate estimation of the economic efficiency, because farmers across the region or country are not the same in input sources as well as socio-economic characteristics. Second, model specification on either parametric or non-parametric model is also important for efficiency analysis. This consideration is addressed by the previous subsection in the thesis. However, the authors mention that the parametric model is not always a reliable estimator because the model does not account for statistical noises. Third, choosing the functional form is also another important process for deriving reliable results, even though the Cobb-Douglas functional form has been widely used in farm efficiency papers in developing and developed countries. Some research has been done for evaluating the outcomes from different functional forms and some concluded that very small difference was revealed in efficiencies. Fourth, assumptions made about the distribution affect the choice of model which may lead to different efficiency results. There are multiple types of distribution that can be assumed in the efficiency model: half normal, truncated normal, exponential, and gamma distribution. Fifth, a researcher must choose whether to use a two-step versus one step procedure for examining the determinants of efficiency. The idea was that socioeconomic variables may have a direct impact on farm efficiency and instead of adding the second procedure for evaluating the impact of socioeconomic variables on efficiency, a researcher may regress directly on the production frontier model in some cases. Sixth, another consideration associated with cross-sectional data is that a single period may be biased by period specific abnormalities. If this occurs, model accuracy would fail. In general, most papers revealed that the mean of technical efficiency from cross-sectional and panel data differed, and panel data with Stochastic frontier model tends to have a higher mean than cross-sectional ones. The last consideration addressed in the paper relates to a distinction between the single equation model and the system equation model. Both have noticeable advantages and disadvantages. For instance, the system of equation has a potential for better asymptotic efficiency than the single equation, however, the single equation better estimates farm level inefficiency. The overall conclusion was that most farmers in developing countries have the potential to increase their efficiency in order to maximize the farm output, while avoiding increasing the inputs and new technologies.

Due to land degradation increasing from farm productivity in most developed countries, the farm production cost has gradually increased by including the following inputs: seed, fertilizer, pesticides, energies, water irrigation, machinery and equipment, and farmland. (Naylor 1996). On the other hand, Nehring, Barnard, Banker, and Breneman (2006) observed that urban development have a direct effect on active farmland, which remains spread amongst nonfarm development. For instance, an estimate of the cost of farmland in the Corn Belt and between rural and urban land prices showed that urban farmland was valued 67 percent higher per acre than rural farmland. In addition, urban development has an impact of more than eight percent on farm variable cost per acre, and according to the estimation of Barnard, 159 million acres of farmland is being affected by urban development. Based on these drawbacks, the research employed SFA to estimate the impact of urban influence on the cost of crop production for traditional corn and soybean farmers in the Corn Belt. The research assumed that urban development has been decreasing the technical efficiency for corn and soybean farms in the research area. Based on the Stochastic Production Frontier analysis, the research found that urban development increased by ten percent, decreasing the technical efficiency of the traditional farm by more than four percent. Moreover, traditional corn, soybean and livestock farms encounter lower technical efficiency, lower productivity as well as lower returns on assets. However, some urban influenced farms have greater technical efficiency scores by increasing their cost effectiveness, deemphasizing their livestock operations, and increasing their grain operations.

Another interesting research study was conducted by Power and Cacho (2013). The research utilized SFA to evaluate the risk-efficiency of crop strategies based on a case study of major crops grown in Southern Queensland, Australia. The authors pointed out that farm business risk has been evaluated by stochastic simulation inappropriately in most cases, because of not accounting for random statistical noise from selected optimal strategies in the presence of uncertainty. Thus, the research resolves this issue by accounting for the statistical noise using SFA while ranking the outputs of a bioeconomic model. The research first developed the bioeconomic model in order to evaluate a sensitivity analysis of the important farm input and output variables and rank the variables in terms of farm profitability. Then, they employed SFA to evaluate the risk-efficiency in order to investigate the effects of management on the trade-offs between farm profit and risk. Basically, this research is unique since it uses the Stochastic Risk Frontier in terms of risk efficiency measurement based on the development of the bioeconomic model. The overall policy implication of the research concludes based on the risk efficiency frontier relative to different strategies, that local farmers can allocate their farmland and water source between cropping enterprises. The results indicated that cotton was the riskiest crop with the highest potential profitability compared to corn, sorghum, and wheat. Moreover, the profitability of cotton, wheat and corn production has a negative relationship with risk-efficiency because of the requirement of severe water, however, the only difference was that cotton has a higher magnitude than corn and wheat. Sorghum production did not show any effect on efficiency difference when changing the region. The research found 25 risk-efficient strategies that could increase the farm profit by $50,000.00 without increasing the farm business risk.

Thus far, this subsection reviewed several types of research that employ the SFA and discovered that the approach has been widely used for numerous objectives within many sectors of agricultural research. Furthermore, the approach is commonly used for measuring technical efficiency, although some methodology developed a more advanced frontier model to measure different objectives relative to the efficiency analysis. One example included above developed the risk frontier model to evaluate the risk-efficiency in response to choosing different crops. Many frontier models have been developed to measure the efficiency of their object. A large number of frontier analyses use the SFA, thus, this thesis chose to review only the ones directly relevant to the objectives in this subsection.

CHAPTER III. METHODOLOGY

Introduction

The objective of the research is to evaluate the yield efficiency of the three dominant crops grown in North Dakota: HRS wheat, corn grain, and soybeans, and to develop the yield efficiency frontier for each of the three crops. This chapter develops the yield frontier models based on the general stochastic frontier production function. First, the chapter discusses the conceptual framework, which explains the fundamental of production economic theory and Cobb-Douglas production function. Moreover, stochastic production frontier is theoretically explained as fundamental model for the yield frontier model. Second, empirical models and procedures will be discussed. Maximum Likelihood, translog functional form, yield frontier empirical model are addressed in detail. In addition, Log Likelihood hypothesis test and the procedure for the consistent farming operation are explained as well. Lastly, the explanations for data source, data type, distribution of observations in regions, cost data deflation method and weather data collection are well presented. Finally, due to large size of the dataset, the descriptive statistics for each three crop's dataset are not placed in this chapter, however, they are located in Appendix A.

Conceptual Framework

This subsection is going to explore the production possibilities of single output farms that can be demonstrated using a production function. The production function is considered in microeconomic theory, which is used to formalize the relationship between farm inputs and outputs. Farms utilize different amounts of multiple inputs: land, labor, capital, and raw materials, to produce a single output, and the farm's production function can be specified as:

$$q = f(X) \tag{1}$$

Where q represents the output and $X = (x_1, x_2, x_3, \ldots\ldots, x_n)$ is a $N \times 1$ vector of inputs.

Based on the production function, Aigner and Chu (1968) developed a Cobb-Douglas production frontier model, which presented as:

$$lnq_i = X_i'\beta - u_i \tag{2}$$

Where q represents the output of the ith farm; and X_i is a $K \times 1$ vector containing the logarithms of inputs; β is a vector of unknown parameters, and u_i is a non-negative random variable associated with technical inefficiency. Afterwards, Aigner, Lovell and Schmidt (1977) and Meeusen and Van den Broeck (1977) proposed the stochastic frontier production model, which is represented as:

$$lnq_i = X_i'\beta + v_i - u_i \tag{3}$$

This model is similar to model (2) except v_i defined as a symmetric random error, which determines the statistical noise. According to Coelli et al (1998), the stochastic (random) variable $\exp(X_i'\beta + v_i)$ determines the upper or lower bound of the output value of the stochastic frontier production function. Thus, a sign of v_i can be negative or positive and stochastic frontier differs depending on the deterministic part of the model, $exp(X_i'\beta)$.

Certain assumptions are held in order to estimate these two random terms: each v_i is distributed independently of each u_i and both errors are not correlated with the explanatory variables in X_i. In addition, the following assumptions have to hold:

$$E(v_i) = 0, \text{ Zero mean} \tag{4}$$

$$E(v_i^2) = 0, \text{ Homoskedastic} \tag{5}$$

$$E(v_i v_j) = 0,\ for\ all\ i \neq j, \text{ Not correlated} \tag{6}$$

$$E(u_i) = constant, \text{ Homoskedastic} \tag{7}$$

and $$E(u_i u_j) = 0, for\ all\ i \neq j, \text{ Not correlated} \tag{8}$$

In order to illustrate the important concept of the stochastic frontier model, let us consider it graphically and by breaking down the Cobb-Douglas stochastic frontier model in the form:

$$lnq_i = \beta_0 + \beta_1 \ln x_i + v_i - u_i \tag{9}$$

$$\text{or } q_i = exp(\beta_0 + \beta_1 \ln x_i) * \exp(v_i) * \exp(u_i) \tag{10}$$

$exp(\beta_0 + \beta_1 \ln x_i)$ presents deterministic component,

$\exp(v_i)$ presents statistical noise, and $\exp(u_i)$ presents technical inefficiency.

Figure 7 illustrates how the Stochastic Production Frontier model works graphically; the figure is from a book written by Coelli et al (2005). The graph demonstrates two individual farms. Farm A uses input level x_A to produce the output q_A, while farm B uses the input level x_B to produce the output q_B; these values are represented by the small (x). If both farms were not inefficient, then the outputs would be on the production frontier; the function forms are presented below:

$$q_A^* \equiv exp(\beta_0 + \beta_1 \ln x_A + v_A) \; and \; q_B^* \equiv exp(\beta_0 + \beta_1 \ln x_B + x_B)$$

Present for farm A and B respectively and the values represented by circled small (x).

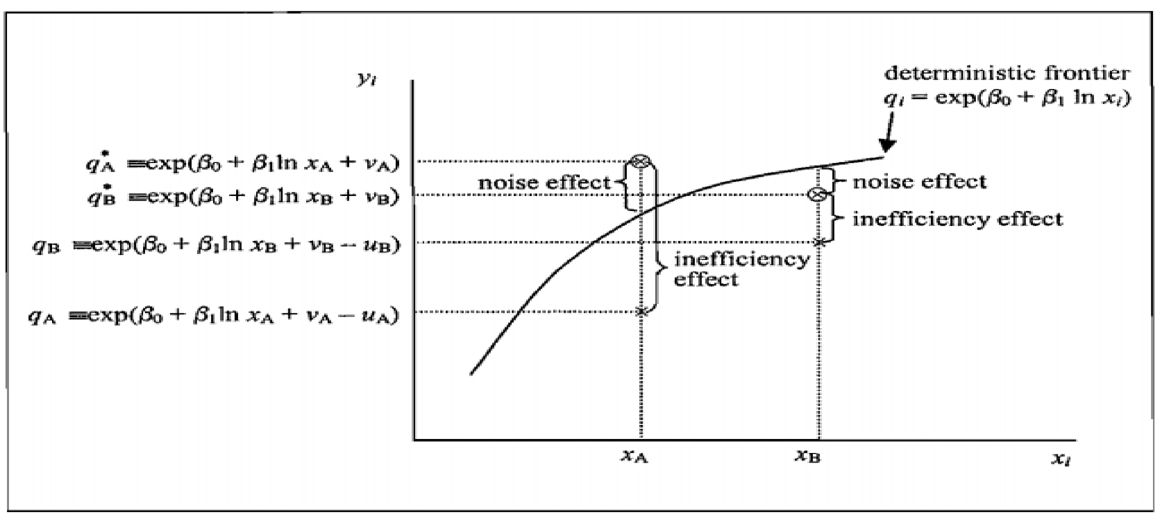

Figure 7. Stochastic Production Frontier. Source: Coelli et al (2005).

Based on Figure 7, if noise effect is positive, then farm the lies above the deterministic production frontier, which occurred for farm A, whereas farm B lies below the frontier, implying a negative noise effect. The observed output for farm A lies below the frontier, because of the sum of the noise effects and inefficiency effects is negative. The only case where observed outputs lie above the deterministic production frontier when the noise effect is positive and larger than the inefficiency effect. This is represented by $q_i^* > exp(X_i'\beta) iff \; \epsilon_i \equiv v_i - u_i > 0$).

Since the research deals with a panel data sample, the model takes into account the panel data using the panel data form developed by Aigner, Lovell, and Schmidt (1977), whose panel data model presents more efficient estimators of the unknown parameters and more efficient predictors of technical efficiencies. The model is represented as:

$$lnq_i = X_{it}'\beta + v_{it} - u_{it} \tag{11}$$

This model is similar to model (3) except the addition of the subscript(t), which represents the time period. The model assumes the v_{it}'s and u_{it}'s are independently distributed in order to estimate the technical efficiency as well as change in efficiency.

Given this background on the stochastic production frontier model, it is capable of developing the output-oriented technical efficiency measure, which is derived from the ratio of the observed output to the corresponding stochastic frontier output:

$$TE_i = \frac{q_i}{exp(X_i'\beta + v_i)} = \frac{exp(X_i'\beta + v_i - u_i)}{exp(X_i'\beta + v_i)} = \exp(-u_i) \tag{12}$$

The technical efficiency score takes the value between zero and one. When the score is close to 1, it implies that the farm is technically efficient in producing the output given a level of input. When the score is near 0, it implies that a farm has potential to increase the output to some degree without increasing the amount of inputs.

Empirical Model and Procedures

Under the assumptions from (4) through (5), a maximum likelihood estimator satisfies the distributional assumptions for two error terms and offers large data sample asymptotic properties, thus it is preferred to other estimators such as Corrected Ordinary Least Squares (COLS). Aigner, Lovell, and Schmidt (1977) generated the Maximum likelihood estimation under additional assumptions; first, v_i's are independently and identically distributed normal random variables with zero means and variances σ_v^2, and second, u_i's are independently and identically distributed half-normal random variables with a scale parameter of σ_u^2. Moreover, estimated parameters from the log-likelihood function in terms of $\sigma^2 = \sigma_v^2 + \sigma_u^2 \ and \ \lambda^2 = \sigma_u^2/\sigma_v^2 \geq 0$. If $\lambda = 0$, then there is no technical inefficiency effect and all deviations from the frontier are due to statistical noise. Therefore, the log-likelihood function form is presented as:

$$lnL(y|\beta,\sigma,\lambda) = -\frac{I}{2}\ln\left(\frac{\pi\sigma^2}{2}\right) + \sum_{i=1}^{I} ln\Phi(-\frac{\varepsilon_i\lambda}{\sigma}) - \frac{1}{2\sigma^2}\sum_{i=1}^{I}\varepsilon_i^2 \quad (13)$$

where y is a vector of log-outputs; $\varepsilon_i \equiv v_i - u_i = lnq_i - x_i'\beta$ is a composite error term, and $\Phi\ (x)$ is the cumulative distribution function of the standard normal random variable evaluated at x. The model cannot analytically solve $\beta, \sigma, and\ \lambda$, because the first-order condition has a nonlinear relationship. Therefore, model 8 uses the iteration optimization procedure and this procedure systematically updates the values for the unknown parameter until the log-likelihood function values are maximized. This procedure is explained in detail by Judge (1985).

The research uses a translog production function form in the empirical model, which is generalized from the Cobb-Douglas function and is commonly used in econometrics for an efficiency measure.

The function form for the empirical translog production frontier model with panel data is:

$$lnq_i = \alpha_0 + \sum_{i=1}^{N} \alpha_i \, lnP_i + \sum_{j=1}^{N} \alpha_j \, lnQ_j + \frac{1}{2}\sum_{i=1}^{N} \sum_{l=1}^{N} \gamma_{il} \, lnP_i lnP_j +$$

$$+ \frac{1}{2}\sum_{j=1}^{N} \sum_{z=1}^{N} \gamma_{jz} \, lnQ_j lnQ_z + \sum_{i=1}^{N} \sum_{l=1}^{N} \delta_{il} \, lnP_i lnP_j + v_i - u_i \tag{14}$$

where lnq_i is the natural logarithm of crop yield, α_0 is the unknown interpret, $\alpha_i lnP_i$ is the unknown parameter with natural logarithms for the input cost variables, $\alpha_j lnQ_j$ is the unknown parameter with natural logarithms for the inputs quantity variables, $\gamma_{il} lnP_i lnP_j$ is the unknown natural logarithms with input cost variables in squared terms, $\gamma_{jz} \, lnQ_j lnQ_z$ is the unknown natural logarithms with input quantity variables in squared terms, $\delta_{il} lnP_i lnP_j$ is the unknown natural logarithms with input cost variables in cross multiplication terms, v_i is the two-sided random error, and u_i is the one-sided half-normal error. Theoretically, v_i is assumed to be iid $N(0, \sigma_v^2)$ random errors and independently distributed of the u_i. Moreover, u_i is non-negative random variables and it is associated with technical inefficiency of production. u_i is also assumed to be independently distributed, which is obtained by $u_i \sim iidG(\lambda, 0)$; exponential with mean λ (Coelli et al., 2005).

Based on these generalizations of the translog production frontier model, the research develops the yield frontier models for each of the three dominant crops, presented as:

$$lnCY' = \alpha_0 + \sum_{i=1}^{6} \alpha_i \, lnP_i' + \sum_{j=1}^{3} \alpha_j \, lnQ_j' + \frac{1}{2}\sum_{i=1}^{6} \sum_{l=1}^{6} \gamma_{il} \, lnP_i' lnP_l' +$$

$$+ \frac{1}{2}\sum_{j=1}^{2} \sum_{z=1}^{2} \gamma_{jz} \, lnQ_j' lnQ_z' + \sum_{i=1}^{7} \sum_{l=1}^{7} \delta_{il} \, lnP_i' lnP_l' + v_i - u_i \tag{15}$$

$$lnSY' = \alpha_0 + \sum_{i=1}^{6} \alpha_i \, lnP_i' + \sum_{j=1}^{3} \alpha_j \, lnQ_j' + \frac{1}{2}\sum_{i=1}^{6} \sum_{l=1}^{6} \gamma_{il} \, lnP_i' lnP_l' +$$

$$+ \frac{1}{2}\sum_{j=1}^{2} \sum_{z=1}^{2} \gamma_{jz} \, lnQ_j' lnQ_z' + \sum_{i=1}^{10} \sum_{l=1}^{10} \delta_{il} \, lnP_i' lnP_l' + v_i - u_i \tag{16}$$

$$lnWY' = \alpha_0 + \sum_{i=1}^{5} \alpha_i \, lnP_i' + \sum_{j=1}^{2} \alpha_j \, lnQ_j' + \frac{1}{2}\sum_{i=1}^{5}\sum_{l=1}^{5} \gamma_{il} \, lnP_i' lnP_l' +$$

$$+ \frac{1}{2}\sum_{j=1}^{1}\sum_{z=1}^{1} \gamma_{jz} \, lnQ_j' lnQ_z' + \sum_{i=1}^{5}\sum_{l=1}^{5} \delta_{il} \, lnP_i' lnP_l' + v_i - u_i \quad (17)$$

Model 15 represents the corn yield model, where $lnCY'$ is the predicted natural logarithm of corn yield, α_0 is the estimated interpret, $\alpha_i lnP_i'$ is the estimated parameter with natural logarithms for the following inputs' costs: seed, pesticide, fertilizer, mechanical maintenance, labor, and farm insurance, $\alpha_j lnQ_j'$ is the estimated parameter with natural logarithms for the following inputs: farmland size, average temperature and total rainfall in growing season, $\gamma_{il} lnP_i' lnP_l'$ is the estimated natural logarithms with input cost variables in squared terms, $\gamma_{jz} \, lnQ_j' lnQ_z'$ is the estimated natural logarithms with input variables in squared terms, $\chi_{il} lnP_i' lnP_l'$ is the estimated natural logarithms with input cost variables in cross multiplication terms, v_i is the two-sided random error, and u_i is the one-sided half-normal error.

Model 16 presents the soybean yield model, where $lnSY'$ is the predicted natural logarithm soybean yield, $\alpha_i lnP_i'$ is the estimated parameter with natural logarithms for the following input costs: seed, fertilizer, crop insurance, mechanical maintenance, labor, and crop and farm insurance, $\alpha_j lnQ_j'$ is the estimated parameter with natural logarithms for the following inputs: farmland size, average temperature and total rainfall in growing season, $\gamma_{il} lnP_i' lnP_l'$ is the estimated natural logarithms with inputs cost variables in squared terms, $\gamma_{jz} \, lnQ_j' lnQ_z'$ is the estimated natural logarithms with inputs variables in squared terms, $\chi_{il} lnP_i' lnP_l'$ is the estimated natural logarithms with input cost variables in cross multiplication terms, v_i is the two-sided random error, and u_i is the one-sided half-normal error.

Model 17 presents the HRS wheat yield model, where $lnWY'$ is the predicted natural logarithms HRSW yield, $\alpha_i lnP_i'$ is the estimated parameter with natural logarithms for the following input costs: pesticide, fertilizer, crop insurance, labor, and crop and farm insurance, $\alpha_j lnQ'_j$ is the estimated parameter with natural logarithms for the following inputs: average temperature and total rainfall in growing season, $\gamma_{il} lnP'_i lnP'_l$ is the estimated natural logarithms with input cost variables in squared terms, $\gamma_{jz}\ lnQ'_j lnQ'_z$ is the estimated natural logarithms with input variables in squared terms, $\chi_{il} lnP'_i lnP'_l$ is the estimated natural logarithms with input cost variables in cross multiplication terms, v_i is the two-sided random error, and u_i is the one-sided half-normal error.

Each statistically insignificant parameter from the three base models are tested by the log likelihood ratio test in order to evaluate the estimated those parameters: $H_0: \beta_n = 0$ versus $H_1: \beta_n \neq 0$, and the mathematical formula used is:

$$\chi^2_{LRT} = -2\{\log[\max_{\theta \epsilon \Omega_0}(f(x|\theta = \theta_0))] - \log[f(x|\theta = \hat{\theta})]\} \tag{18}$$

where χ^2_{LRT} is the chi-square estimated value from the likelihood ratio test and the value derives from negative two times the difference between the log likelihood value of the unrestricted model and the log likelihood value of the restricted model. If the chi-square value is greater than the chi-square table value with the proper degrees of freedom, then we reject a null hypothesis, which implies that the tested parameters are statistically significant in conjunction in the model. Therefore, the variables should be included, even though the t-values of the variables are still statistically insignificant by themselves in the model.

The yield frontier models 15, 16 and 17 passed the log likelihood ratio test and can estimate technical efficiency for corn, soybean and HRS wheat farmers in ND. Furthermore, each model enhanced the accuracy of estimation and leads to an even more parsimonious model. Noticeably, each translog yield frontier model should not have the same number of independents after testing is done because all the corresponding independent variables unequally passed the log likelihood ratio test in each model. Statistical Analysis System (SAS) is the main software tool for solving all the econometric estimations. Under the software, the Qualitative and Limited Dependent Variable model (QLIM) provides the procedure that supports the stochastic production frontier model (QLIM, 2014). Thus, the model is appropriate to use in the research in order to solve the yield frontier models and to generate the technical efficiency scores for each of the three crop's yield improvement.

Consistency on Efficient Farms

The research has multiple objectives, however, one of the objectives focuses on the overall efficient farm performance from 1994 to 2015. In other words, based on the technical efficiency score of the yield efficiency frontier models, the research is able to identify the farms that have a consistently high technical efficiency in the past 22 years. In order to implement this objective, the research is going to divide all the technical efficiency scores by three criteria: (1) scores equal to and greater than 0.75, (2) scores in between 0.50 and 0.75, and (3) scores equal to and less than 0.50. This procedure applies to each of the three crops' technical efficiency scores. Thus, the research can provide information on how many and what percent of farmers are being technically efficient for these three criteria within each year. Furthermore, the consistency of farms being technically efficient is found by the number of times a farm is technically efficient in the past 22 years. The research uses selected three criteria for consistency evaluation and this evaluation is used for all three crop. The procedure used for the three criteria and the consistency evaluation uses the simple sorting function and pivot table function in Microsoft Excel.

Data

The data used for the research was obtained from two main sources: NDFBMEP and NDAWN. North Dakota Farm Business Education Management program provides educational assistance for farm owners and producers to help them meet their business and financial goals. The program provides assistance through four main areas: business and family goal setting, farm and ranch business accounting, farm a ranch planning, and business analysis (NDFBMEP, 2011). The program has been collecting data from the farmers who have enrolled in the program since 1989. Every year, the number of farmers change and every farmer reports the record differently such that some submit general farm records while others provide detailed farm records for the enterprise analysis (Bayde, 2003).

The North Dakota Agricultural Weather Network contains 72 stations distributed across North Dakota state and all stations monitor and record local weather conditions and distribute these to provide accurate weather data and reports to the local civilians. Moreover, the NDAWN was initially designed to provide records for model development and operational use for agricultural purposes. According to the information and models provided by the NDAWN, local agricultural producers are able to monitor the weather conditions, which helps them make better decisions in managing their farm operations. (NDAWN, 2016).

The research collected and organized the three panel dataset for the three crops from the NDFBME program's data records and NDAWN's data records. The panel dataset is unbalanced, consisting of farm inputs and outputs and weather data from 1994 to 2015. Moreover, the state's total land is divided by nine different regions in each dataset: northwest, north central, northeast, north valley, southwest, south central, southeast, south valley, and east central. The research developed these nine regions based on the map for North Dakota Crop Budget Regions. The projected budgets for crop and livestock are created annually by NDFBMEP (2016) and projected budgets for each different crops vary from one region to another region. The crop budget regions' map is presented in Figure 8.

Figure 8. North Dakota Crop Budget Regions.

Since each of the three dataset is unbalanced, each region and each year have a different number of observations and each observation is not necessarily captured in each year and year regions. Therefore, Table 2 explains the overall distribution for each of the three crops' observations based on the region:

Table 2. Distributed Numbers of Observation in Each Region

Regions	1 (NW)	2 (NC)	3 (NE)	4 (SW)	5 (SC)	6 (SE)	7 (SV)	8 (NV)	9 (EC)	Total
corn	2	229	91	194	128	198	552	22	361	1777
soybean	6	295	230	23	127	164	715	41	468	2069
HRSW	45	1035	317	533	293	212	505	70	629	3639

Note: Numbers of observations for each region varied, because each regions have different crops every year.

The total number of observations for corn, soybeans, and HRSW to evaluate the yield frontier model is 1777, 2069, and 3639, respectively, for a total of 7488 observations for all three panel datasets are combined.

North Dakota is a land rich state, where every region has a relatively different soil type and agro-climatic condition. Each region has a different competitive advantage for one crop over another, for instance, the farm in northwestern North Dakota tends to have more wheat fields, whereas, south and southeastern North Dakota tends to have more corn and soybean fields.

To evaluate the technical efficiency from the three crop yield efficiency frontier models, farm data and weather data are combined to obtain 11 independent variables and one dependent variables for the each three model. The dependent variables for the each three model are crop yield, soybean yield, and HRS wheat yield. The independent variables for the each three model are the following variables: seed cost, fertilizer cost, chemical cost, fuel and oil cost, maintenance and repair cost, labor cost, crop insurance cost, farm insurance cost, crop acreage, weather temperature, and precipitation. The dependent variables are measured in bushel per acre and all cost independent variables are measured in dollar per acre. The weather temperature and precipitation are measured as average temperatures in each region within crop growing season and total rainfall in each region within crop growing season, respectively, these two variables are going to be discussed presently in detail. Lastly, the crop acreage variable is measured as one acre per crop field. In order to estimate the unbiased estimate of technical efficiency, the research has deflated the input cost variables with the base year of 2015. The year 2015 is selected to be a base year, because it is the most current year in the dataset. Based on the Gross Domestic Product (GDP) deflator, the research utilizes this formula:

$$GDP\ deflator = \frac{Nominal\ GDP}{Real\ GDP} * 100 \tag{19}$$

where the GDP deflator measures price inflation, nominal GDP is the market value of goods and services unadjusted for inflation, and the real GDP is the nominal GDP adjusted for inflation to reflect changes in the real output (Goodwin, Nelson, Harris, Torras, & Roach, 2013). In the research, all input cost variables are deflated by the following equation:

$$Input\ \widehat{costs}\ of\ year_1^{21} = \frac{deflated\ year\ of\ 2015}{deflated\ year_1^{21}} * input\ price\ of\ year_1^{21} \tag{20}$$

where input costs of year[21] is the adjusted input costs for each of the 21 years from 1994 to 2014, and the deflated year of 2015 is the adjusted market value of goods and services in the year 2015, and the deflated year[21] is the adjusted market value of goods and services for each of the 21 years from 1994 to 2014, and the input price of year[21] is the unadjusted input cost for each of the 21 years from 1994 to 2014. The real GDP adjusted market value of goods and services in each year is calculated by the Standard and Poor's 500 index (S&P 500); the index table is provided by the GDP Deflator by Year (2015).

The research mentioned earlier a detailed explanation of how weather variables are processed and why temperature and precipitation vary by region, etc. North Dakota state is divided by six different weather zones and each zone consists of multiple weather stations that provide data to NDAWN.

Figure 9 represents the map of North Dakota state that divided by six different weather zones. Each zone has its own weather information and has certain counties in it. For instance, zone 1 has five counties that averaged a total rainfall of 11.25 inches and a temperature of 60.04 Fahrenheit across the past 22 years. The rest of the zones can be explained in a similar way. Weather variables' data varies each year, which makes it difficult to include in a weather data zone

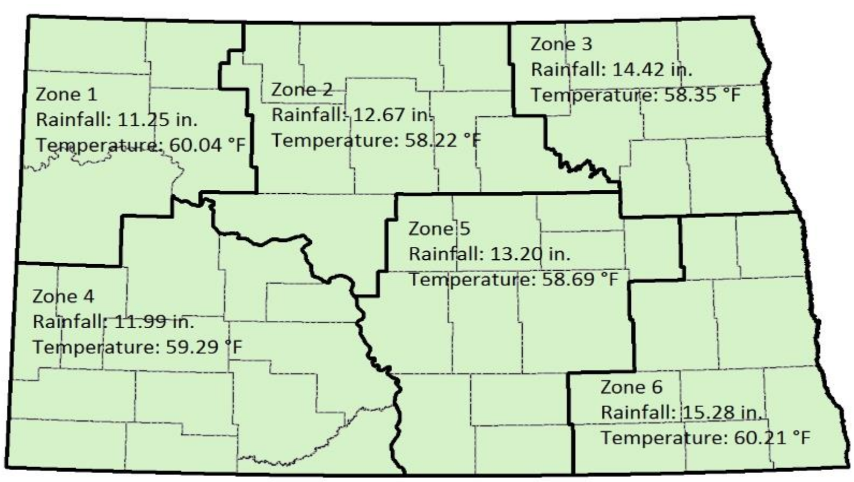

Figure 9. Weather Data Zones

map, thus, Figure 9 merely summarizes weather data and the weather zones. The temperature data is collected as a monthly average and precipitation is collected as monthly total rainfall. Since the research is merely concentrating on the crop growing season, data is only collected from April to September each year. All stations' temperatures and total rainfall for the growing season each year are averaged in order to determine the average temperature and total rainfall for each weather zone.

Table A1, A2, A3, and A4 provide descriptive statistics for the output and inputs for each crop dataset for variables that were used in the yield efficiency frontier models. Due to the large volume of the dataset, the research placed them in Appendix A.

Summary

Technical efficiency for all farms in each of the three panel datasets across the nine different regions and over the 22 period (1994-2015) were generated using SAS software with QLIM procedure. The econometric models were employed to estimate the relationship between crop yield and crop input costs, crop acreage size, and weather variables. Lastly, technical efficiency farm consistency evaluation was discussed and procedures were explained. Results and findings for the research are presented and discussed in the next chapter.

CHAPTER IV. RESULTS

Introduction

This chapter has four sections. First, the estimated econometric results for each of the three empirical models are presented and the relationship between crop yield inefficiency and selected independent variables are interpreted. Second, each of the three crops' efficient yield frontiers are graphically presented for each year and each region. Moreover, the graphical comparison between predicted yield and actual yield for each crop is presented as well. Lastly, the distribution of the farm efficiency scores are presented based on the three criteria for each year and each region. In addition, farm technically efficient consistency is presented.

Econometric Estimations

Maximum Likelihood estimation estimates the elasticity effect of selected independent variables on the three crop yields. Each of three crops' yield frontier model fit summaries are presented in table 3, 6, and 9. The results of corn, soybean, and HRS wheat yield frontier model are presented in table 4, 7, and 10, respectively. Since the research used the translog production function, elasticity is the appropriate way to interpret parameters by accumulating the coefficients of parameter in terms of the input identities for each of the three models. Table 5, 8, and 11 represents the summary for accumulated elasticity effect of the independent variables for the corn, soybean, and HRS Wheat yield in the model, respectively.

Table 3 presents the statistical fit summary for the corn yield frontier model. A total of 1785 observations are used in the model and the log likelihood value is -726.99. Log likelihood value has no meaning for model fit, however it is useful for testing the model performance and identifying the joint significance from insignificant individual variables in the model.

Table 3. Corn Yield Frontier Model Fit Summary	
Number of Observations	1785
Log Likelihood	-726.99993
Maximum Absolute Gradient	0.00276
Number of Iterations	181
Optimization Method	Dual Quasi-Newton
AIC	1508
Schwarz Criterion	1656
Sigma	0.46808
Lambda	4.59579
Algorithm	Converged
Number of LR testing	12
χ^2_{LRT}	25.08496

Based on the interpretation of Coelli et al (2005), the Maximum Absolute Gradient and Number of Iteration are explained after 181 iterations, when the estimated gradients are all close to zero, which implies that first-order derivatives of the log-likelihood function with respect to the parameters are very close to zero value. Optimization method is called Dual Quasi-Newton and this optimization algorithm works well in medium and large optimization problem by allowing a much faster computing gradient, thus it requires more iterations than other methods. Akaike Information Criterion (AIC) has a value of 1508 and Schwarz Criterion (SC) has a value of 1656. Both values have no meaning themselves towards explaining model fit, however, both are useful for comparing two or more models and prefer models with a minimum value of AIC and SC. In fact, both criterions' values are smaller than the values of an unrestricted model, thus, both revealed that the corn yield frontier model is definitely considered a more parsimonious model. The model fit summaries for the three crop yield frontier unrestricted models are attached in Appendix B, if further reference is needed. Sigma is the standard deviation of the error and sigma has a value of 0.4681 (σ = 0.4681), which implies that the probability of error is 46.8 percent for estimating the standard deviation. Lambda is an inefficiency parameter and is a calculation of the ratio the standard deviation of the inefficiency term to the standard deviation of the stochastic term, (λ =

4.5957), thus, standard deviation of the inefficiency effect is much larger than statistical noise (4.59 versus 1). In order to evaluate the goodness of fit to the model, likelihood ratio test used in 12 times for testing the statistically insignificant parameters from the unrestricted model. Likelihood ratio test of chi-square value is 25.08 with 25 degrees of freedom. Since 25.08 is smaller than the chi-square table values of 34.38 ($p<0.10$), 37.65 ($p<0.05$), and 44.31 ($p<0.01$), we reject the $H_1: \beta_n \neq 0$. This means that the selected 25 variables from the unrestricted model were statistically insignificant have no joint explanatory power for the results of corn frontier model as well as goodness of fit to the model. Thus, the current corn yield frontier model can predict the technical efficiency without including those variables.

Table 4 presents the estimated results for the corn yield frontier model. The model estimated a total of 28 parameter including a dependent variable, independent variables, and two error terms (v and u). 14 out of 28 parameters are statistically significant; specifically, 10 of 14 are at the 1% significance level, 2 out of 14 are at the 5% significance level, and 2 out 14 are at the 10% significance level in the model. Sigma v is the statistical noise effect in the model and has a value of 0.100 with a 1% significance level. Sigma u is the inefficiency effect in the model and has value of 0.457 with a 1 % significance level. According to the hypothesis test on the sigma u, SFA is an appropriate approach to use to model the agricultural production analysis. Because sigma u indicates that there is one sided error term that represents technical inefficiency.

Table 4. Maximum Likelihood Estimation of Corn Yield Frontier Model

Dependent Variable	Mean	St. Error				
$lnCY'$	4.480714	1.21769				
Independent Variables	**Parameter**	**Estimate**	**St.Error**	**t-Value**	**Pr > |t|**	
Intercept	α_0	-14.036	2.059	-6.820	<.0001	***
lnP'_S	α_S	0.252	0.275	0.920	0.360	
lnP'_C	α_C	0.111	0.073	1.520	0.130	
lnP'_F	α_F	0.174	0.105	1.660	0.098	*
lnP'_M	α_M	0.017	0.114	0.150	0.882	
lnP'_L	α_L	0.124	0.043	2.880	0.004	***
lnP'_{Fi}	α_{Fi}	0.145	0.054	2.710	0.007	***
$1/2\ lnP'_S * lnP'_S$	γ_{SS}	-0.019	0.033	-0.580	0.559	
$1/2\ lnP'_C * lnP'_C$	γ_{CC}	-0.018	0.012	-1.480	0.138	
$1/2\ lnP'_F * lnP'_F$	γ_{FF}	0.017	0.012	1.460	0.145	
$1/2\ lnP'_M * lnP'_M$	γ_{MM}	0.023	0.009	2.640	0.008	***
$1/2\ lnP'_L * lnP'_L$	γ_{LL}	0.000	0.002	0.140	0.889	
$1/2\ lnP'_{Fi} * lnP'_{Fi}$	γ_{FiFi}	-0.001	0.004	-0.150	0.880	
$lnP'_S * lnP'_M$	χ_{SM}	0.036	0.038	0.940	0.348	
$lnP'_S * lnP'_L$	χ_{SL}	-0.034	0.011	-3.020	0.003	***
$lnP'_F * lnP'_M$	χ_{FM}	-0.065	0.028	-2.350	0.019	**
$lnP'_I * lnP'_L$	χ_{IL}	0.006	0.003	1.890	0.058	*
$lnP'_M * lnP'_{Fi}$	χ_{MFi}	-0.031	0.015	-2.050	0.040	**
$lnP'_M * lnP'_L$	χ_{ML}	0.006	0.006	1.000	0.320	
$lnP'_L * lnP'_{Fi}$	χ_{LFi}	-0.005	0.005	-0.970	0.334	
lnQ'_A	α_A	0.031	0.025	1.220	0.223	
$1/2 lnQ'_A lnQ'_A$	γ_{AA}	-0.001	0.002	-0.390	0.700	
lnQ'_T	α_T	2.443	0.229	10.650	<.0001	***
lnQ'_P	α_P	2.850	0.614	4.650	<.0001	***
$1/2 lnQ'_P lnQ'_P$	γ_{PP}	-0.289	0.068	-4.280	<.0001	***
Sigma v	v_i	0.100	0.005	18.720	<.0001	***
Sigma u	u_i	0.457	0.013	36.190	<.0001	***

CY-Corn Yield, P-Input Expenditure, & Q-Input Quantity,
Subscripts: S-Seed, C-Chemical, F-Fertilizer, M-M/Repair, L-Labor, Fi-Farm Insurance, A-Acreage, T-Temperature, & P-Rainfall.

*** Significant at 1% level (p<0.01).

** Significant at 5% level (p<0.05).

* Significant at 10% level (p<0.10).

Table 5. Estimated Cumulative Elasticity Effects on the Corn Yield

Input Expenditure	Corn Yield Elasticity
Corn Seed	0.234
Corn Chemical	0.093
Corn Fertilizer	0.126
Corn M/Repair	-0.013
Corn Hired Labor	0.097
Corn F/Insurance	0.109
Input Quantity	**Corn Yield Elasticity**
Corn Acreage	0.030
Average Temperature	2.154
Total Rainfall	2.561

Table 5 represents the summary for accumulated elasticity effects of the independent variables on the corn yield in the model. Based on the estimates of the corn yield frontier model, the corn yield elasticities change depending on the selected independent variables of cost inputs and quantity of inputs. As Table 5 indicates, the corn yield would increase the most (0.23 percent) from a one percent increase in corn seed amongst input costs. The second most important input is fertilizer at 0.126 percent, the third is farm insurance at 0.109 percent, the fourth is hired labor at 0.097 percent and the fifth is chemicals at 0.093 percent for increasing corn yield. A strong boost in corn yield is definitely caused by average temperature and total rainfall, where an increase in one percent of average temperature and total rainfall in the growing season predicts a corn yield improvement of 2.15 and 2.56 percent, respectively. Corn maintenance and equipment repair cost are the only input costs that have a negative impact on corn yield. While a relatively small percent, however, it may have an important economic implication. For instance, spending more money and time on maintenance and repair might lead to delays in farming operations that are needed for certain stages of growth for the corn.

Table 6 presents the statistical model fit summary for the soybean yield frontier model. The research provides a detailed explanation for model fit summary for the corn yield frontier model.

Since the other two models' fit summaries can be explained similarly, the soybean and HRS Wheat model fit summaries are explained briefly and only important values from Table 6 and 9 will be explained in detail.

Table 6. Soybean Yield Frontier Model Fit Summary

Number of Observations	2069.00
Log Likelihood	-4.78
Maximum Absolute Gradient	0.0000048
Number of Iterations	19.00
Optimization Method	Newton-Raphson Ridge
AIC	69.56
Schwarz Criterion	238.61
Sigma	0.27
Lambda	1.88
Algorithm	Converged
Number of LR testing	14
χ^2_{LRT}	16.98312

As shown in Table 6, 19 iterations are used in the optimization, which can be expected since Newton-Raphson Ridge is the optimization algorithm used. Because of the nature of the optimization algorithm, it does not require as many iterations as other optimization algorithm methods. AIC has a value of 69.56 and SC has a value of 238.61. Both criterions' values are smaller than the values of the unrestricted model, thus, the soybean yield frontier model definitely improves the condition of parsimonies. In order to evaluate the goodness of fit to the model, likelihood ratio test used in 14 times for testing the statistically insignificant parameters from the unrestricted model. Log-likelihood test of chi-square value is 16.98 with 22 degree of freedom. Since, 16.98 is smaller than chi-square table values of 30.81 ($p<0.10$), 33.92 ($p<0.05$), and 40.28 ($p<0.01$), we reject the $H_1: \beta_n \neq 0$. This means that the selected 22 variables from the unrestricted model were statistically insignificant and have no joint explanatory power for the results of the soybean frontier model. Thus, the current soybean yield frontier model can predict the technical efficiency without including these variables

Table 7. Maximum Likelihood Estimation of Soybean Yield Frontier Model

Dependent Variable	Mean	St. Error				
$lnSY'$	3.396833	0.318704				
Independent Variables	Parameter	Estimate	St. Error	t-Value	Pr > $\lvert t \rvert$	
Intercept	α_0	-7.447	1.279	-5.82	<.0001	***
lnP'_S	α_S	-0.252	0.116	-2.17	0.0304	**
lnP'_F	α_F	0.041	0.011	3.67	0.0002	***
lnP'_I	α_I	-0.110	0.064	-1.71	0.0881	*
lnP'_M	α_M	-0.317	0.076	-4.16	<.0001	***
lnP'_L	α_L	0.074	0.018	4.12	<.0001	***
lnP'_{Fi}	α_{Fi}	0.117	0.041	2.79	0.0052	***
1/2 $lnP'_S * lnP'_S$	γ_{SS}	0.003	0.014	0.22	0.8252	
1/2 $lnP'_F * lnP'_F$	γ_{FF}	0.001	0.001	0.81	0.4191	
1/2 $lnP'_I * lnP'_I$	γ_{FF}	-0.003	0.005	-0.64	0.5226	
1/2 $lnP'_M * lnP'_M$	γ_{MM}	0.014	0.005	2.63	0.0085	***
1/2 $lnP'_L * lnP'_L$	γ_{LL}	0.003	0.001	2.24	0.0249	**
1/2 $lnP'_{Fi} * lnP'_{Fi}$	γ_{FiFi}	-0.001	0.004	-0.36	0.7209	
$lnP'_S * lnP'_I$	χ_{SI}	0.033	0.017	1.91	0.0563	*
$lnP'_S * lnP'_M$	χ_{SM}	0.060	0.017	3.4	0.0007	***
$lnP'_F * lnP'_C$	χ_{FC}	-0.005	0.002	-2.37	0.0177	**
$lnP'_F * lnP'_I$	χ_{FI}	-0.004	0.002	-1.64	0.101	
$lnP'_F * lnP'_M$	χ_{FM}	-0.005	0.002	-2.07	0.0386	**
$lnP'_F * lnP'_{Fi}$	χ_{FFi}	0.005	0.002	2.32	0.0203	**
$lnP'_C * lnP'_{FO}$	χ_{CFO}	0.008	0.004	1.9	0.0578	*
$lnP'_C * lnP'_M$	χ_{CM}	0.011	0.005	2.08	0.0379	**
$lnP'_C * lnP'_L$	χ_{CL}	-0.021	0.005	-3.86	0.0001	***
$lnP'_M * lnP'_{Fi}$	χ_{MFi}	-0.029	0.013	-2.31	0.0207	**
lnQ'_A	α_A	0.047	0.040	1.17	0.2402	
$1/2 lnQ'_A lnQ'_A$	γ_{AA}	-0.003	0.003	-0.82	0.413	
lnQ'_T	α_T	2.156	0.197	10.95	<.0001	***
lnQ'_P	α_P	1.139	0.345	3.3	0.001	***
$1/2 lnQ'_P lnQ'_P$	γ_{PP}	-0.117	0.038	-2.9	0.0037	***
Sigma v	v_i	0.127	0.005	24.67	<.0001	***
Sigma u	u_i	0.240	0.008	28.78	<.0001	***

SY-Soybean Yield, P-Input expenditure, & Q-Input Quantity
Subscripts: S-Seed, C-Chemical, F-Fertilizer, FO-Fuel & Oil, I-Crop Insurance, M-M/Repair, L-Labor, Fi-Farm Insurance, A-Acreage, T-Temperature, & P-Rainfall.

*** Significant at 1% level (p<0.01).
** Significant at 5% level (p<0.05).
* Significant at 10% level (p<0.10).

Table 7 presents the maximum likelihood estimates of the soybean yield frontier model. The model estimates a total of 31 parameters including dependent variables, independent variables, and two error terms (v and u). 23 out of 30 parameters are statistically significant; specifically, 13 of 23 are at a 1% significance level, 7 out of 23 are at a 5% significance level, and 3 out 23 are at a 10% significance level in the model. Sigma v is the statistical noise effect in this model and has a value of 0.127 with a 1% significance level. Sigma u is the inefficiency effect in the model and has a value of 0.240 with a 1 % significance level. Based on the hypothesis test on the sigma u, SFA is an appropriate approach to use to model the agricultural production analysis. Because sigma u indicates that there is one sided error term that represents technical inefficiency.

Table 8 presents the summary for the cumulative elasticity effect of the independent variables on the model's soybean yield. Based on the estimates of the soybean yield frontier model, soybean yield elasticities change in relation to selected independent variables of cost inputs and input quantities. As Table 8 indicates, soybean yield would decrease the most (-0.26 percent) from a one percent increase in soybean maintenance and repair costs amongst cost inputs.

Table 8. Estimated Cumulative Elasticity Effects on the Soybean Yield

Input Expenditure	Soybean Yield Elasticity
Soybean Seed	-0.156
Soybean Fertilizer	0.033
Soybean Chemical	-0.002
Soybean C/Insurance	-0.084
Soybean M/Repair	-0.266
Soybean Hired Labor	0.079
Soybean Fuel and Oil	0.008
Soybean F/Insurance	0.091
Input Quantity	Soybean Yield Elasticity
Soybean Acreage	0.045
Average Temperature	2.045
Total Rainfall	1.029

This is similar to the corn yield elasticity effects, however, the magnitude of percentage is much larger for soybean yield, which may due to soybeans needing more attention in their growing stages. Secondly, soybean seed is another cost input that reduces soybean yield (-0.156), if soybean seed increases by one percent. Soybean insurance and soybean chemicals also indicate that a one percent increase in these two cost variables have a negative impact, -0.084 and -0.002 respectively. Interestingly, farm insurance, fertilizer, hired labor, and fuel and oil have a positive impact on soybean yield, with farm insurance having the most impact and fuel and oil expense having the least impact. Soybeans do not require fertilizer as much as other crops, thus, most soybean growers may believe soybeans do not need fertilizer, however, it may not always be the case according to the results. Weather impacts are similar to corn yield improvement, where average temperature and total rainfall in the growing season have a positive impact on soybean yield, and their impacts are much greater than the cost variables.

Table 9. HRS Wheat Yield Frontier Model Fit Summary

Number of Observations	3649
Log Likelihood	-1823
Maximum Absolute Gradient	0.00277
Number of Iterations	108
Optimization Method	Dual Quasi-Newton
AIC	3687
Schwarz Criterion	3811
Sigma	0.48932
Lambda	3.27363
Algorithm	Converged
Number of LR testing	10
χ^2_{LRT}	34

Table 9 presents the statistical fit summary for the HRS wheat yield frontier model. 108 iterations are used in the optimization, which can be expected since the optimization algorithm is Dual Quasi-Newton. The data sample for HRS wheat yield estimation is much larger than the other two models, however, this optimization algorithm still performs well in the HRS wheat yield frontier model. AIC has value of 3687 and SC has value of 3811. Both criterions' values are relatively smaller than the values of the unrestricted model, thus, the research expectation is satisfied with the HRS wheat yield frontier model as well. Sigma has a value of 0.489 (σ = 0.489) and lambda is an inefficiency parameter with a value of (λ = 3.273). Log-likelihood test of chi-square value is 34.00 with 32 degrees of freedom. In order to evaluate the goodness of fit to the model, likelihood ratio test used in 14 times for testing the statistically insignificant parameters from the unrestricted model. Since 34.00 is smaller than the chi-square table values of 42.58 ($p<0.10$), 46.19 ($p<0.05$), and 53.48 ($p<0.01$), we reject the $H_1: \beta_n \neq 0$. This means that the selected 32 variables from the unrestricted model were statistically insignificant and have no joint explanatory power for the results of the HRS wheat frontier model. Thus, the current HRS wheat yield frontier model can predict the technical efficiency without including these variables.

Table 10 presents the maximum likelihood estimates of the HRS wheat yield frontier model. The model estimated a total of 21 parameters including dependent variables, independent variables, and two error terms (v and u). 12 out of 21 parameters are statistically significance; specifically, 11 of 12 are at a 1% significance level, and 1 out of 23 is at a 5% significance level in the model. Table 5.3 summarizes the cumulative elasticity effect of the independent variables on the HRS wheat yield. Sigma v is the statistical noise effect in this model and has a value of 0.143 with a 1% significance level. Sigma u is the inefficiency effect in the model and has a value of 0.468 with a 1 % significance level. This implies that SFA is a definitely appropriate to model the agricultural production analysis.

Table 10. Maximum Likelihood Estimation of HRS Wheat Yield Frontier Model

Dependent Variable	Mean	St. Error				
$lnWY'$	3.491248	1.011505				
Independent Variables	**Parameter**	**Estimate**	**St. Error**	**t-Value**	**Pr > |t|**	
Intercept	α_0	7.596	0.927	8.19	<.0001	***
lnP'_F	α_F	-0.093	0.082	-1.13	0.2588	
lnP'_C	α_C	-0.032	0.041	-0.78	0.4328	
lnP'_I	α_I	0.061	0.020	2.95	0.0032	***
lnP'_L	α_L	0.085	0.016	5.15	<.0001	***
lnP'_{Fi}	α_{Fi}	0.031	0.031	1	0.3194	
1/2 $lnP'_F * lnP'_F$	γ_{FF}	0.044	0.011	3.99	<.0001	***
1/2 $lnP'_C * lnP'_C$	γ_{CC}	0.028	0.007	3.72	0.0002	***
1/2 $lnP'_I * lnP'_I$	γ_{II}	-0.005	0.003	-1.33	0.1823	
1/2 $lnP'_L * lnP'_L$	γ_{LL}	0.002	0.001	1.39	0.1657	
1/2 $lnP'_{Fi} * lnP'_{Fi}$	γ_{FiFi}	0.011	0.004	2.53	0.0115	**
$lnP'_C * lnP'_L$	χ_{CL}	-0.022	0.005	-4.15	<.0001	***
$lnP'_I * lnP'_{FO}$	χ_{IFO}	-0.006	0.006	-1.12	0.2626	
$lnP'_{FO} * lnP'_{Fi}$	χ_{FOFi}	0.043	0.012	3.47	0.0005	***
$lnP'_M * lnP'_{Fi}$	χ_{MFi}	-0.034	0.008	-3.9	<.0001	***
lnQ'_T	α_T	-1.085	0.186	-5.81	<.0001	***
lnQ'_P	α_P	-0.092	0.192	-0.48	0.6299	
$1/2 lnQ'_P lnQ'_P$	γ_{PP}	0.028	0.023	1.25	0.2109	
Sigma v	v_i	0.142	0.005	29.54	<.0001	***
Sigma u	u_i	0.467	0.009	47.94	<.0001	***

WY-HRS Wheat Yield, P-Input expenditure, & Q-Input Quantity
Subscripts: F-Fertilizer, C-Chemical, I-Crop Insurance, L-Labor, Fi-Farm Insurance, FO-Fuel & Oil, M-M/Repair, A-Acreage, T-Temperature, & P-Rainfall.

*** Significant at 1% level (p<0.01).
** Significant at 5% level (p<0.05).
* Significant at 10% level (p<0.10).

Table 11 summarizes the cumulative elasticity effect of the independent variables on the HRS wheat yield in the model. Based on the estimates of the HRS wheat yield frontier model, HRS wheat yield elasticities change in relation to selected independent variables of cost inputs and input quantities. According to the Table 11, HRS wheat yield would increase the most (0.065 percent) from a one percent increase in HRS wheat labor costs among the cost inputs. Other positive impacts on HRS wheat yield are farm insurance (0.055), HRS wheat insurance cost (0.049), and finally, fuel and oil cost (0.044). Whereas, the costs of fertilizer, chemical, and maintenance and repair have a negative impact, -0.048, -0.027, and -0.031, respectively.

Surprisingly, the elasticity effects of average temperature and total rainfall both have a negative impact on HRS Wheat yield. This result supports the assumption that HRS Wheat yield has been affected by weather changes, especially extreme weather events. In addition, there are numerous factors associated with HRS Wheat yield variability. For instance, the number of HRS Wheat growers decreased as farmers began growing different crops, which also resulted in significant variations in where HRS Wheat was grown. Yield has also been susceptible to and reduced by excessive rainfalls in past years.

Table 11. Estimated Cumulative Elasticity Effects on the HRS Wheat Yield

Input Expenditure	HRS Wheat Yield Elasticity
HRS Wheat Fertilizer	-0.048
HRS Wheat Chemical	-0.027
HRS Wheat C/Insurance	0.049
HRS Wheat Hired Labor	0.065
HRS Wheat F/Insurance	0.055
HRS Wheat M/Repair	-0.031
HRS Wheat Fuel and Oil	0.044
Input Quantity	HRS Wheat Yield Elasticity
Average Temperature	-1.056
Total Rainfall	-0.064

Table 12 presents the overall comparison among the three crops' cumulative elasticity effects from their selected inputs. The most with plus sign indicates the most positive or least negative impacts from selected cost and quantity inputs. The least with minus sign indicates the least positive or most negative impacts form selected cost and quantity inputs. As table 8 indicates, most of the selected inputs indicate that corn yield has much strong relationship with following inputs; seed, chemicals, fertilizer, repair, labor, farm insurance, temperature and rainfall. Two other crops' yields have an interesting relationship with the selected production input costs and input quantities. One surprising finding is related to soybean seed expenditure, as shown in Table 8 and Table 12.

Table 12. Comparison for Corn, Soybeans, and HRS Wheat Yield Elasticities

Input Expenditure	Corn Yield Elasticity	Soybean Yield Elasticity	HRS Wheat Yield Elasticity
Seed	0.2343	-0.1555	N/A
Chemical	0.0932	-0.0023	-0.0268
Fertilizer	0.1264	0.0330	-0.0481
M/Repair	-0.0135	-0.2660	-0.0314
Hired Labor	0.0971	0.0793	0.0652
F/Insurance	0.1086	0.0909	0.0552
C/Insurance	N/A	-0.0837	0.0494
Fuel and Oil	N/A	0.0077	0.0436
Input Quantity	Corn Yield Elasticity	Soybean Yield Elasticity	HRS Wheat Yield Elasticity
Acreage	0.0297	0.0447	N/A
Average Temperature	2.1542	2.0452	-1.0565
Total Rainfall	2.5609	1.0286	-0.0643

An increase in soybean seed expenditure of one percent predicts a decrease in soybean yield of 0.15 percent. This is a logically challenging interpretation, however, most of the elasticity effects from the observed input variables on the three selected crops' yield make feasible sense. This could be due to an excessive amount of seed potentially competing for soil nitrogen, since farmers traditionally do not apply extra nitrogen in soybean fields.

Yield and Efficiency Frontiers

The research developed the yield efficiency frontier based on the technical efficiency scores, which were generated from the yield frontier models. The technical efficiency scores have ranged from 0.00 to 1.00. Zero implies poor technical efficiency and interpreted as 0.00 percent efficiency production performance, whereas one implies 100 percent efficiency production performance.

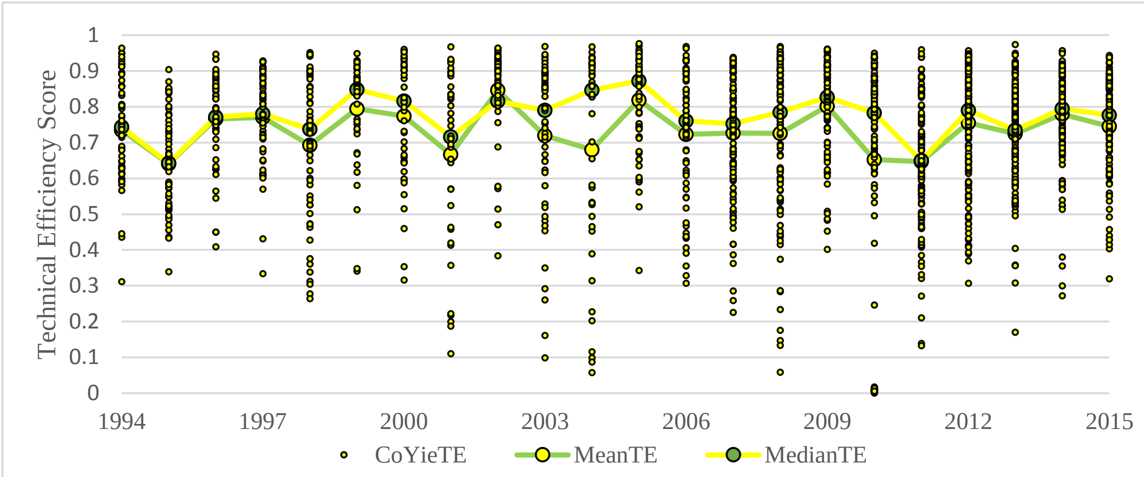

Figure 10. Each Year’s Corn Yield Efficiency Frontier from Corn Yield Frontier Model.

Figure 10 presents the corn yield efficiency frontier across the 22 years (1994 to 2015). There are two trend lines indicating: (1) mean technical efficiency across the years and (2) median technical efficiency across the years. Based on Figure 10, the means and medians of corn growers’ technical efficiency scores stayed in the range between 0.65 and 0.85 across all years, which means at least half of the corn growers were doing better on technical efficiency than 0.65 every year. In addition to this interpretation, a majority of corn growers in North Dakota have been pushing the technical efficiency close to the technical efficiency frontier, and more than half of the corn production stayed above 0.65. On the other hand, half of the corn growers’ technical efficiency scores were widely distributed below the mean technical efficiency scores across the years.

For instance, in some of the years, technical efficiency distribution has a strong negative skew, particularly 2001, 2003, 2004, 2008, and 2011. According to the weather data, the average temperature in the growing season in 2004 was 2.02 degrees Fahrenheit lower than the annual average temperature between 1994 and 2015. This is considered a much cooler summer than average, which was not favorable for growing corn. In 2011, the average rainfall in the growing season across the state was 15.00 inches more than the annual average of the past 22 years. Thus, some of the years had noticeable weather differences, which could have impacted overall farm technical efficiency.

In addition, other factors could also have impacted crop yield, such as unpredicted extreme weather events in the growing season, variation in length of growing season, and certain diseases at particular times. Overall, the corn yield frontier model predicts most of the years' technical efficiency scores well.

Figure 11 compares predicted average corn yield versus actual average corn yield across the 22 years (1994 to 2015).

Based on Figure 11, the corn yield frontier model predicts potential corn yield based on the given data sample set for 100 percent efficient corn production. The actual corn yield averages are below the predicted corn yield averages, implying that there is some potential to increase the corn yield without increasing the cost of inputs, or that the model prediction is overestimating the corn yield frontier. In addition, Figure 11 was observed that both actual yield and predicted corn yield frontier increased in during the study period, which is going to explained more in Table 13 at the end of this section.

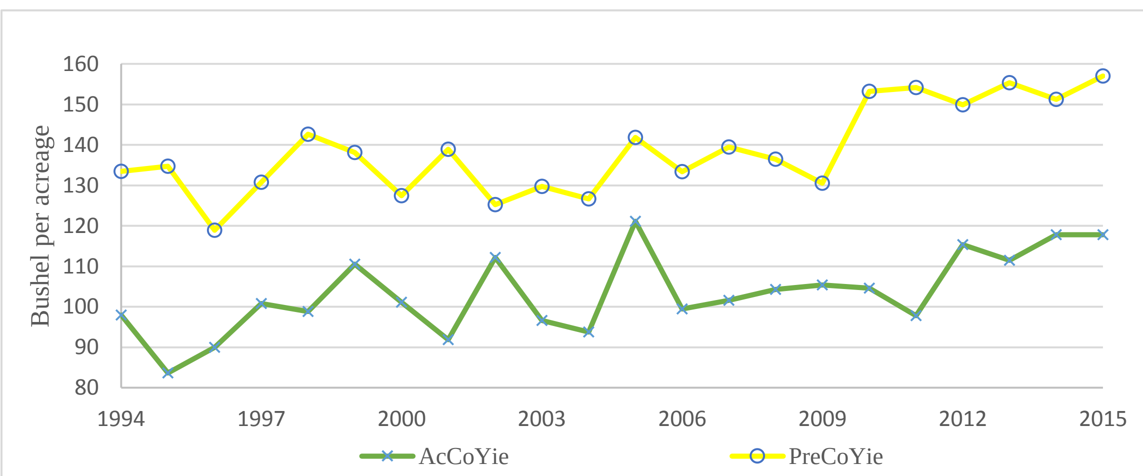

Figure 11. Comparison between Actual Corn Yield Average and Predicted Corn Yield Average from 1994 to 2015.

The next section will look at regional weather impacts to provide additional granularity to this analysis. Farms generally encounter different weather each year, varying by region, thus, the technical efficiency trend line for different regions provides additional information for a corn efficiency analysis.

Figure 12 represents the corn yield efficiency frontier across the nine regions. Due to unequal distribution of the observations collected in the data sample, some of the regions have fewer technical efficiency scores than other regions. This is explained in the Table 2 data section. Therefore, some of the regions do not have enough observations for their efficiency frontier to explain the whole region's corn farmer's efficiency such as the northwestern region. At same time, there is not many of corn growers in that region. Moreover, the research can justify the situation by assuming it may due to the relatively small number of corn growers, agro-climate conditions or different macroeconomic industry factors. The average and median for corn technical efficiency frontier for corn growers in each region stayed between 0.70 and 0.90, excluding the northwestern region. Overall, corn growers in the North Valley, Southeastern, South Central, and North Eastern regions are relatively consistent in efficiently growing corn.

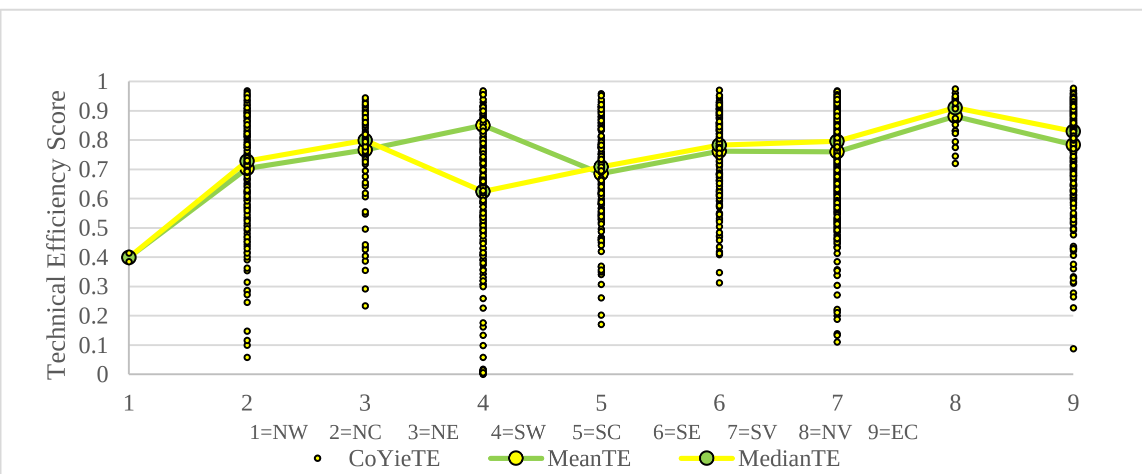

Figure 12. Each Region's Corn Yield Efficiency Frontier from Corn Yield Frontier Model.

Figure 13 compares the predicted average corn yield versus actual average corn yield across the nine regions. The corn yield frontier model predicts the potential corn yield that each region could reach by being as technically efficient as possible. The model estimate for predicting the potential corn yield in each of the nine regions is relatively similar to actual corn yield.

Lastly, actual corn yield in north valley is much closer to the predicted corn yield. This may be due to a couple of reasons: few numbers of corn producers with relatively higher yield are reported, and/or throughout the 22 years, corn growers have consistently improved the corn yield in the north valley region with lower weather stresses.

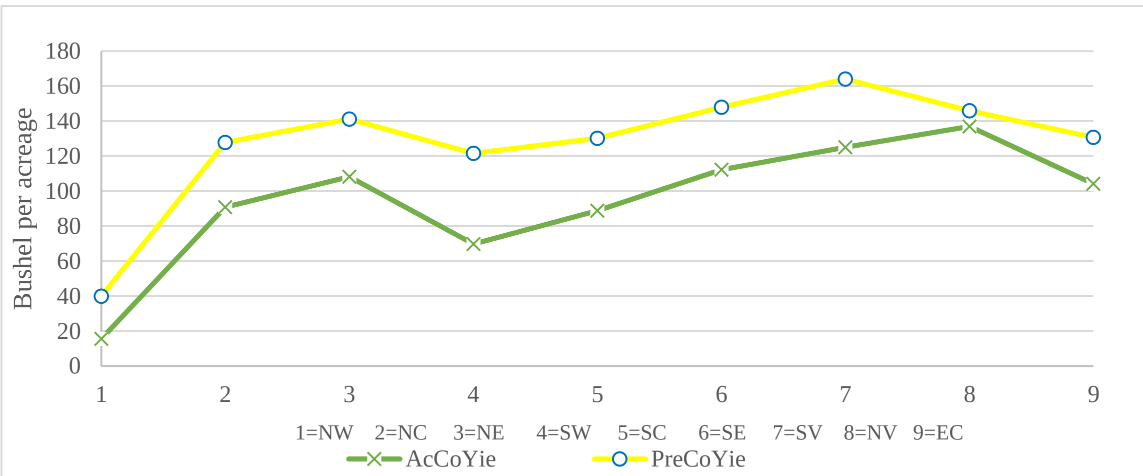

Figure 13. Comparison between Actual Corn Yield Average and Predicted Corn Yield Average in Each Region.

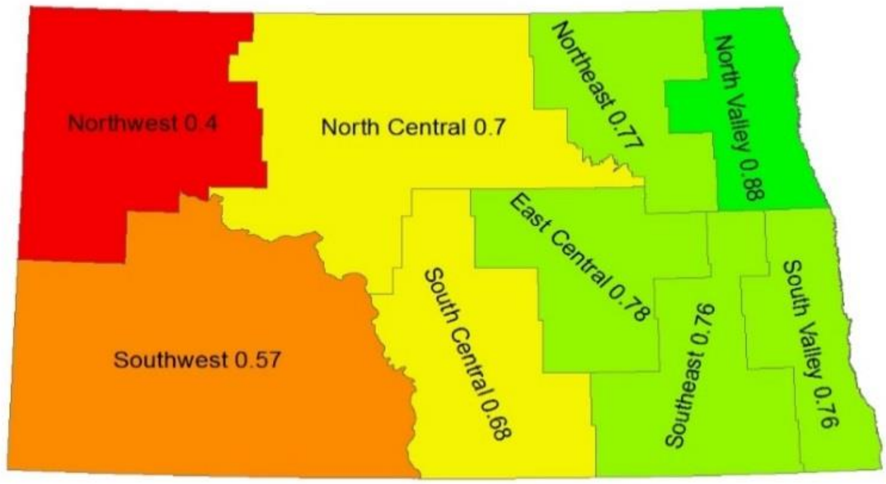

Figure 14. Average Technical Efficiency Score for Corn Production by Nine Regions.

Figure 14 indicates the each region’s average technical efficiency score for corn production. In addition, it demonstrates each regions’ location and they are colored based on their technical efficiency scores. For instance, red represents poor efficiency, whereas green represents the best efficiency.

Figure 15 and 16 indicate each region’s average predicted corn yield and average actual corn yield, respectively.

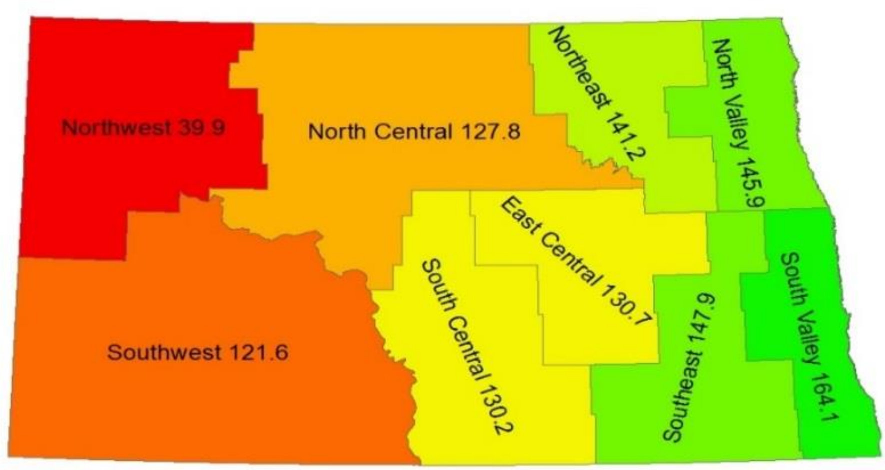

Figure 15. Average Predicted Corn Yield by Corn Yield Frontier Model.

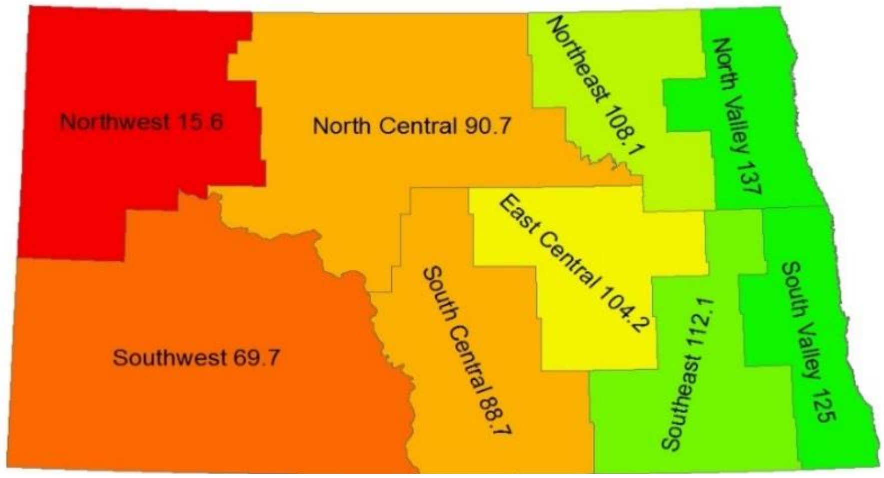

Figure 16. Average Actual Corn Yield from Observed Data Sample.

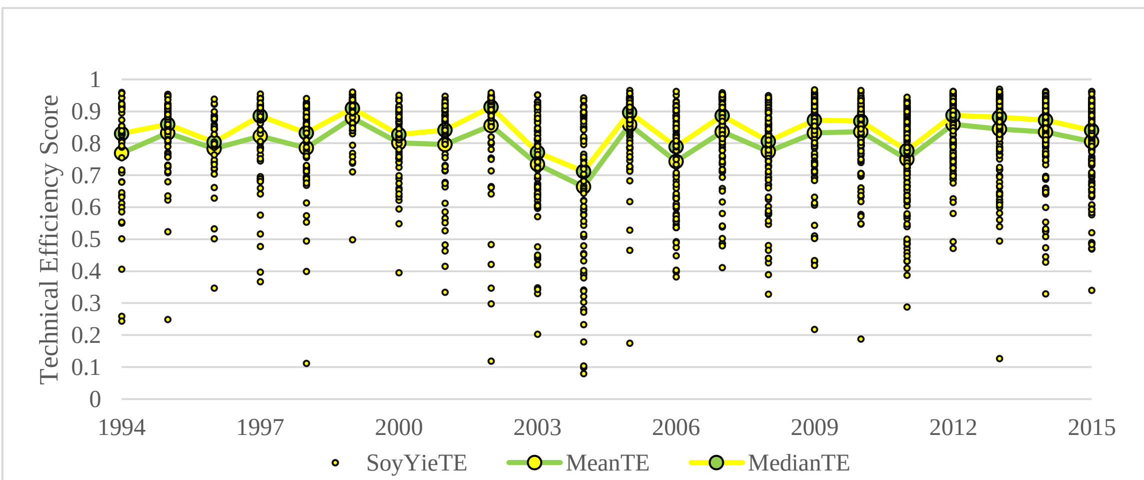

Figure 17. Each Year's Soybean Yield Efficiency Frontier from Soybean Yield Frontier Model.

Figure 17 presents the soybean yield efficiency frontier across the 22 years, 1994 to 2015. Based on Figure 17, the means and medians of soybean growers' technical efficiency scores stayed in the range between 0.70 and 0.95 across all years. Soybean growers' technical efficiency scores are more stable than corn growers, since most years' technical efficiency scores were distributed in a small range, except in 2004. In other words, a majority of the soybean growers stayed around the mean and median technical efficiency (0.50 to 0.95) and few of them stayed below the mean and median with a wide range of lower technical efficiency (0.00 to 0.50).

The mean and median technical efficiency in 2004 was relatively lower than other years, which could be due to the cooler summer that occurred in 2004; the average temperature was 2.36 degrees Fahrenheit lower than the annual average temperature between 1994 and 2015.

Figure 18 compares predicted average soybean yield versus actual average soybean yield across the 22 years. The soybean yield frontier model predicts potential soybean yield, which implies that each year's actual average yield could have reached that frontier.

Figure 18. Comparison between Actual Soybean Yield Average and Predicted Soybean Yield Average from 1994 to 2015.

Moreover, the actual average in some years was much closer to the predicted average efficiency frontier, which may due to a few reasons: soybean growers managed their inputs well despite weather conditions throughout the year or it is mostly due to weather effects. In addition, Figure 18 was observed that both actual yield and predicted soybean yield frontier were stayed in during the study period, which will be explained in Table 13.

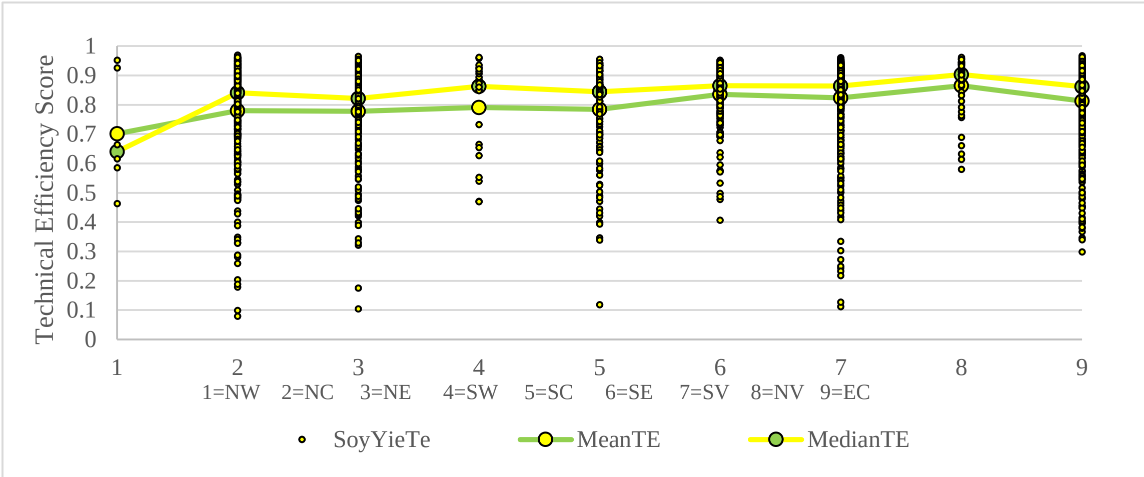

Figure 19. Each Region's Soybean Yield Efficiency Frontier from Soybean Yield Frontier Model.

Figure 19 presents the soybean yield efficiency frontier across the nine regions. Figure 19, similar to Figure 12, shows an unequally distributed technical efficiency score in each region, which implies that fewer observations in some regions may underestimate the technical efficiency score for those regions. However, the soybean growers' efficiency is still captured well. For instance, North Central, Northeastern, South Central, South Valley, and East Central regions have plenty of soybean technical efficiency scores, thus the research can evaluate the soybean efficiency performance based on that data. Overall, soybean growers in most regions performed efficiently in improving the soybean yield.

Figure 20 compares the predicted average soybean yield versus the actual average soybean yield across the nine regions. The soybean yield frontier model predicts the possible potential soybean yield based on the given information of soybean yield and selected inputs. Thus, each region's actual average yield could be averaged as predicted.

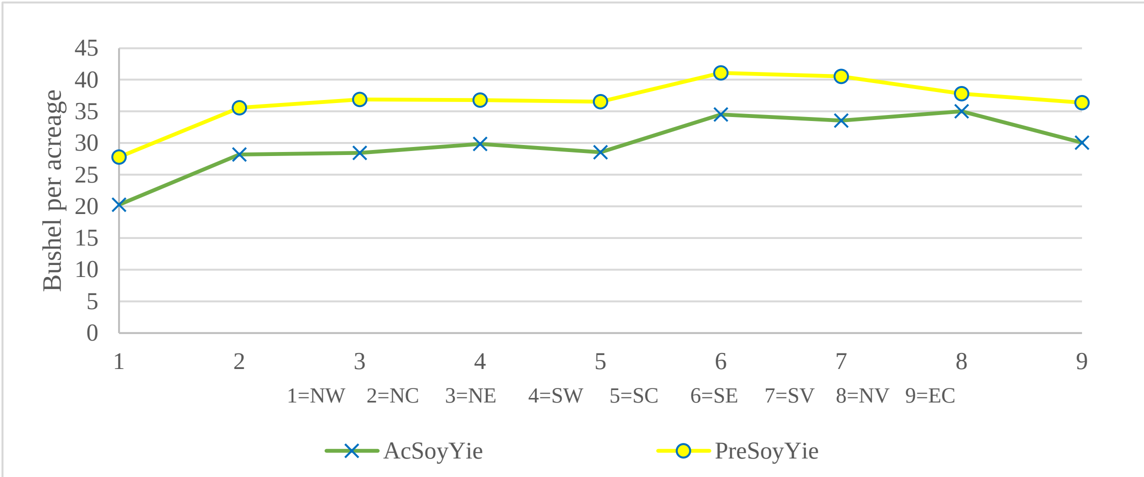

Figure 20. Comparison between Actual Soybean Yield Average Model and Predicted Soybean Yield Average in Each Region.

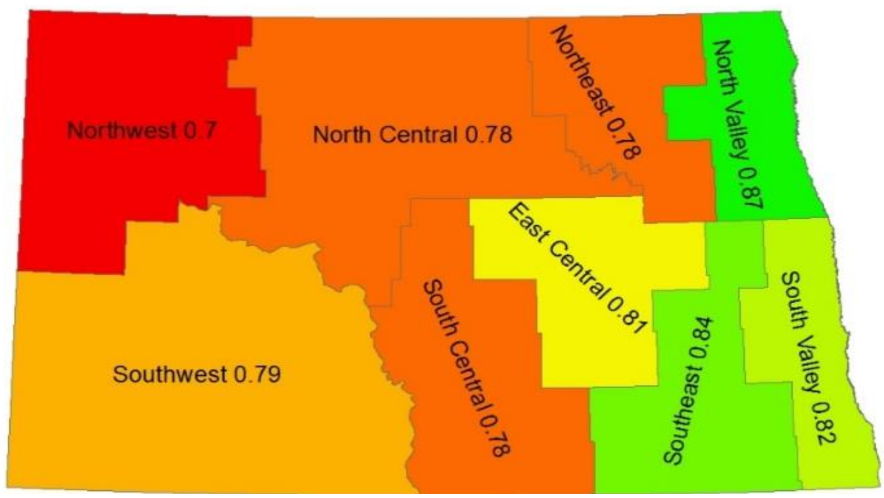

Figure 21. Average Technical Efficiency Score for Soybean Production for Nine Regions.

Figure 21 indicate each region's average technical efficiency score for soybean production. In addition, it demonstrates each region's location and they are colored based on their technical efficiency scores. For instance, red represents poor efficiency, whereas green represents the best efficiency.

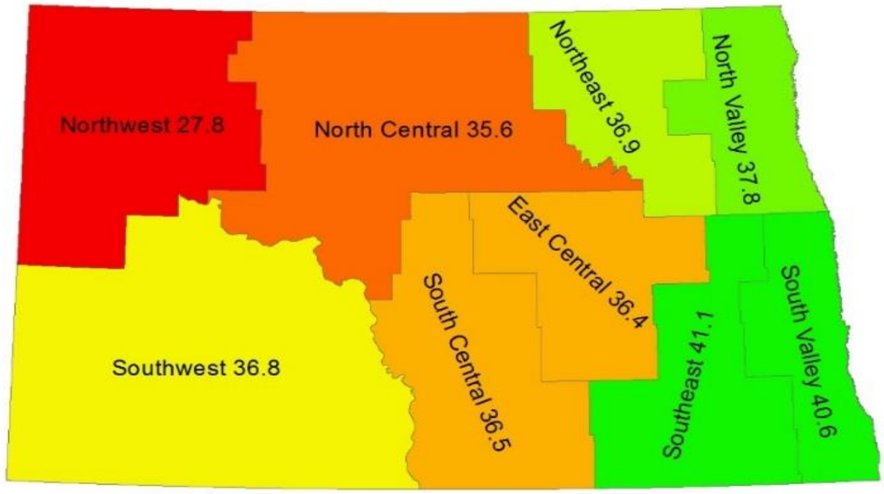

Figure 22. Average Predicted Soybean Yield from Soybean Yield Frontier Model.

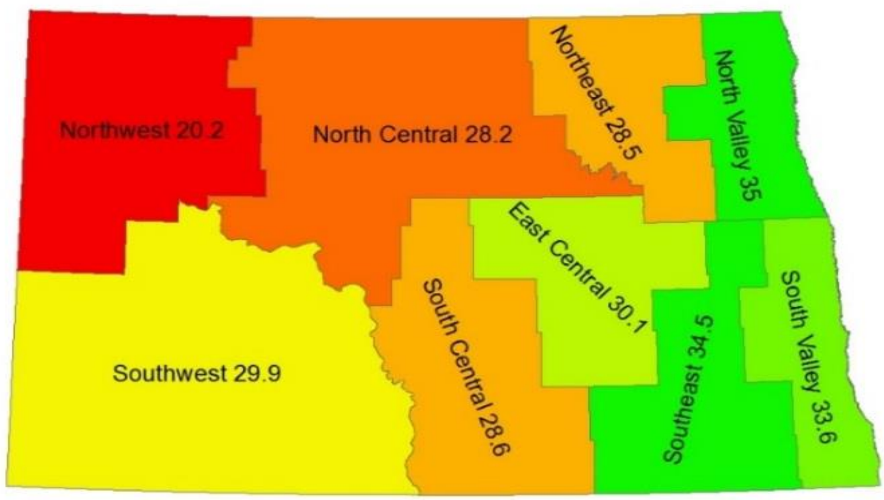

Figure 23. Average Actual Soybean Yield from Observed Data Sample.

Figure 22 and 23 indicates each region's average predicted soybean yield and average actual soybean yield, respectively.

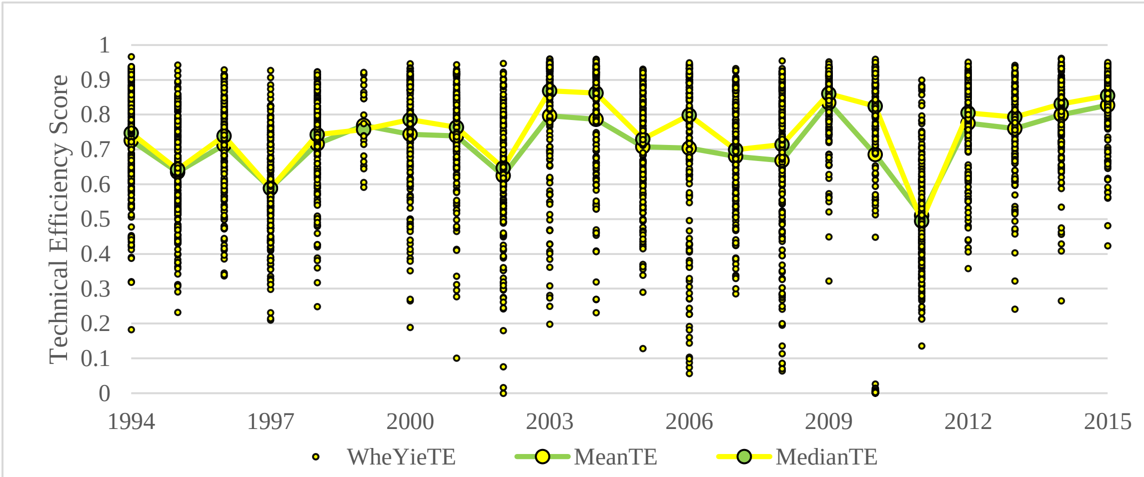

Figure 24. Each Year’s HRS Wheat Yield Efficiency Frontier from HRS Wheat Frontier Model.

Figure 24 presents the HRS wheat yield efficiency frontier across the 22 years, 1994 to 2015. Based on Figure 24, the means and medians of HRS Wheat growers’ technical efficiency scores stayed in the range between 0.65 and 0.85 across all years, excluding 1997 and 2011. As Figure 24 indicates, some years had a much wider range of technical efficiency distribution, particularly 2002, 2006, 2008, and 2011. Based on the comparison between these years’ averaged weather information and averaged weather information across the past 22 years, 2002 had 8.70 inches less rainfall than average and was 0.74 degrees Fahrenheit less than average; 2006 had 21.73 inches less rainfall than average with 2.40 degrees Fahrenheit more than average; 2008 had 1.85 inches more rainfall than average with 1.22 degrees Fahrenheit less than average; and 2011 had 15.80 inches more rainfall than average with 0.50 degrees Fahrenheit less than average. Basically, this suggests that HRS Wheat yield is more sensitive to significant changes in weather variabilities. As a consequence, HRS Wheat growers’ technical efficiency could vary significantly. Weather variability is one of the many factors that affect crop yield directly and indirectly. Ultimately, there could be many factors that impact HRS Wheat yield and HRS Wheat growers’ technical efficiency. For instance, other factors could be different regions’ soil types and agro-climatic conditions, market conditions, and other industry influences such as the oil industry in western North Dakota. Furthermore, other years stayed closely between 0.45 and 0.90, which considered as positive kurtosis in statistical term. This basically implies the majority of HRS wheat growers stay above 50 percent technically efficient in HRS wheat production in the last 22 years.

Figure 25 compares the predicted average HRS wheat yield versus the actual average HRS wheat yield across the 22 years. The HRS wheat yield frontier model predicts the potential HRS wheat yield, showing that each year's actual average yield had the potential to be more efficient.

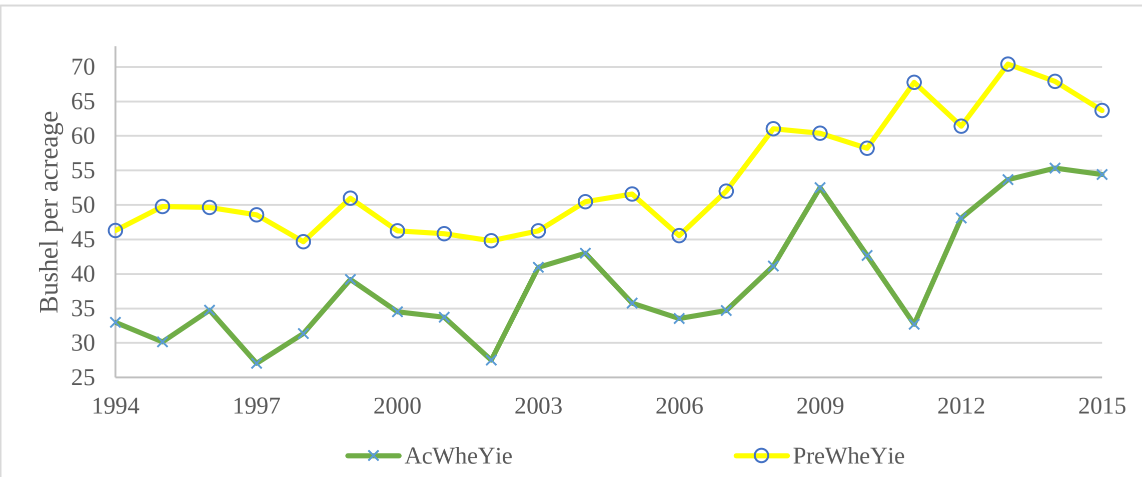

Figure 25. Comparison between Actual HRS Wheat Yield Average and Predicted HRS Wheat Yield Average from 1994 to 2015.

In general, average yield increased gradually and the gap between these averages were closer in some years. In the last couple of years, wheat prices have been low in the market, which may help the farmers reduce their costs. Thus, gaps between predicted and actual yield may decreased further. In addition, Figure 25 was observed that both actual yield and predicted soybean yield frontier were stayed in during the study period, which will be explained in Table 13.

Figure 26 presents the HRS wheat yield efficiency frontier across the nine regions. Based on Figure 26, most of the regions have plenty of technical efficiency scores, therefore, each region could provide significant insight into efficiency performance. In general, almost all of the regions have equally efficient HRS wheat growers.

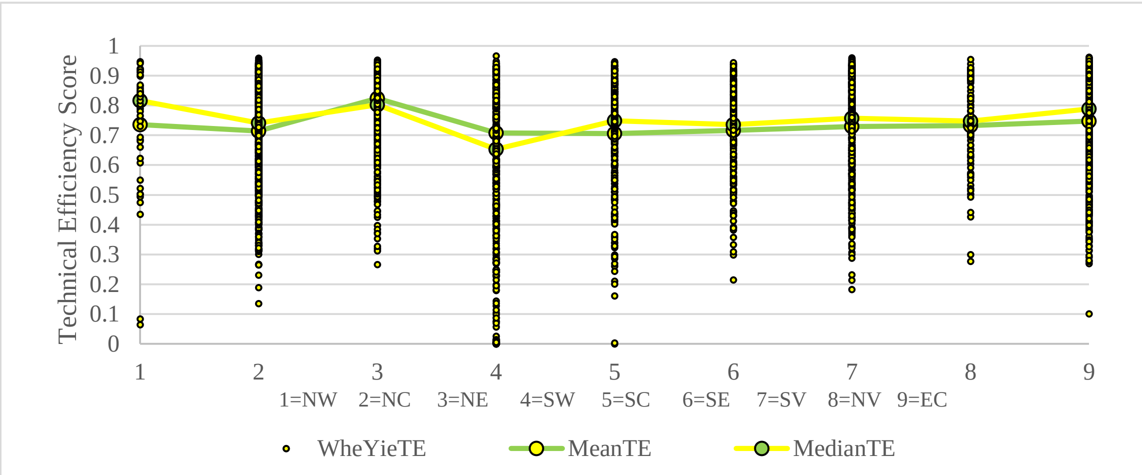

Figure 26. Each Region's HRS Wheat Yield Efficiency Frontier from HRS Wheat Frontier Model.

In other words, the averages and medians of the technical efficiency scores for all regions are in a fairly small range between 0.70 and 0.80. Although the averages and medians are in that range, half of the HRS wheat growers stayed above the averages and medians. On the other hand, there are lots of growers that have the potential to increase their technical efficiency for their HRS wheat production.

Figure 27 compares predicted the average HRS wheat yield versus the actual average HRS wheat yield across the nine regions. The HRS wheat yield frontier model predicts the potential yield based on the given information of yield and selected inputs. Thus, each regions actual average yield could be averaged as predicted.

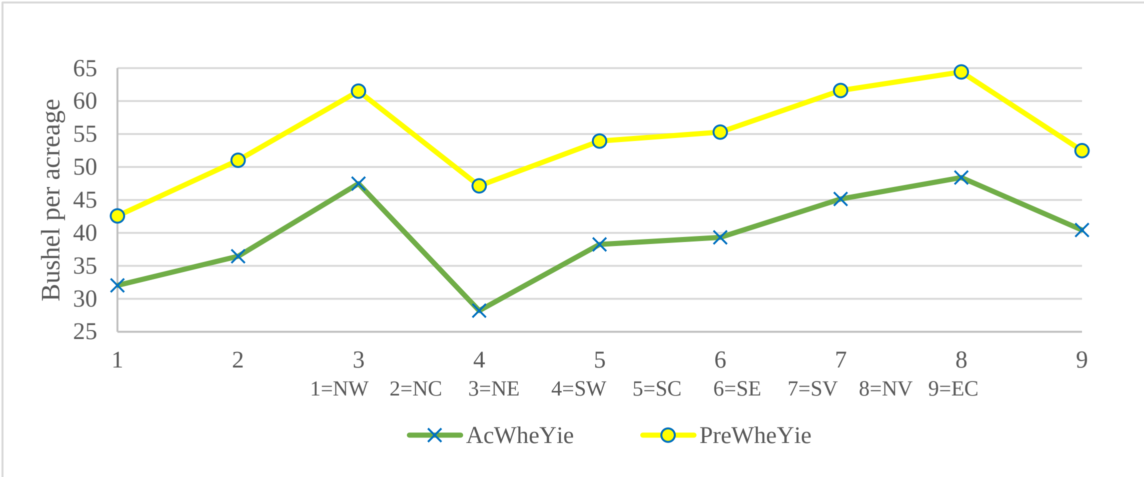

Figure 27. Comparison between Actual HRS Wheat Yield Average and Predicted HRS Wheat Yield Average in each Region.

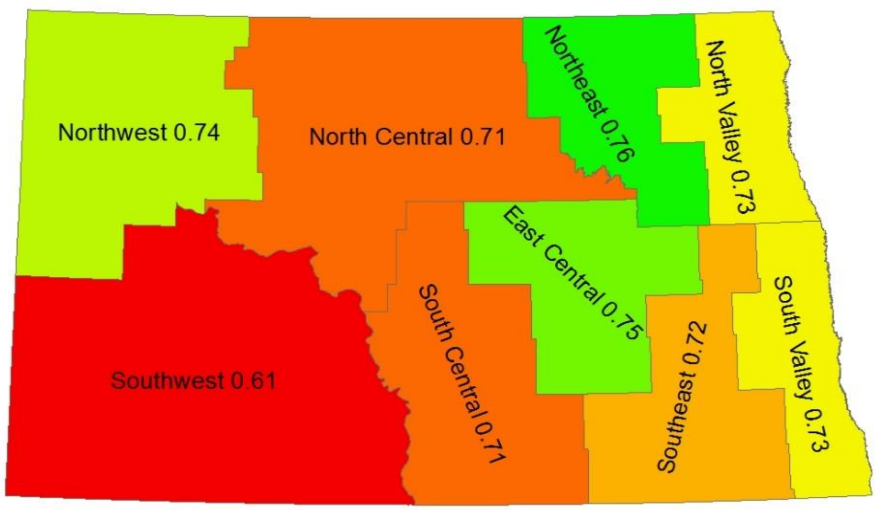

Figure 28. Average Technical Efficiency Score for HRS Wheat Production for Nine Regions.

Figure 28 indicates each region's average technical efficiency scores for the HRS wheat production. In addition, it demonstrates each region's location and technical efficiency scores. For instance, red represents poor efficiency, whereas green represents the best efficiency.

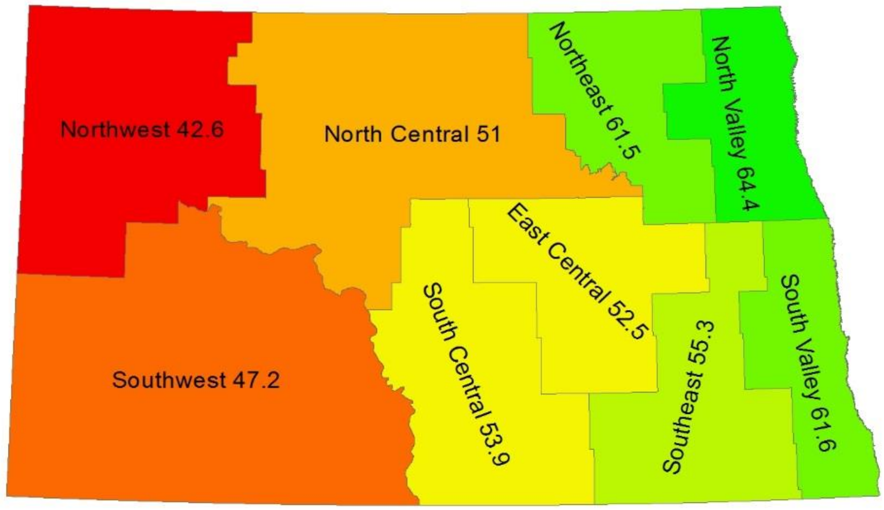

Figure 29. Average Predicted HRS Wheat Yield from HRS Wheat Yield Frontier Model.

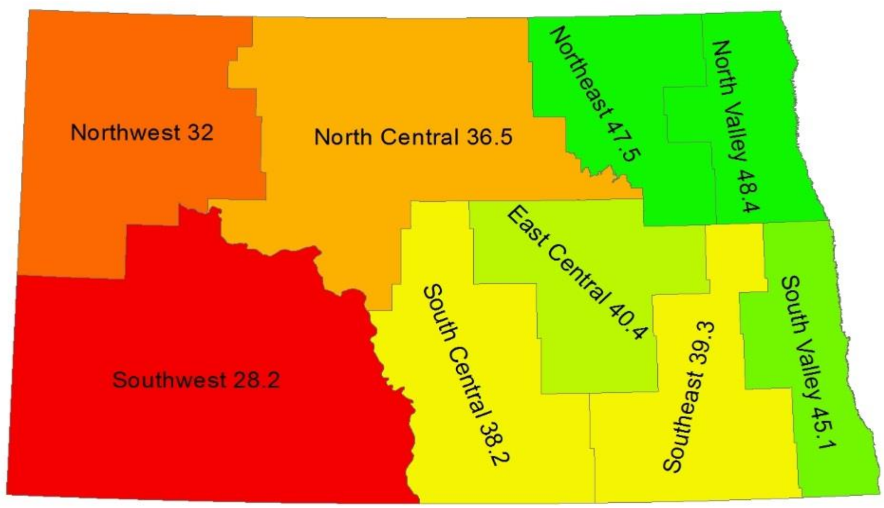

Figure 30. Average Actual HRS Wheat Yield from Observed Data Sample.

Figure 29 and 30 indicates each region's average predicted corn yield and average actual corn yield, respectively.

Table 13 presents the overall comparisons among the three crops' predicted yield frontier trend and actual yield trend in during study period. The results for Table 13 were based on the linear regression of crop yield (or predicted yield frontier) on year.

Table 13. Comparison for Corn, Soybeans, and HRS Wheat Predicted Yield Frontier Trend and Actual Yield Trend

Crop	Corn Yield		Soybeans Yield		HRS Wheat Yield	
Parameter	Frontier	Actual	Frontier	Actual	Frontier	Actual
Intercept	123.5***	90.8***	38.2***	30.1***	42.1***	27.0***
Trend	1.3***	1.0***	-0.01	0.08***	1.02***	1.01***
R-square	0.10	0.03	0.003	0.003	0.30	0.19

*** Significant at 1% level (p<0.01).
** Significant at 5% level (p<0.05).
* Significant at 10% level (p<0.10).

The result revealed the actual yields and predicted yield frontiers for corn increased a little more than one bushel per acre per year on average during the study period ($p \leq 0.0001$). Similarly, the result for the actual yields and predicted yield frontiers for HRS wheat increase a little more than one bushel per acre per year on average during the same period ($p \leq 0.0001$). In contrast, the regression result for the predicted yield frontiers for soybeans did not reveal any statistically discernable time trend, while the actual yields have trended upward about 0.08 of bushel per acre per year during the study period ($p \leq 0.0001$).

Efficiency Scores and Consistency Performance

Yield technical efficiency scores for the selected three crops were estimated using the yield frontier models and these models were based on the SFA. In this section, the research presents the distribution of each of the three crop yield technical efficiency scores based on the three criteria. After all the analyses from the previous section, the research observed that each of the three criteria should logically range in three ways.

The top yield efficiency scores for each of the three crop stayed in a much smaller range between 0.70 and 0.95, thus, the first criteria consists of the range between 0.75 and 1.0. The second criteria consists of a score range between 0.50 and 0.75, and the last criteria consists of the score range between 0.00 and 0.50.

Table 14. Corn, Soybeans, HRS Wheat Yield Efficiency Scores for Three Criteria Across Twenty Two Years

Criteria	(1) 1.0>TES>0.75						(2) 0.75>TES>0.50						(3) 0.50>TES>0.0					
Year	Corn		Soybean		HRS Wheat		Corn		Soybean		HRS Wheat		Corn		Soybean		HRS Wheat	
	#	%	#	%	#	%	#	%	#	%	#	%	#	%	#	%	#	%
1994	26	46	33	66	105	49	27	48	14	28	92	43	3	5	3	6	17	8
1995	13	22	49	83	56	26	39	65	9	15	121	56	8	13	1	2	40	18
1996	36	64	23	68	94	46	17	30	10	29	92	45	3	5	1	3	18	9
1997	37	65	47	78	26	13	18	32	10	17	122	61	2	4	3	5	52	26
1998	27	45	46	71	76	47	22	37	16	25	71	44	11	18	3	5	14	9
1999	30	73	42	91	10	50	9	22	3	7	10	50	2	5	1	2	0	0
2000	29	62	40	74	96	59	15	32	13	24	49	30	3	6	1	2	17	10
2001	18	44	47	75	83	51	13	32	12	19	69	42	10	24	4	6	11	7
2002	42	88	70	89	46	29	4	8	4	5	77	49	2	4	5	6	34	22
2003	31	58	40	53	113	73	13	25	27	36	26	17	9	17	9	12	15	10
2004	24	57	36	44	100	66	7	17	27	33	40	26	11	26	19	23	11	7
2005	45	70	82	89	76	46	18	28	8	9	71	43	1	2	2	2	19	11
2006	36	55	53	57	90	57	19	29	32	34	36	23	11	17	8	9	32	20
2007	56	50	80	81	69	41	44	39	15	15	76	46	12	11	4	4	22	13
2008	61	58	76	68	79	45	28	27	28	25	64	36	16	15	7	6	34	19
2009	67	74	98	80	151	85	19	21	20	16	24	14	4	4	4	3	2	1
2010	64	58	116	86	121	65	25	23	18	13	32	17	22	20	1	1	32	17
2011	35	29	75	54	13	7	62	52	50	36	79	42	22	18	13	9	97	51
2012	101	61	139	87	118	70	49	30	18	11	43	25	16	10	2	1	8	5
2013	72	47	125	86	85	60	76	49	19	13	49	35	6	4	2	1	7	5
2014	85	67	136	86	115	72	38	30	19	12	38	24	4	3	4	3	6	4
2015	55	54	108	73	125	84	39	38	33	22	21	14	8	8	6	4	2	1
#	990	56	1561	75	1847	51	601	34	405	20	1302	36	186	10	103	5	490	13
%	58.8%						30.8%						10.4%					

The distribution number of the observations for the three crops' yield efficiency scores and relative percentages are presented in Table 14 across the 22 years and Table 15 for the nine regions based on the three selected criteria. In Table 14, the research can evaluate which crop has the most stable efficiency performance based on each of the three criteria. For instance, soybean technical efficiency score for criteria 1 is 75 percent, which means 75 percent of all soybean growers had technical efficiency scores ranging between 0.75 and 1.0 in the past 22 years. On the other hand, 56 percent of corn growers and 51 percent of HRS Wheat growers have been technically efficient between 0.75 and 1.0 in the past 22 years. Moreover, the research is also able to analyze the specific year for comparing which crop has a larger volume of more efficient farmers as well as the percent relative to the farmers' technical efficiency scores. For instance, 54 percent of corn growers, 73 percent of soybean growers, and 84 percent of HRS wheat growers had technical efficiency scores ranging between 0.75 and 1.0 in 2015. Lastly, the comparison among the three criteria explores how well North Dakota farms efficiently operated the selected three crops in the past 22 years in general. Overall, the research observes that 58.8 percent of all three crops' growers were operating at criteria 1, 30.8 percent of all three crops' grower were operating at criteria 2, and 10.4 percent of all three crop's growers were operating at criteria 3. Therefore, the research states that almost 6 out of 10 farms (58.8%) have a technically efficiency of 75 percent or above for the farm operation.

Table 15 presents the distribution of the number of the observations for each of the three crop growers and relative to the percentage based on the selected three criteria for nine regions in North Dakota. Based on Table 15, the research can analyze which region's crop growers were the most technically efficient for each criteria. For instance, according to criteria 1, 67 percent of the corn growers in region 9 (East Central) were operating at a technical efficiency score ranging between 0.75 and 1.0 for the past 22 years. Moreover, 75 percent of soybean and 51 percent of HRS wheat growers in region 9 (East Central) were operating at a technical efficiency score ranging between 0.75 and 1.0 for the past 22 years.

Table 15. Corn, Soybeans, HRS Wheat Yield Efficiency Scores for Three Criteria Across Nine Regions

Criteria	1.0>CYES>0.75						0.75>CYES>0.50						0.50>CYES>0.0					
Regions	Corn		Soybean		HRS Wheat		Corn		Soybean		HRS Wheat		Corn		Soybean		HRS Wheat	
	#	%	#	%	#	%	#	%	#	%	#	%	#	%	#	%	#	%
1 NW	0	0	2	33	28	62	0	0	3	50	12	27	2	100	1	17	5	11
2 NC	102	45	196	66	497	48	96	42	73	25	420	41	31	14	26	9	118	11
3 NE	65	71	161	70	206	65	17	19	51	22	92	29	9	10	18	8	19	6
4 SW	53	27	15	65	205	38	81	42	6	26	172	32	60	31	2	9	156	29
5 SC	55	43	88	69	146	50	54	42	28	22	104	35	19	15	11	9	43	15
6 SE	125	63	138	84	102	48	63	32	22	13	91	43	10	5	4	2	19	9
7 SV	328	59	573	80	266	53	189	34	123	17	184	36	35	6	19	3	55	11
8 NV	20	91	36	88	34	49	2	9	5	12	31	44	0	0	0	0	5	7
9 EC	242	67	352	75	363	58	99	27	94	20	196	31	20	6	22	5	70	11
Total	990	56	1561	75	1847	51	601	34	405	20	1302	36	186	10	103	5	490	13

Lastly, the research is able to analyze among the three crops which regions tend to have higher technical efficiency scores or lower technical efficiency scores. For instance, region 6, region 7, and region 8 have an 80 percent or above for soybean growers in criteria 1, which may be due to many positive factors for soybean growth such as: soil type, suitable climate condition, better management, better input market service and/or better farm extension service. On the other hand, region 1, region 2, and region 4, have a greater percent of corn growers in criteria 3 (score ranging between 0.50 and below), which may due to many negative factors for corn growth such as: poor soil type, unsuitable climate conditions, and/or poor farm environment conditions.

The analysis of consistency for the technically efficient farms is one of the objectives of this research. Thus, the research aims to evaluate how many farms were consistently technically efficient in a certain technical efficiency range. The analysis of consistency can be estimated by simply counting the number of times any particular farm has a certain technically efficiency score. This analysis is presented in Table 16. Table 16 compares farm consistency for each of the three crops based on the three selected criteria. Moreover, each criteria estimated how many farms were in that criteria and how many time those farms consistently stayed in that criteria's range. For instance, criteria 1 (0.75 to 1.0 technical efficiency scores) qualifies a total of 325 corn growers, 386 soybean growers, and 545 HRS wheat growers. From a total of 325 corn growers, one farm was consistently efficient at least 0.75 or above 17 times, two soybean grower were consistently efficient 20 times, and one HRS wheat grower was consistently efficient 18 times. In the Table 16, row A presents the total number observation, which is simply calculated by summation after each consistency multiplied by the number of farms. This is one way to evaluate all the values accurately based on the number of observations from the data sample for each of the three crops. Row B presents the percentage of farms that meet a set level of consistency for being technical efficiency based on the green lines. The green line sets a level for interpretation purposes. For example, the interpretation of Row B would be that 4.31 percent of corn growers in criteria 1 have a technical efficiency of at least 75 percent or above at least 10 times or more in the past 22 years. Furthermore, 10.36 percent of soybean growers in criteria 1 have a technical efficiency of at least 75 percent or above at least 10 times or more in the past 22 years. Lastly, 5.87 percent of HRS wheat growers have a technical efficiency of at least 75 percent or above and at least 10 times or more in the past 22 years. Whereas, 3.91 percent of corn growers, 3.85 percent of soybean growers, and 7.67 percent of HRS wheat growers are more likely to have 50 percent or below inefficiency (criteria 3) consistently, that is, at least 4 times or more. Row C presents the total percent of the three crop growers based on the three selected criteria. For instance, 43.3 percent of total corn observations' technical efficiency scores fall into criteria 1 for corn growers, 56.5 percent of total soybean observations' technical efficiency scores fall into criteria 1 for soybean growers, and 39.5 percent of total HRS wheat observations' technical scores fall into criteria 1. Policy wise, the research is more interested in criteria 3, which represents low technical efficiency performance. Looking at this criteria, 17.1 percent of corn growers, 11.4 percent of soybean growers, and 20.8 percent of

HRS wheat growers did not effectively improve their efficiency in the past 22 years. Moreover, the research validates that the three crop growers with poor technical efficiency could improve their efficiency.

The rest of the values can be explained similarly to the one already explained above, thus this section focuses more on the overall implications of the table. Based on Table 16, the research provides some interesting insights about consistency. For instance, a greater number of farms have high technical efficiency scores than have lower technical efficiency scores. The farms with high technical efficiency tend to stay in that range more frequently, and at the same time, they aim to improve their efficiency, while other farms aim to improve their less efficient operation. It would be interesting to find out what farms with consistently high efficiency do differently than farms with medium and low technical efficiency.

Based on this analysis, extension agents could identify those farmers who may need more farming assistance. They could also use this evaluation to help farmers examine their inputs and exchange their knowledge between farmers with high technical efficiency and those with low technical efficiency. One other idea that can be drawn from this analysis is that distribution of consistency is quite different for farms amongst these criteria, implying that every farm manages their crop production differently. However, each farm does not always stay in their efficiency score, which is highly dependent on farm management, either improving the efficiency or sustaining their high efficiency operation. Although some of the three crop growers' technical efficiency was estimated to be relatively high, overall, a majority of the three crop growers have much to learn about management of input sources and from each other in order to be consistently technically efficient at a high level.

Table 16. Consistency for Technically Efficient Farms

																					A	B	C
1.0>TES>0.75	Corn	# of time	1	2	3	4	5	6	7	8	9	10	11	12	13	15	17						
		# of Farm	128	58	47	25	22	11	10	3	7	1	5	3	3	1	1				990	4%	43 %
	Soybean	# of time	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	17	18	20			
		# of Farm	129	65	41	35	18	21	16	15	6	3	9	4	9	4	4	3	2	2	1561	10 %	57 %
	Wheat	# of time	1	2	3	4	5	6	7	8	9	10	11	12	13	14	16	17	18				
		# of Farm	217	92	46	41	38	24	24	16	15	6	13	6	3	1	1	1	1		1847	6%	40 %
0.75>TES>0.50	Corn	# of time	1	2	3	4	5	6	7	8													
		# of Farm	163	52	42	18	7	8	3	4											601	2%	40 %
	Soybean	# of time	1	2	3	4	5	6	7	9													
		# of Farm	120	55	24	9	4	4	2	1											405	1%	32 %
	Wheat	# of time	1	2	3	4	5	6	7	8	9	10	11	12									
		# of Farm	257	107	75	39	28	19	10	4	3	2	1	3							1302	4%	40 %
0.50>TES>0.0	Corn	# of time	1	2	3	4	5	6															
		# of Farm	95	19	9	1	2	2													186	4%	17 %
	Soybean	# of time	1	2	3	4	5																
		# of Farm	63	10	2	1	2														103	4%	11 %
	Wheat	# of time	1	2	3	4	5	6	7	8													
		# of Farm	171	69	25	12	5	3	1	1											490	8%	21 %

TES- Technical Efficiency score,
A-total number of observations,
B-Consistency percent based on the Green Lines
C-Total percent of the three crops' growers qualified in selected three criteria.

CHAPTER V. SUMMARY AND CONCLUSION

Introduction

Chapter V provides an overall summary of the research, summarizes the procedures used, and generates conclusions from the findings and results. Management implications based on the findings are discussed as well. This section also discusses the limitations of this research and potential areas for future research based on these findings.

Research Summary

The research identified agriculture as a cornerstone for the North Dakota economy and one of the few stable industries significantly contributing to the economy. In addition, a few crops have become dominant: corn, soybeans, and wheat, due to their economic value in terms of demand volume and food consumption worthiness. As a consequence, farms have become specialized in these crops and non-diversified farms may encounter profit loss when market prices for these crops are low and highly volatile. Weak commodity prices, high trade volume volatility, a strong US Dollar, and many other direct and indirect impacts caused a shortfall in the state's budget.

Historically, agriculture was adopted by North Dakota in the early 18th century and it already operates over 90 percent of the total land with no space to expand the supply of land. Therefore, while facing the limited supply of land, efficient farming operations could help stabilize farm income, partially offsetting high price volatility for these crops. Thus, in the research, each of the three crops' yield were focused on in order to determine crops' yield efficiency frontiers and farm technical efficiency during the study period and in the selected regions.

Perceiving this background, the research developed the stochastic yield frontier models based on the fundamentals of the SFA to estimate technical efficiency for the three selected crops dominantly grown in North Dakota. The research focused on nine different regions in the state on an annual basis from 1994 to 2015. Unbalanced panel data of 7488 observations from the nine regions and over the 22 years used in the research. Panel data consists of one output variable and 11 input variables for each of the three crops. The Statistical Analysis System (SAS) software was employed for maximum likelihood procedure to evaluate each yield frontier model and to estimate the cumulative elasticity effects on each of the three crops yields' from respective input costs as well as input quantities. In addition, based on the maximum likelihood procedure, the research developed technical efficiency scores for each of the observations in the data. Based on the technical efficiency scores, the research developed the technical efficiency frontier as well as potential predicted yield frontier for each of the three crops.

Conclusions for Results

The results of the maximum likelihood procedure revealed the coefficients for cumulative elasticity effects from the weather variables were much greater than the coefficients of input cost variables. Weather variables had a positive impact on corn and soybeans and a negative impact on HRS wheat. Therefore, an increase in the average temperature and total rainfall during the growing season could potentially increase the yield of corn and soybeans while reducing the yield for HRS wheat in North Dakota.

The cumulative elasticity effect of the maintenance and repair cost variables have a negative effect for each of the three crops' yield, thus, either of the three crops' yield could be reduced by increasing the cost of maintenance as well as repair. In addition, the maintenance and repair cost variable is the only cost with a negative elasticity effect on corn yield. Otherwise, other input cost variables have a potential to increase the corn yield by some level; each of the coefficients of the elasticity effects are presented in Table 5. Seed, chemical, repair and crop insurance cost variables negatively impact soybean yield, implying the additional cost of increasing these variables could reduce the soybean yield at some level; especially for repair and seed cost variables since they have the greatest negative impact and each of the coefficients of the elasticity effects are presented in Table 8. Chemical, fertilizer, and repair cost variables negatively impact HRS wheat yield, however, each of the three inputs' elasticity effects are relatively identical. Therefore, each of the three input costs are equally important in terms of increasing the HRS wheat yield and each of the coefficients of the elasticity effects are presented in Table 11.

Corn growers' technical efficiency scores are generated from the corn yield frontier model and scores are on average 0.73 for 1994 to 2015. Soybean growers' technical scores are generated from the soybean yield frontier model and scores averaged 0.80 for 1994 to 2015. HRS wheat growers' technical scores are generated from the HRS wheat yield frontier model and scores are on average 0.72 for 1994 to 2015. Therefore, each of the three crops' growers could potentially increase their efficiency 27 percent for corn, 20 percent for soybean, and 28 percent for HRS wheat, without increasing the amount of inputs for each of the three crops' production.

The results indicated the North and South Valley regions had better average technical efficiency scores than other regions in corn and soybean production. The North Eastern region had better average technical efficiency scores than other regions in HRS wheat production for the past 22 years. The North Western region had the lowest average technical efficiency scores when compared to all other regions in corn and soybean production, and the South Central region had the lowest average technical efficiency scores for HRS wheat production in the past 22 years.

Based on the three selected criteria for the technical efficiency scores, 56 percent of corn growers, 75 percent of soybean growers, and 51 percent of HRS wheat growers are qualified for criteria 1; these farms were technically efficient at 0.75 or above in the past 22 years. Each of the three crops' growers are combined and accounted for 58.8 percent of total observations. Thus, the research concludes overall, almost 6 out of 10 farms in North Dakota were technically efficient at least 75 percent or above in the past 22 years.

For criteria 2, 34 percent for corn growers, 20 percent of the soybean growers, and 36 percent of the HRS wheat growers met the criteria, technically efficient between 0.50 and 0.75 in the past 22 years. The combined percentage is 30.8 percent of the total observations. Thus, the research concludes overall, almost 4 out of 10 farms in North Dakota were technically efficient between 50 percent and 75 percent.

For criteria 3, 10 percent of the corn growers, 5 percent of the soybean growers, and 13 percent of the HRS wheat growers met the criteria, technically efficient at 0.50 or below in the past 22 years; the combined percent is 10.4 percent of the total observations. Therefore, the research concludes that overall, 1 out of 10 farms in North Dakota was technically efficient at 50 percent or below. In other words, they were not particularly technically efficient in any of these three crops.

The consistency analysis for the technically efficient farms used the three selection criteria as well. Criteria 1 indicated 4.31 percent of the corn growers, 10.36 percent of the soybean growers, and 5.78 percent of HRS wheat growers have a technical efficiency of at least 75 percent or more at least 10 times or more in the past 22 years. Criteria 2 indicated 2.36 percent of the corn growers, 1.37 percent of the soybean growers, and 4.20 percent of HRS wheat growers have a technical efficiency between 50 percent and 75 percent at least 7 times or more in the past 22 years. Criteria 3 indicated 3.91 percent of the corn growers, 3.85 percent of the soybean growers, and 7.67 percent of HRS wheat growers have a technical efficiency at 50 percent or below at least 4 times or more in the past 22 years.

Management Implication

The relationship between each of the three crops' yields and respective input costs, crop acres, and weather variables have rarely been studied for the three major crops in North Dakota. An understanding of this relationship could provide farmers and input suppliers with information that may help them manage input costs more effectively and efficiently in order sustain or increase the current level of yield without increasing input costs.

The results of the research revealed each of the three crops' yields are susceptible to changes in some of the direct input costs as well as weather variability. For instance, changes in average temperature and total rainfall in the crop growing season have a significant effect on the three selected crops' yields. The cost of maintenance and repair has a negative impact on all three crops' yields. Increasing the acreage planted for corn and soybeans has a positive impact on yield quantity, which is expected, and farmers' crop choice has shifted towards growing more corn and soybeans. This trend may continue to impact crop land use value in a land scarcity scenario where almost 90 percent of the total land is already operated for agricultural activities. An increase in the expense of seed, chemicals, repairs, and crop insurance in soybean production could reduce the yield. This implies these expenses' input quantity may already be at the optimal point where a maximum level of soybean yield is already produced. Therefore, additional expenses for these inputs could reduce soybean yield as well as soybean technical efficiency scores. A similar policy implication would apply for HRS wheat yield. For instance, increasing the expense of chemicals, fertilizer, and repairs could reduce the HRS wheat yield as well as HRS wheat technical efficiency scores.

Increasing labor expenses could positively affect each of the three crops' yields, which may be due to the importance of labor operations. This could be explained in two ways. High yield could cause more labor expense, as a farmer hires people to help with a large harvest. Or, more labor or better paid labor could result in higher yield.

Based on the distribution of technical efficiency scores for the three selected criteria, it is clearly revealed roughly 31 percent of the total North Dakota farms were straining to be technically efficient at higher than 75 percent. A little over 10 percent of total North Dakota farms were really struggling to be technically efficient at higher than 50 percent. Overall, soybean growers were relatively more technically efficient than corn and HRS wheat growers over the past 22 years. Therefore, the agricultural extension service could pay more attention to those farms that have lower technically efficient operations for any of these three crops. In addition, based on the regional efficiency performance, extension agents could particularly focus on certain regions that have low-efficiency scores for one of these three crops.

The consistency analysis for technically efficient farms clearly revealed some farms consistently stayed in the higher efficiency range between 0.75 and 1.0, whereas some farms consistently stayed in the lower efficiency ranges between 0.75 and 0.50, and between 0.50 and 0.00. This cannot be simply interpreted, however, the results implied some of the farms managed their inputs much more efficiently and some managed their inputs less efficiently and weather affected them both.

Limitations and Future Research

One research limitation is that a few regions did not generate many technical efficiency scores, which made it difficult to present these regions as whole. For instance, the number of observations for technical efficiency scores in corn and soybean farms were much less in region 1. Therefore, overall findings should be interpreted carefully and some of the regions may not be explained individually.

Due to time limitations, the research could not analyze the technical changes in the selected 22 years. In addition, the research also could not evaluate the relationship between predicted technical efficiency scores and selected input cost variations as well as changes in weather variables.

Future research could address the observed limitations. For instance, more farm information could be collected for the analysis, especially in the regions with few observations, which would be helpful for evaluating those regions with more confidence. Moreover, incorporating North Dakota soil information could be helpful in evaluating these three crops' yield improvements.

Based on the distributions of each of the three crops' technical efficiency scores, the research should able to forecast the expected yields and technical efficiencies for the selected regions in each of the three crops. The research could expand analysis for comparing North Dakota with neighboring states in terms of expected yield and efficiency for each of the three crops.

Lastly, adding more crops in the analysis could be another direction for expanding the research, however, due to data limitations, it may not be easy to achieve.

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APPENDIX A. DETAILED DESCRIPTIVE STATISTICS

Table A1. Output and Input Variables for North Dakota Farms Sampled for Corn: Descriptive Statistics

Corn		Yield	Seed	Fertilizer	Chemical	C/Ins	Fuel Oil	M/Repair	Labor	F/Ins	Acre
Year	Unit	bu/acre	$/acre	$/acre	$/acre	$/acre	$/acre	$/acre	$/acre	$/acre	acre
1994	Mean	97.9	$45.1	$55.8	$36.5	$17.7	$18.0	$29.2	$9.9	$4.2	234
	St.Dev	27.0	$9.6	$22.2	$14.9	$8.6	$7.3	$16.0	$10.1	$3.2	229
	Min	33.8	$23.7	$20.9	$7.2	$1.1	$9.3	$3.3	$0.1	$0.4	15
	Max	175.3	$76.1	$105.4	$74.1	$37.1	$51.6	$72.7	$48.8	$18.9	1032
1995	Mean	83.6	$45.8	$68.4	$40.6	$15.8	$18.7	$31.9	$11.8	$5.2	328
	St.Dev	16.8	$9.3	$23.5	$15.8	$10.0	$8.8	$17.0	$13.4	$5.0	270
	Min	40.0	$25.1	$19.9	$17.4	$0.2	$6.8	$6.5	$0.1	$1.2	16
	Max	125.0	$65.2	$131.6	$87.8	$47.3	$47.1	$82.8	$67.2	$32.4	1075
1996	Mean	90.0	$43.7	$56.9	$47.5	$14.9	$21.6	$32.9	$12.6	$4.5	209
	St.Dev	20.4	$9.0	$24.6	$20.7	$10.9	$7.6	$14.3	$10.3	$3.2	155
	Min	47.8	$22.4	$21.6	$10.1	$0.4	$10.6	$8.3	$0.1	$1.6	30
	Max	137.7	$71.2	$133.7	$127.4	$48.0	$44.5	$68.5	$44.8	$15.5	656
1997	Mean	100.8	$48.7	$63.0	$43.1	$15.6	$20.7	$28.9	$12.5	$5.2	294
	St.Dev	26.6	$12.1	$22.5	$16.6	$10.6	$8.3	$11.9	$12.6	$4.6	263
	Min	33.0	$20.8	$19.6	$19.6	$0.5	$8.5	$9.2	$0.0	$0.3	8
	Max	150.0	$89.7	$110.9	$95.2	$51.4	$59.6	$55.7	$58.3	$26.4	1219
1998	Mean	98.9	$49.4	$49.0	$42.9	$13.8	$14.2	$26.7	$12.2	$4.7	248
	St.Dev	34.5	$15.0	$22.6	$17.3	$11.5	$5.9	$14.1	$10.7	$3.6	216
	Min	27.0	$17.8	$7.8	$10.8	$0.1	$0.1	$1.1	$0.0	$0.5	12
	Max	180.5	$92.7	$102.4	$96.3	$65.3	$38.1	$91.1	$42.2	$22.1	858
1999	Mean	110.5	$47.8	$50.2	$44.3	$11.5	$18.2	$29.7	$14.1	$4.2	300
	St.Dev	29.4	$13.3	$21.3	$17.0	$8.0	$8.1	$17.3	$13.2	$2.8	270
	Min	35.8	$20.5	$11.8	$12.9	$0.4	$7.6	$0.5	$0.1	$0.7	36
	Max	162.9	$69.4	$101.2	$86.2	$29.4	$55.4	$105.7	$46.9	$14.2	1007
2000	Mean	101.1	$45.3	$44.7	$34.9	$13.4	$19.3	$28.2	$11.8	$4.1	264
	St.Dev	30.5	$14.1	$18.8	$12.8	$8.9	$6.6	$14.5	$11.3	$3.0	267
	Min	35.5	$20.4	$12.7	$9.7	$0.6	$7.1	$5.4	$0.2	$0.3	11
	Max	158.3	$70.2	$87.2	$65.4	$44.7	$36.5	$83.9	$48.2	$14.9	1152
2001	Mean	91.8	$46.8	$55.4	$36.1	$12.0	$18.8	$27.9	$12.7	$4.5	288
	St.Dev	37.2	$13.6	$20.5	$16.8	$7.4	$6.1	$14.1	$10.4	$2.5	255
	Min	16.6	$17.8	$19.9	$2.5	$1.7	$7.5	$6.6	$0.6	$0.9	31
	Max	157.4	$69.9	$103.2	$96.3	$37.3	$40.6	$67.9	$39.5	$12.8	937
2002	Mean	112.1	$48.3	$47.0	$32.1	$12.4	$15.2	$25.7	$10.6	$4.7	284
	St.Dev	34.8	$12.6	$18.7	$12.1	$7.5	$5.4	$14.7	$9.7	$2.9	251
	Min	13.5	$17.7	$20.0	$8.2	$0.5	$3.9	$0.7	$0.1	$1.0	12
	Max	173.6	$68.6	$92.1	$60.8	$34.4	$31.7	$82.2	$43.7	$15.0	965

Note: C/Ins- Crop Insurance, M/Repair- Maintenance and Repair, F/Ins- Farm Insurance

Table A1. Output and Input Variables for North Dakota Farms Sampled for Corn: Descriptive Statistics (Continued)

Corn Year	Unit	Yield bu/acre	Seed $/acre	Fertilizer $/acre	Chemical $/acre	C/Ins $/acre	Fuel Oil $/acre	M/Repair $/acre	Labor $/acre	F/Ins $/acre	Acre acre
2003	Mean	96.6	$49.9	$47.3	$29.8	$12.6	$16.1	$24.7	$10.4	$4.0	311
	St.Dev	39.1	$12.5	$20.7	$13.2	$7.3	$6.7	$13.5	$10.0	$2.2	275
	Min	9.7	$26.2	$12.1	$7.6	$0.8	$0.6	$0.5	$0.0	$1.3	27
	Max	162.6	$82.9	$97.6	$85.1	$35.8	$43.9	$67.2	$41.6	$9.4	1080
2004	Mean	85.6	$55.0	$54.8	$26.3	$15.2	$16.5	$23.5	$12.8	$4.6	380
	St.Dev	55.0	$13.7	$23.6	$11.2	$7.8	$6.2	$10.9	$11.6	$2.6	353
	Min	0.0	$23.2	$9.8	$7.0	$2.9	$5.3	$4.1	$0.3	$0.7	10
	Max	185.8	$84.5	$106.3	$46.1	$33.4	$29.3	$55.7	$41.0	$12.8	1527
2005	Mean	121.1	$53.3	$57.6	$22.7	$14.4	$22.8	$24.6	$10.9	$4.0	336
	St.Dev	34.6	$13.4	$23.2	$12.1	$6.3	$6.7	$11.4	$9.6	$2.4	309
	Min	37.0	$21.4	$10.0	$4.2	$5.0	$8.1	$7.9	$0.1	$0.7	10
	Max	176.9	$81.5	$101.3	$51.7	$32.3	$38.9	$57.9	$42.1	$12.9	1583
2006	Mean	96.5	$52.3	$57.5	$20.4	$15.7	$20.9	$22.0	$9.4	$4.1	364
	St.Dev	43.5	$12.2	$24.7	$12.5	$7.2	$7.7	$10.7	$9.6	$2.6	369
	Min	0.0	$24.9	$3.4	$3.6	$3.1	$1.9	$2.5	$0.0	$0.1	20
	Max	181.2	$88.9	$134.9	$55.6	$33.6	$39.2	$57.5	$41.0	$10.9	1812
2007	Mean	100.7	$55.7	$56.9	$20.5	$22.4	$22.3	$24.6	$9.8	$3.7	425
	St.Dev	32.7	$14.5	$25.0	$17.5	$11.2	$6.8	$10.7	$9.5	$2.2	392
	Min	0.0	$19.2	$18.1	$3.5	$0.5	$7.7	$7.8	$0.0	$0.6	2
	Max	156.9	$93.2	$150.3	$163.0	$52.5	$41.9	$64.2	$45.2	$12.6	2149
2008	Mean	103.3	$64.9	$86.2	$24.3	$32.9	$28.0	$29.3	$11.3	$3.8	485
	St.Dev	46.6	$14.8	$34.2	$9.7	$15.8	$9.2	$15.1	$10.9	$1.9	430
	Min	0.0	$29.0	$18.1	$5.4	$0.2	$5.1	$2.5	$0.0	$0.6	20
	Max	197.4	$98.1	$176.2	$53.1	$80.9	$55.0	$96.6	$57.1	$10.7	2240
2009	Mean	105.4	$76.7	$102.7	$23.6	$22.1	$21.8	$34.7	$13.4	$3.9	367
	St.Dev	25.8	$18.5	$48.9	$9.5	$10.8	$8.0	$19.2	$12.3	$2.2	333
	Min	39.6	$32.2	$18.2	$5.4	$0.6	$4.9	$8.1	$0.0	$0.3	1
	Max	156.3	$119.4	$224.5	$63.9	$48.2	$45.0	$102.2	$47.7	$12.4	1900
2010	Mean	104.6	$73.9	$72.4	$18.1	$18.8	$23.3	$33.0	$14.8	$3.9	384
	St.Dev	53.8	$21.3	$31.3	$9.5	$10.8	$8.2	$15.9	$13.0	$2.4	341
	Min	0.0	$32.5	$17.4	$2.2	$0.4	$2.5	$4.3	$0.0	$0.2	15
	Max	174.1	$154.6	$213.7	$45.9	$61.2	$48.6	$85.4	$56.5	$17.7	1640
2011	Mean	97.9	$80.1	$102.7	$19.5	$27.3	$31.3	$38.7	$15.1	$4.8	429
	St.Dev	29.6	$19.6	$40.0	$10.9	$13.5	$11.0	$20.9	$13.0	$4.2	425
	Min	21.4	$31.2	$22.0	$2.7	$6.6	$4.0	$5.4	$0.0	$0.0	1
	Max	175.5	$132.1	$232.4	$61.8	$72.4	$63.3	$101.5	$54.6	$37.3	2355

Note: C/Ins- Crop Insurance, M/Repair- Maintenance and Repair, F/Ins- Farm Insurance

Table A1. Output and Input Variables for North Dakota Farms Sampled for Corn: Descriptive Statistics (Continued)

Corn Year	Unit	Yield bu/acre	Seed $/acre	Fertilizer $/acre	Chemical $/acre	C/Ins $/acre	Fuel Oil $/acre	M/Repair $/acre	Labor $/acre	F/Ins $/acre	Acre acre
2012	Mean	115.4	$82.3	$116.7	$22.1	$25.3	$28.4	$37.9	$14.8	$5.0	523
	St.Dev	36.7	$19.1	$47.8	$10.4	$13.2	$10.3	$19.3	$12.5	$3.3	555
	Min	40.0	$20.2	$22.4	$4.2	$3.1	$4.3	$5.8	$0.0	$0.4	4
	Max	223.8	$131.3	$262.6	$55.2	$81.8	$57.0	$132.8	$64.1	$20.8	3425
2013	Mean	111.4	$89.5	$121.0	$24.1	$26.7	$31.4	$41.2	$17.8	$5.4	599
	St.Dev	26.2	$19.4	$46.6	$12.0	$13.4	$13.7	$25.1	$15.6	$3.5	632
	Min	22.9	$32.9	$12.6	$5.1	$2.1	$5.4	$7.7	$0.0	$0.3	1
	Max	212.1	$143.6	$277.0	$82.5	$69.2	$136.0	$209.2	$109.8	$24.5	3450
2014	Mean	117.8	$86.4	$105.0	$23.2	$22.2	$28.8	$32.5	$16.4	$5.1	552
	St.Dev	26.9	$18.0	$37.2	$10.8	$13.3	$11.0	$16.7	$15.8	$3.3	602
	Min	35.0	$33.6	$25.3	$5.5	$0.8	$7.5	$0.3	$0.2	$0.1	1
	Max	173.0	$144.6	$249.5	$56.8	$97.2	$69.1	$99.4	$118.7	$19.9	2973
2015	Mean	117.8	$86.1	$99.6	$22.2	$20.1	$19.6	$32.3	$13.3	$5.4	548
	St.Dev	35.1	$16.3	$33.5	$9.5	$9.1	$6.7	$15.6	$10.9	$2.7	553
	Min	38.3	$43.1	$10.5	$4.7	$3.5	$7.9	$8.7	$0.0	$0.0	10
	Max	189.6	$121.1	$175.8	$43.6	$59.8	$43.1	$99.5	$53.5	$15.1	3674
All Years	Mean	105.0	$66.7	$81.2	$27.0	$20.5	$23.5	$31.6	$13.3	$4.6	413
	St.Dev	36.2	$23.1	$42.9	$15.3	$12.7	$10.4	$17.6	$12.4	$3.1	439
	Min	0.0	$17.7	$3.4	$2.2	$0.1	$0.1	$0.3	$0.0	$0.0	1
	Max	223.8	$154.6	$277.0	$163.0	$97.2	$136.0	$209.2	$118.7	$37.3	3674

Table A2. Output and Inputs Variables for North Dakota Farms Sampled for Soybean: Descriptive Statistics

Soybeans Year	Unit	Yield bu/acre	Seed $/acre	Fertilizer $/acre	Chemical $/acre	C/Ins $/acre	Fuel Oil $/acre	M/Repair $/acre	Labor $/acre	F/Ins $/acre	Acre Acre
1994	Mean	30.1	$26.2	$7.8	$38.5	$18.5	$16.7	$27.3	$11.9	$4.8	419
	St.Dev	8.6	$10.1	$11.5	$14.0	$10.3	$6.3	$16.6	$11.5	$3.7	371
	Min	8.0	$1.9	$0.0	$14.4	$5.4	$8.3	$3.3	$0.1	$1.0	30
	Max	48.2	$57.6	$40.8	$73.9	$47.9	$33.3	$109.5	$39.6	$18.9	2174
1995	Mean	31.3	$26.1	$11.1	$44.0	$18.7	$16.9	$30.7	$14.5	$5.1	481
	St.Dev	6.1	$10.2	$16.3	$11.9	$10.0	$7.6	$16.7	$15.5	$4.7	467
	Min	8.8	$1.5	$0.0	$23.0	$0.9	$6.5	$6.3	$0.1	$1.0	18
	Max	44.3	$58.1	$65.6	$75.3	$64.3	$42.4	$82.8	$67.2	$32.4	3073
1996	Mean	27.9	$32.4	$13.6	$48.6	$20.1	$20.5	$33.4	$15.7	$4.5	409
	St.Dev	5.9	$10.5	$17.5	$14.9	$11.5	$5.9	$14.1	$14.4	$3.0	265
	Min	11.3	$2.8	$0.0	$30.4	$0.3	$13.1	$10.8	$0.2	$1.1	40
	Max	39.7	$50.7	$59.1	$84.6	$55.2	$37.4	$62.6	$58.2	$14.5	1125

Note: C/Ins- Crop Insurance, M/Repair- Maintenance and Repair, F/Ins- Farm Insurance

Table A2. Output and Inputs Variables for North Dakota Farms Sampled for Soybean: Descriptive Statistics (Continued)

Soybeans		Yield	Seed	Fertilizer	Chemical	C/Ins	Fuel Oil	M/Repair	Labor	F/Ins	Acre
Year	Unit	bu/acre	$/acre	$/acre	$/acre	$/acre	$/acre	$/acre	$/acre	$/acre	acre
1997	Mean	31.1	$31.0	$9.5	$49.8	$17.0	$18.5	$30.2	$12.8	$4.7	463
	St.Dev	7.5	$11.8	$11.8	$18.3	$9.0	$6.2	$13.6	$12.5	$3.4	308
	Min	10.7	$6.7	$0.0	$17.6	$0.3	$5.9	$8.1	$0.0	$0.3	26
	Max	45.4	$60.4	$43.2	$105.0	$38.1	$33.5	$67.5	$52.8	$21.1	1333
1998	Mean	31.8	$31.9	$9.9	$44.7	$17.0	$13.0	$24.9	$12.4	$4.8	406
	St.Dev	7.4	$9.4	$11.7	$15.9	$8.7	$4.7	$10.5	$10.3	$3.0	353
	Min	4.5	$10.4	$0.0	$10.1	$0.1	$4.9	$6.6	$0.0	$0.3	25
	Max	50.4	$50.3	$44.3	$81.0	$56.7	$28.1	$45.5	$37.1	$14.1	1546
1999	Mean	37.4	$27.5	$8.1	$41.0	$13.8	$14.5	$23.4	$12.7	$4.3	595
	St.Dev	7.5	$9.9	$10.8	$13.7	$6.7	$5.7	$11.3	$11.6	$2.8	526
	Min	18.5	$10.0	$0.0	$16.0	$2.4	$5.6	$0.4	$0.1	$0.5	11
	Max	52.0	$55.6	$37.9	$74.6	$31.2	$30.7	$53.5	$52.7	$15.6	2700
2000	Mean	30.1	$30.9	$9.4	$35.6	$14.6	$16.6	$27.7	$11.6	$4.0	566
	St.Dev	6.2	$12.6	$10.4	$9.9	$10.1	$6.1	$15.0	$9.3	$2.2	463
	Min	11.9	$10.3	$0.0	$13.2	$4.0	$6.3	$6.0	$0.2	$0.7	20
	Max	43.6	$66.0	$41.1	$60.4	$68.2	$42.3	$67.1	$39.5	$10.9	2429
2001	Mean	31.0	$33.8	$9.7	$30.9	$12.6	$15.7	$23.9	$10.5	$4.8	538
	St.Dev	7.8	$15.3	$13.3	$10.7	$6.9	$5.0	$10.7	$8.9	$2.8	461
	Min	10.0	$9.9	$0.0	$5.9	$2.0	$7.2	$5.9	$0.1	$1.2	24
	Max	45.0	$83.1	$47.2	$51.0	$33.6	$33.2	$54.3	$32.3	$13.6	1949
2002	Mean	33.3	$39.4	$9.6	$26.6	$12.0	$11.8	$21.0	$9.0	$4.1	518
	St.Dev	8.5	$15.0	$10.2	$11.7	$6.2	$3.9	$11.2	$8.9	$2.6	400
	Min	3.9	$11.3	$0.0	$2.7	$2.5	$5.0	$0.5	$0.1	$0.7	38
	Max	47.2	$70.2	$48.8	$52.8	$28.8	$26.0	$67.2	$41.0	$15.0	1946
2003	Mean	27.0	$43.2	$10.6	$23.7	$14.8	$12.8	$20.2	$8.8	$4.0	686
	St.Dev	7.8	$14.9	$11.5	$10.1	$6.8	$4.5	$9.6	$8.3	$2.3	638
	Min	7.1	$11.0	$0.0	$5.6	$1.2	$6.9	$3.0	$0.0	$0.9	15
	Max	43.8	$108.6	$36.7	$46.8	$31.2	$32.9	$55.0	$35.8	$13.1	3266
2004	Mean	22.6	$44.3	$10.8	$18.7	$16.0	$14.1	$18.8	$8.2	$4.1	819
	St.Dev	9.6	$12.4	$9.7	$7.9	$7.1	$4.3	$10.1	$8.6	$2.7	790
	Min	2.3	$12.1	$0.0	$3.7	$5.1	$4.3	$4.0	$0.1	$0.3	48
	Max	39.0	$67.2	$35.0	$38.9	$37.7	$24.1	$45.6	$35.2	$12.8	3836
2005	Mean	35.5	$47.3	$8.9	$18.3	$14.4	$17.7	$19.3	$8.3	$4.0	709
	St.Dev	7.7	$12.7	$8.7	$8.8	$5.8	$5.0	$9.3	$8.2	$2.2	624
	Min	6.0	$8.3	$0.0	$4.9	$4.4	$9.0	$5.2	$0.1	$0.4	13
	Max	51.9	$78.6	$37.5	$41.9	$32.1	$29.0	$48.5	$31.6	$12.9	2959

Note: C/Ins- Crop Insurance, M/Repair- Maintenance and Repair, F/Ins- Farm Insurance

Table A2. Output and Inputs Variables for North Dakota Farms Sampled for Soybean: Descriptive Statistics (Continued)

Soybeans		Yield	Seed	Fertilizer	Chemical	C/Ins	Fuel Oil	M/Repair	Labor	F/Ins	Acre
Year	Unit	bu/acre	$/acre	$/acre	$/acre	$/acre	$/acre	$/acre	$/acre	$/acre	acre
2006	Mean	28.2	$46.1	$7.2	$18.0	$13.9	$17.9	$18.0	$7.4	$4.1	796
	St.Dev	9.2	$11.1	$8.4	$9.8	$6.2	$6.1	$9.0	$7.6	$2.7	689
	Min	12.3	$9.7	$0.0	$3.6	$1.7	$1.9	$2.5	$0.0	$0.1	53
	Max	48.0	$70.7	$37.3	$49.7	$33.4	$32.4	$51.6	$32.9	$13.7	3715
2007	Mean	33.6	$47.8	$4.1	$16.6	$15.5	$19.5	$20.6	$8.3	$3.7	622
	St.Dev	7.3	$10.9	$6.1	$9.4	$6.5	$5.9	$9.5	$8.5	$2.2	554
	Min	13.0	$14.7	$0.0	$5.0	$1.1	$8.8	$1.7	$0.0	$0.2	18
	Max	48.7	$92.7	$32.5	$50.3	$33.6	$37.8	$51.3	$45.2	$12.6	2727
2008	Mean	27.8	$47.9	$10.1	$29.9	$28.2	$22.5	$23.4	$8.9	$3.8	753
	St.Dev	7.3	$11.1	$14.2	$12.2	$9.3	$6.5	$13.4	$8.2	$2.0	673
	Min	10.3	$16.3	$0.0	$7.8	$9.2	$8.0	$2.3	$0.1	$0.6	79
	Max	45.3	$74.0	$69.8	$64.1	$58.8	$42.8	$77.1	$32.8	$10.7	3931
2009	Mean	29.6	$59.6	$13.3	$24.5	$20.7	$15.3	$24.5	$8.5	$3.8	748
	St.Dev	6.9	$13.9	$17.5	$10.4	$9.0	$5.8	$12.7	$7.5	$2.1	744
	Min	7.5	$22.4	$0.0	$4.8	$3.6	$1.7	$2.6	$0.0	$0.3	43
	Max	45.7	$98.0	$118.5	$63.9	$57.6	$34.4	$66.6	$30.6	$12.4	4159
2010	Mean	33.5	$57.3	$10.3	$16.1	$16.8	$16.2	$22.3	$9.1	$3.8	846
	St.Dev	6.4	$12.7	$10.8	$8.6	$7.1	$4.8	$11.4	$7.6	$2.2	764
	Min	6.4	$22.9	$0.0	$1.6	$0.7	$2.5	$0.7	$0.0	$0.1	4
	Max	54.0	$95.7	$43.9	$57.3	$49.7	$27.6	$61.6	$31.1	$17.7	4369
2011	Mean	28.4	$62.4	$14.5	$20.3	$24.3	$21.4	$26.3	$9.2	$4.8	781
	St.Dev	7.0	$14.0	$15.1	$8.9	$10.6	$6.7	$13.3	$7.8	$3.8	686
	Min	10.5	$14.4	$0.0	$4.7	$5.7	$2.4	$4.8	$0.0	$0.4	26
	Max	43.0	$102.3	$55.7	$53.9	$57.9	$36.4	$75.5	$36.4	$37.3	3349
2012	Mean	35.0	$65.0	$20.0	$20.9	$20.9	$20.4	$26.6	$9.8	$4.9	856
	St.Dev	7.1	$13.7	$17.8	$9.4	$10.3	$6.7	$13.5	$8.5	$3.1	783
	Min	16.6	$14.2	$0.0	$4.9	$3.1	$2.2	$3.7	$0.0	$0.4	10
	Max	51.3	$107.5	$76.3	$54.5	$72.4	$48.3	$72.7	$44.6	$20.8	5058
2013	Mean	32.9	$72.4	$19.8	$22.6	$21.6	$21.2	$28.0	$11.3	$5.2	822
	St.Dev	7.2	$17.4	$18.7	$10.3	$11.3	$7.5	$15.7	$9.6	$3.1	782
	Min	4.7	$32.8	$0.0	$4.3	$3.1	$4.3	$5.1	$0.0	$0.1	34
	Max	55.9	$155.8	$73.6	$88.9	$73.0	$72.5	$125.5	$65.9	$19.6	4056
2014	Mean	32.0	$71.4	$18.3	$23.6	$17.7	$20.1	$21.7	$9.8	$4.7	939
	St.Dev	7.1	$15.9	$15.4	$13.1	$9.3	$7.2	$12.1	$9.5	$2.6	791
	Min	11.0	$17.3	$0.0	$3.4	$0.8	$0.9	$0.2	$0.0	$0.1	79
	Max	49.5	$134.9	$61.5	$134.7	$50.9	$41.5	$79.5	$64.7	$14.6	4599

Note: C/Ins- Crop Insurance, M/Repair- Maintenance and Repair, F/Ins- Farm Insurance

Table A2. Output and Inputs Variables for North Dakota Farms Sampled for Soybean: Descriptive Statistics (Continued)

Soybeans		Yield	Seed	Fertilizer	Chemical	C/Ins	Fuel Oil	M/Repair	Labor	F/Ins	Acre
Year	Unit	bu/acre	$/acre	$/acre	$/acre	$/acre	$/acre	$/acre	$/acre	$/acre	acre
2015	Mean	31.1	$69.3	$14.6	$23.6	$15.8	$13.4	$20.9	$8.4	$5.0	996
	St.Dev	7.7	$14.3	$13.9	$11.0	$7.6	$4.6	$11.0	$7.4	$2.9	934
	Min	10.4	$22.3	$0.0	$4.5	$3.4	$2.3	$0.1	$0.0	$0.0	32
	Max	48.8	$121.0	$54.7	$63.2	$43.0	$29.0	$79.6	$34.3	$23.9	5948
All Years	Mean	31.2	$52.1	$12.5	$25.8	$18.1	$17.6	$23.7	$9.8	$4.4	735
	St.Dev	8.0	$20.0	$14.4	$14.3	$9.5	$6.7	$12.8	$9.3	$2.9	697
	Min	2.3	$1.5	$0.0	$1.6	$0.1	$0.9	$0.1	$0.0	$0.0	4
	Max	55.9	$155.8	$118.5	$134.7	$73.0	$72.5	$125.5	$67.2	$37.3	5948

Table A3. Output and Inputs Variables for North Dakota Farms Sampled for HRS Wheat: Descriptive Statistics

HRS Wheat		Yield	Seed	Fertilizer	Chemical	C/Ins	Fuel&Oil	M/Repair	Labor	F/Ins	Acre
Year	Unit	bu/acre	$/acre	$/acre	$/acre	$/acre	$/acre	$/acre	$/acre	$/acre	acre
1994	Mean	33.0	$18.7	$35.5	$15.4	$12.0	$12.4	$19.8	$7.0	$2.8	585
	St.Dev	7.8	$6.5	$15.9	$10.3	$5.7	$4.6	$9.1	$6.9	$2.2	498
	Min	9.3	$2.8	$2.8	$0.6	$2.8	$2.2	$1.3	$0.1	$0.2	19
	Max	63.9	$47.1	$115.3	$57.9	$35.4	$27.4	$45.8	$38.6	$14.7	3427
1995	Mean	30.2	$18.0	$40.3	$17.8	$12.2	$12.8	$21.5	$7.7	$3.1	606
	St.Dev	8.1	$6.2	$15.5	$10.8	$6.2	$5.0	$10.2	$8.5	$2.5	492
	Min	10.9	$3.5	$4.0	$1.5	$0.1	$1.3	$3.3	$0.0	$0.3	30
	Max	48.1	$53.8	$86.4	$73.2	$36.6	$34.6	$62.1	$50.4	$22.0	3485
1996	Mean	34.8	$21.1	$39.1	$20.1	$14.1	$14.1	$21.0	$7.0	$2.8	729
	St.Dev	9.9	$5.8	$14.9	$10.5	$6.9	$5.5	$9.6	$7.2	$1.9	613
	Min	10.1	$4.0	$7.3	$1.9	$0.0	$4.2	$2.7	$0.0	$0.2	18
	Max	59.5	$49.0	$93.9	$54.3	$45.0	$38.2	$53.9	$38.8	$11.6	4128
1997	Mean	27.0	$17.8	$39.5	$20.7	$11.6	$12.9	$19.7	$7.4	$2.9	652
	St.Dev	7.3	$5.9	$13.2	$11.0	$5.8	$4.3	$9.5	$7.8	$2.2	469
	Min	8.1	$5.4	$8.7	$1.9	$0.1	$1.4	$0.7	$0.0	$0.3	51
	Max	46.0	$41.1	$79.1	$58.7	$31.9	$28.6	$57.8	$45.2	$16.8	3113
1998	Mean	31.4	$15.8	$32.7	$19.3	$11.3	$9.9	$18.7	$7.1	$3.1	635
	St.Dev	9.0	$4.3	$14.5	$11.0	$5.5	$3.1	$8.3	$7.3	$2.2	511
	Min	8.2	$5.0	$3.4	$1.4	$0.1	$4.4	$2.8	$0.0	$0.1	59
	Max	55.0	$31.1	$76.3	$67.5	$32.0	$19.4	$63.4	$36.2	$12.5	2731
1999	Mean	39.2	$17.1	$30.9	$20.9	$11.7	$22.1	$18.9	$10.9	$4.0	713
	St.Dev	9.3	$5.5	$8.8	$12.2	$4.7	$66.7	$7.6	$8.7	$2.2	488
	Min	25.8	$8.7	$10.6	$8.4	$4.3	$0.2	$5.5	$0.4	$1.7	25
	Max	62.7	$32.8	$45.8	$58.7	$20.7	$302.9	$33.6	$35.1	$10.4	1767

Note: C/Ins- Crop Insurance, M/Repair- Maintenance and Repair, F/Ins- Farm Insurance

Table A3. Output and Inputs Variables for North Dakota Farms Sampled for HRS Wheat: Descriptive Statistics (Continued)

HRS Wheat		Yield	Seed	Fertilizer	Chemical	C/Ins	Fuel Oil	M/Repair	Labor	F/Ins	Acre
Year	Unit	bu/acre	$/acre	$/acre	$/acre	$/acre	$/acre	$/acre	$/acre	$/acre	acre
2000	Mean	34.5	$13.2	$26.8	$20.2	$11.8	$12.3	$18.7	$6.2	$2.9	650
	St.Dev	10.4	$4.1	$11.0	$12.1	$7.7	$4.2	$9.0	$5.8	$2.0	581
	Min	8.0	$5.0	$6.4	$1.8	$0.7	$0.3	$0.6	$0.0	$0.1	47
	Max	59.7	$24.4	$63.5	$66.3	$71.4	$36.9	$50.3	$26.3	$10.8	3793
2001	Mean	33.7	$13.4	$32.3	$20.5	$10.5	$12.8	$18.7	$6.3	$3.2	706
	St.Dev	10.2	$4.2	$12.3	$12.0	$5.0	$4.1	$8.3	$6.3	$2.3	590
	Min	4.3	$6.6	$4.6	$2.8	$2.8	$3.7	$4.9	$0.0	$0.1	22
	Max	61.9	$39.8	$76.5	$72.5	$26.5	$27.5	$47.6	$26.9	$11.4	3983
2002	Mean	27.2	$11.8	$26.2	$20.1	$8.9	$9.4	$16.9	$5.7	$3.1	665
	St.Dev	11.1	$3.5	$10.9	$10.1	$4.4	$3.4	$8.2	$6.1	$2.1	525
	Min	0.0	$4.7	$6.0	$1.6	$1.9	$2.0	$0.4	$0.1	$0.2	33
	Max	53.5	$23.1	$74.6	$52.9	$26.0	$22.5	$44.8	$32.1	$15.0	3580
2003	Mean	41.0	$13.6	$30.2	$21.8	$12.1	$10.9	$16.5	$5.7	$3.2	697
	St.Dev	16.0	$4.4	$11.1	$10.5	$5.7	$3.5	$7.7	$5.6	$2.0	587
	Min	7.0	$4.8	$6.4	$3.9	$3.3	$2.3	$3.0	$0.0	$0.3	8
	Max	86.0	$31.9	$68.3	$60.6	$42.6	$25.0	$49.9	$24.3	$12.1	4062
2004	Mean	42.7	$13.4	$32.9	$21.4	$11.5	$12.3	$16.8	$6.1	$3.3	641
	St.Dev	16.2	$3.7	$12.1	$10.9	$5.2	$3.9	$8.2	$6.3	$2.3	623
	Min	0.0	$7.0	$4.6	$3.0	$2.6	$0.6	$1.0	$0.1	$0.3	4
	Max	74.6	$25.5	$69.1	$57.3	$30.2	$29.3	$53.0	$29.6	$12.8	4279
2005	Mean	35.8	$13.5	$37.4	$24.2	$11.8	$14.6	$15.8	$6.1	$3.2	782
	St.Dev	9.9	$5.6	$14.8	$10.6	$5.1	$4.7	$7.4	$6.3	$1.9	777
	Min	6.3	$4.9	$9.1	$1.2	$2.1	$4.2	$3.6	$0.0	$0.4	30
	Max	58.5	$64.6	$106.8	$56.2	$39.4	$27.5	$43.8	$31.6	$12.9	4567
2006	Mean	33.3	$12.8	$36.8	$20.7	$11.3	$14.9	$14.6	$5.3	$3.3	790
	St.Dev	14.8	$4.5	$13.8	$9.2	$4.9	$5.0	$7.0	$5.6	$2.3	592
	Min	0.0	$4.2	$5.9	$2.4	$2.6	$1.4	$1.9	$0.0	$0.1	30
	Max	73.0	$46.8	$92.4	$56.6	$30.0	$28.5	$38.7	$30.8	$13.7	3032
2007	Mean	34.7	$14.4	$38.6	$25.9	$13.4	$15.5	$16.2	$5.6	$3.2	780
	St.Dev	11.0	$5.7	$14.9	$11.7	$5.5	$5.5	$7.1	$5.7	$2.0	730
	Min	9.5	$7.5	$11.1	$3.6	$0.1	$1.4	$0.9	$0.0	$0.2	10
	Max	62.1	$57.6	$117.6	$60.3	$36.3	$31.4	$38.5	$33.9	$12.6	5697
2008	Mean	40.0	$27.0	$57.2	$29.6	$28.9	$19.0	$18.4	$6.2	$3.3	755
	St.Dev	17.6	$9.8	$18.4	$12.1	$9.6	$6.0	$10.1	$6.0	$1.8	581
	Min	0.0	$1.0	$11.9	$5.5	$9.8	$4.6	$1.7	$0.0	$0.2	15
	Max	81.5	$69.0	$119.6	$75.7	$63.2	$35.8	$58.0	$26.5	$10.7	3184

Note: C/Ins- Crop Insurance, M/Repair- Maintenance and Repair, F/Ins- Farm Insurance

Table A3. Output and Inputs Variables for North Dakota Farms Sampled for HRS Wheat: Descriptive Statistics (Continued)

HRS Wheat		Yield	Seed	Fertilizer	Chemical	C/Ins	Fuel Oil	M/Repair	Labor	F/Ins	Acre
Year	Unit	bu/acre	$/acre	$/acre	$/acre	$/acre	$/acre	$/acre	$/acre	$/acre	acre
2009	Mean	52.5	$18.6	$65.3	$31.1	$17.4	$14.4	$21.2	$6.9	$3.3	823
	St.Dev	11.5	$5.0	$27.2	$11.8	$7.4	$5.4	$11.2	$6.6	$1.8	662
	Min	20.9	$4.6	$9.0	$0.9	$2.3	$4.4	$4.6	$0.0	$0.3	30
	Max	78.0	$37.9	$151.9	$77.3	$43.8	$36.5	$66.6	$34.5	$12.4	4286
2010	Mean	42.7	$15.6	$51.3	$28.3	$14.2	$15.0	$19.8	$7.0	$3.2	820
	St.Dev	22.0	$5.1	$17.2	$10.8	$6.2	$4.6	$9.4	$6.3	$1.8	755
	Min	0.0	$5.2	$11.8	$4.3	$2.9	$3.1	$0.7	$0.0	$0.2	59
	Max	79.0	$38.6	$104.1	$64.9	$35.7	$27.5	$56.0	$31.1	$17.7	5005
2011	Mean	32.8	$22.9	$75.1	$32.2	$23.0	$20.7	$24.7	$8.6	$4.0	793
	St.Dev	10.4	$7.0	$25.2	$12.0	$9.8	$7.0	$12.3	$8.6	$2.4	701
	Min	7.0	$0.6	$26.1	$5.9	$4.6	$2.4	$3.2	$0.0	$0.0	23
	Max	65.0	$49.6	$170.7	$75.3	$60.0	$49.5	$75.5	$74.8	$18.0	5295
2012	Mean	48.0	$22.5	$80.3	$31.2	$17.6	$18.5	$22.6	$8.2	$4.3	749
	St.Dev	12.6	$6.3	$27.0	$11.2	$8.3	$6.2	$11.0	$7.2	$2.6	745
	Min	20.9	$5.3	$22.4	$5.3	$3.1	$2.6	$3.5	$0.0	$0.4	7
	Max	75.9	$42.9	$163.2	$59.6	$59.7	$48.3	$64.7	$38.4	$20.8	5320
2013	Mean	53.2	$21.8	$77.5	$34.8	$20.0	$19.3	$24.4	$9.7	$4.5	794
	St.Dev	14.9	$7.4	$27.9	$13.9	$8.3	$6.4	$12.1	$7.8	$2.6	802
	Min	0.0	$8.2	$8.2	$6.3	$3.9	$3.3	$5.1	$0.0	$0.1	21
	Max	88.1	$54.4	$174.4	$76.7	$48.0	$38.0	$63.7	$35.3	$19.6	5343
2014	Mean	55.3	$20.1	$70.0	$33.9	$15.4	$19.1	$20.4	$8.6	$4.2	896
	St.Dev	12.6	$7.1	$21.2	$13.3	$7.4	$7.0	$11.4	$8.0	$2.1	817
	Min	19.5	$7.4	$16.9	$7.3	$0.8	$4.8	$0.2	$0.0	$0.1	41
	Max	83.6	$51.0	$131.5	$75.1	$35.4	$38.9	$68.7	$43.0	$12.4	5084
2015	Mean	54.4	$17.8	$68.9	$31.4	$14.1	$12.6	$19.1	$7.1	$4.5	831
	St.Dev	11.8	$7.0	$22.9	$11.3	$6.2	$4.5	$9.4	$6.5	$2.2	735
	Min	21.3	$3.1	$19.2	$7.0	$3.3	$2.6	$0.1	$0.0	$0.0	40
	Max	81.7	$50.4	$182.0	$60.6	$37.8	$29.0	$59.7	$29.2	$12.4	4717
All Years	Mean	38.5	$17.5	$47.1	$24.5	$14.5	$14.5	$19.4	$7.0	$3.4	729
	St.Dev	15.2	$7.1	$24.9	$12.7	$8.1	$7.6	$9.8	$7.0	$2.2	644
	Min	0.0	$0.6	$2.8	$0.6	$0.0	$0.2	$0.1	$0.0	$0.0	4
	Max	88.1	$69.0	$182.0	$77.3	$71.4	$302.9	$75.5	$74.8	$22.0	5697

Note: C/Ins- Crop Insurance, M/Repair- Maintenance and Repair, F/Ins- Farm Insurance

Table A4. Weather Variables: Descriptive Statistics

Year	Variable	Unit	Mean	Std Dev	Minimum	Maximum
1994	Temperature	°F	59.4	0.7	58.5	60.2
	Precipitation	In.	84.7	30.2	22.6	126.8
1995	Temperature	°F	58.2	0.8	57.4	59.2
	Precipitation	In.	85.5	18.6	23.1	109.3
1996	Temperature	°F	57.3	0.8	56.5	58.6
	Precipitation	In.	73.9	16.8	18.7	100.3
1997	Temperature	°F	58.8	0.5	57.6	60.6
	Precipitation	In.	73.0	23.3	18.2	107.2
1998	Temperature	°F	61.4	0.8	60.4	62.5
	Precipitation	In.	83.4	27.6	16.8	123.7
1999	Temperature	°F	58.6	0.9	57.9	59.9
	Precipitation	In.	111.5	24.9	20.1	143.3
2000	Temperature	°F	58.7	0.9	57.6	60.1
	Precipitation	In.	92.6	19.6	19.2	121.6
2001	Temperature	°F	60.1	0.8	59.3	61.3
	Precipitation	In.	79.5	25.4	21.3	120.9
2002	Temperature	°F	58.2	1.1	56.9	59.8
	Precipitation	In.	77.4	24.8	18.2	114.1
2003	Temperature	°F	59.7	0.6	59.0	61.3
	Precipitation	In.	79.9	16.9	15.7	110.2
2004	Temperature	°F	56.6	1.0	55.5	57.9
	Precipitation	In.	82.5	27.3	15.6	128.5
2005	Temperature	°F	59.9	0.8	59.1	61.5
	Precipitation	In.	101.9	31.5	20.9	164.0
2006	Temperature	°F	61.3	0.6	60.8	62.4
	Precipitation	In.	65.2	19.3	20.3	100.4
2007	Temperature	°F	59.8	0.7	59.0	61.2
	Precipitation	In.	99.2	26.1	18.9	146.7
2008	Temperature	°F	57.7	0.9	56.7	59.6
	Precipitation	In.	88.8	26.1	15.9	135.5
2009	Temperature	°F	57.5	0.7	56.9	58.9
	Precipitation	In.	72.4	13.5	18.8	90.8
2010	Temperature	°F	59.6	1.0	58.6	61.4
	Precipitation	In.	117.4	24.0	27.8	157.6
2011	Temperature	°F	58.6	0.9	58.0	60.1
	Precipitation	In.	107.6	22.9	32.3	146.1

Table A4. Weather Variables: Descriptive Statistics (Continued)

2012	Temperature	°F	61.0	1.0	59.9	62.7
	Precipitation	In.	63.2	7.9	16.4	71.7
2013	Temperature	°F	58.0	1.1	56.9	59.6
	Precipitation	In.	101.9	21.7	30.3	131.8
2014	Temperature	°F	57.8	0.9	56.9	59.3
	Precipitation	In.	101.6	18.9	21.3	127.6
2015	Temperature	°F	59.4	1.5	56.9	61.5
	Precipitation	In.	89.7	19.0	17.1	111.0

APPENDIX B. UNRESTRICTED MODEL FOR EACH OF THE THREE CROPS' YIELDS

Table B1. Unrestricted Model for Corn Yield

The QLIM Procedure

Summary Statistics of Continuous Responses

Variable	Mean	Standard Error	Type
lnCoYie	4.480714	1.21769	Frontier (Prod)

Model Fit Summary

Number of Endogenous Variables	1		
Endogenous Variable	lnCoYie		
Number of Observations	1785		
Missing Values	2		
Log Likelihood	-714.457		
Maximum Absolute Gradient	0.01495		
Number of Iterations	412		
Optimization Method	Dual Quasi-Newton		
AIC	1533	-2	1428.915
Schwarz Criterion	1818	LR $\sim \chi^2_7$	0
Sigma	0.46651	0.1	12.02
Lambda	4.7193	0.05	14.07
		0.01	18.48

Algorithm converged.

Parameter Estimates

Parameter	DF	Estimate	Standard Error	t Value	Approx Pr > |t|	
Intercept	1	-15.0468	2.17421	-6.92	<.0001	***
lnCoSe	1	0.385593	0.336436	1.15	0.2517	
lnCoSesq	1	-0.01657	0.049978	-0.33	0.7403	
lnCoFe	1	0.228759	0.198716	1.15	0.2497	
lnCoFesq	1	0.02212	0.015279	1.45	0.1477	
lnCoCh	1	0.359029	0.155821	2.3	0.0212	**
lnCoChsq	1	-0.02556	0.013037	-1.96	0.0499	**
lnCoIn	1	-0.01326	0.126329	-0.1	0.9164	
lnCoInsq	1	-0.00455	0.006195	-0.73	0.4629	
lnCoFO	1	0.339976	0.222224	1.53	0.126	
lnCoFOsq	1	-0.01514	0.024888	-0.61	0.5431	
lnCoRe	1	-0.31905	0.183932	-1.73	0.0828	*
lnCoResq	1	0.020145	0.010493	1.92	0.0549	*

Table B1. Unrestricted Model for Corn Yield (Continued)

lnCoHl	1	0.120945	0.050916	2.38	0.0175	**
lnCoHlsq	1	0.000615	0.001729	0.36	0.7222	
lnCoFi	1	0.2716	0.11794	2.3	0.0213	**
lnCoFisq	1	-0.00366	0.00453	-0.81	0.4196	
lnCoSeFe	1	0.000532	0.05399	0.01	0.9921	
lnCoSeCh	1	-0.02743	0.038908	-0.71	0.4807	
lnCoSeIn	1	0.031758	0.03712	0.86	0.3922	
lnCoSeFO	1	-0.10288	0.065039	-1.58	0.1137	
lnCoSeRe	1	0.09524	0.050281	1.89	0.0582	*
lnCoSeHl	1	-0.03312	0.015791	-2.1	0.0359	**
lnCoSeFi	1	-0.0316	0.033782	-0.94	0.3496	
lnCoFeCh	1	-0.02182	0.026946	-0.81	0.4181	
lnCoFeIn	1	-0.03437	0.022585	-1.52	0.128	
lnCoFeFO	1	0.049437	0.042743	1.16	0.2474	
lnCoFeRe	1	-0.08093	0.035048	-2.31	0.0209	**
lnCoFeHl	1	-0.00249	0.010733	-0.23	0.8163	
lnCoFeFi	1	-0.02194	0.023012	-0.95	0.3404	
lnCoChIn	1	-0.01382	0.014669	-0.94	0.3462	
lnCoChFO	1	-0.01922	0.026954	-0.71	0.4758	
lnCoChRe	1	0.028982	0.023137	1.25	0.2103	
lnCoChHl	1	-0.00403	0.006717	-0.6	0.5482	
lnCoChFi	1	0.008755	0.017199	0.51	0.6107	
lnCoInFO	1	-0.00644	0.025119	-0.26	0.7977	
lnCoInRe	1	0.026653	0.020819	1.28	0.2005	
lnCoInHl	1	0.010772	0.005576	1.93	0.0534	*
lnCoInFi	1	0.009855	0.01329	0.74	0.4584	
lnCoFORe	1	0.00603	0.032436	0.19	0.8525	
lnCoFOHl	1	0.006602	0.01106	0.6	0.5506	
lnCoFOFi	1	0.02263	0.024185	0.94	0.3494	
lnCoReHl	1	0.002734	0.007938	0.34	0.7305	
lnCoReFi	1	-0.03542	0.019607	-1.81	0.0708	*
lnCoHlFi	1	-0.00654	0.005908	-1.11	0.2686	
lnToCoAc	1	0.02665	0.027072	0.98	0.3249	
lnToCoAcsq	1	-0.00056	0.002633	-0.21	0.8321	
lnAvgTe	1	2.496534	0.23742	10.52	<.0001	***
lnToRaFa	1	2.851327	0.621329	4.59	<.0001	***
lnToRaFasq	1	-0.28935	0.068414	-4.23	<.0001	***
_Sigma_v	1	0.096705	0.00541	17.88	<.0001	***
_Sigma_u	1	0.456381	0.012632	36.13	<.0001	***

*** Significant at 1% level (p<0.01).
** Significant at 5% level (p<0.05).
* Significant at 10% level (p<0.10).

Table B2. Unrestricted Model for Soybean Yield

The QLIM Procedure

Summary Statistics of Continuous Responses

Variable	Mean	Standard Error	Type
lnSoYie	3.396833	0.318704	Frontier (Prod)

Model Fit Summary

Number of Endogenous Variables	1		
Endogenous Variable	lnSoYie		
Number of Observations	2069		
Missing Values	7		
Log Likelihood	3.70995		
Maximum Absolute Gradient	1.05E-04		
Number of Iterations	381		
Optimization Method	Dual Quasi-Newton		
AIC	96.5801	-2	-7.4199
Schwarz Criterion	389.5908	LR $\sim \chi^2_7$	0
Sigma	0.27149	0.1	12.02
Lambda	1.91006	0.05	14.07
		0.01	18.48

Algorithm converged.

Parameter Estimates

Parameter	DF	Estimate	Standard Error	t Value	Approx Pr > |t|	
Intercept	1	-7.21678	1.324083	-5.45	<.0001	***
lnSoSe	1	-0.25882	0.16318	-1.59	0.1127	
lnSoSesq	1	0.007809	0.016235	0.48	0.6305	
lnSoFe	1	0.027752	0.019535	1.42	0.1554	
lnSoFesq	1	0.000837	0.001191	0.7	0.4823	
lnSoCh	1	-0.04479	0.126943	-0.35	0.7242	
lnSoChsq	1	0.011875	0.011758	1.01	0.3125	
lnSoIn	1	-0.18906	0.11736	-1.61	0.1072	
lnSoInsq	1	-0.00753	0.005591	-1.35	0.1783	
lnSoFO	1	0.277261	0.184074	1.51	0.132	
lnSoFOsq	1	-0.01771	0.021145	-0.84	0.4024	
lnSoRe	1	-0.47216	0.127754	-3.7	0.0002	***
lnSoResq	1	0.010805	0.00698	1.55	0.1216	
lnSoHl	1	0.018127	0.042932	0.42	0.6729	
lnSoHlsq	1	0.002656	0.00146	1.82	0.0688	*
lnSoFi	1	0.048635	0.100207	0.49	0.6274	

Table B2. Unrestricted Model for Soybean Yield (Continued)

lnSoFisq	1	-0.00087	0.003853	-0.23	0.8212	
lnToSoAc	1	0.043603	0.040585	1.07	0.2827	
lnToSoAcsq	1	-0.00238	0.003371	-0.7	0.4809	
lnSoSeFe	1	0.00218	0.003219	0.68	0.4984	
lnSoSeCh	1	0.002257	0.023699	0.1	0.9241	
lnSoSeIn	1	0.033556	0.019542	1.72	0.086	*
lnSoSeFO	1	-0.03272	0.029735	-1.1	0.2711	
lnSoSeRe	1	0.069352	0.022542	3.08	0.0021	***
lnSoSeHl	1	0.009477	0.007869	1.2	0.2285	
lnSoSeFi	1	0.009654	0.016307	0.59	0.5538	
lnSoFeCh	1	-0.00445	0.00255	-1.75	0.0808	*
lnSoFeIn	1	-0.00434	0.002455	-1.77	0.0768	*
lnSoFeFO	1	0.001532	0.003596	0.43	0.6701	
lnSoFeRe	1	-0.00492	0.002579	-1.91	0.0563	*
lnSoFeHl	1	0.000431	0.000907	0.47	0.6348	
lnSoFeFi	1	0.003913	0.002027	1.93	0.0535	*
lnSoChIn	1	0.011938	0.017001	0.7	0.4826	
lnSoChFO	1	-0.04579	0.026123	-1.75	0.0796	*
lnSoChRe	1	0.037558	0.017274	2.17	0.0297	**
lnSoChHl	1	-0.01717	0.006088	-2.82	0.0048	***
lnSoChFi	1	-0.00277	0.014639	-0.19	0.8501	
lnSoInFO	1	0.01419	0.023608	0.6	0.5478	
lnSoInRe	1	0.001882	0.017433	0.11	0.914	
lnSoInHl	1	-0.00557	0.006218	-0.9	0.3707	
lnSoInFi	1	0.020933	0.013279	1.58	0.1149	
lnSoFORe	1	0.022138	0.022891	0.97	0.3335	
lnSoFOHl	1	0.007622	0.009827	0.78	0.438	
lnSoFOFi	1	0.003452	0.020312	0.17	0.8651	
lnSoReHl	1	0.000763	0.006512	0.12	0.9068	
lnSoReFi	1	-0.03886	0.014932	-2.6	0.0093	***
lnSoHlFi	1	-8.1E-06	0.004845	0	0.9987	
lnAvgTe	1	2.125216	0.19646	10.82	<.0001	***
lnToRaFa	1	1.145526	0.354291	3.23	0.0012	***
lnToRaFasq	1	-0.11177	0.039285	-2.85	0.0044	***
_Sigma_v	1	0.125923	0.005215	24.15	<.0001	***
_Sgima_u	1	0.24052	0.008372	28.73	<.0001	***

*** Significant at 1% level (p<0.01).
** Significant at 5% level (p<0.05).
* Significant at 10% level (p<0.10).

Table B3. Unrestricted Model for HRS Wheat Yield

The QLIM Procedure

Summary Statistics of Continuous Responses

Variable	Mean	Standard	Type Error	
lnSWYie		3.491248	1.011505	Frontier (Prod)

Model Fit Summary

Number of Endogenous Variables		1		
Endogenous Variable	lnSWYie			
Number of Observations	3649			
Missing Values	6			
Log Likelihood	-1806			
Maximum Absolute Gradient	0.03105			
Number of Iterations	352			
Optimization Method	Dual Quasi-Newton			
AIC	3716	-2	3612	
Schwarz Criterion	4039	LR	$\sim \chi^2_7$	0
Sigma	0.48699	0.1		12.02
Lambda	3.27364	0.05		14.07
		0.01		18.48

Algorithm converged.

Parameter Estimates

Parameter	DF	Estimate	Standard Error	t Value	Approx Pr > |t|	
Intercept	1	7.854704	0.972214	8.08	<.0001	***
lnSWSe	1	-0.13666	0.137365	-0.99	0.3198	
lnSWSesq	1	-0.00088	0.0174	-0.05	0.9598	
lnSWFe	1	0.062118	0.114639	0.54	0.5879	
lnSWFesq	1	0.063626	0.016241	3.92	<.0001	***
lnSWCh	1	-0.10731	0.077269	-1.39	0.1649	
lnSWChsq	1	0.028528	0.010144	2.81	0.0049	***
lnSWIn	1	0.190361	0.082113	2.32	0.0204	**
lnSWInsq	1	-0.00443	0.004885	-0.91	0.3642	
lnSWFO	1	-0.18908	0.115961	-1.63	0.103	
lnSWFOsq	1	0.010471	0.009904	1.06	0.2904	
lnSWRe	1	-0.00283	0.09052	-0.03	0.9751	
lnSWResq	1	-0.00083	0.009794	-0.08	0.9325	
lnSWHl	1	0.083504	0.033838	2.47	0.0136	**

Table B3. Unrestricted Model for HRS Wheat Yield (Continued)

lnSWHlsq	1	0.002104	0.001495	1.41	0.1592	
lnSWFi	1	0.050461	0.066554	0.76	0.4483	
lnSWFisq	1	0.011796	0.004814	2.45	0.0143	**
lnToSWAc	1	-0.02866	0.04282	-0.67	0.5033	
lnToSWAcsq	1	0.003446	0.003604	0.96	0.339	
lnSWSeFe	1	-0.04556	0.031138	-1.46	0.1434	
lnSWSeCh	1	0.026443	0.026085	1.01	0.3107	
lnSWSeIn	1	-0.01438	0.02533	-0.57	0.5703	
lnSWSeFO	1	0.057742	0.037999	1.52	0.1286	
lnSWSeRe	1	0.030201	0.026275	1.15	0.2504	
lnSWSeHl	1	0.008424	0.010435	0.81	0.4195	
lnSWSeFi	1	-0.00053	0.020769	-0.03	0.9797	
lnSWFeCh	1	-0.01539	0.020276	-0.76	0.4477	
lnSWFeIn	1	-0.00658	0.021029	-0.31	0.7545	
lnSWFeFO	1	-0.02099	0.03348	-0.63	0.5308	
lnSWFeRe	1	-0.01785	0.024701	-0.72	0.47	
lnSWFeHl	1	-0.00266	0.00855	-0.31	0.7557	
lnSWFeFi	1	0.009869	0.017885	0.55	0.5811	
lnSWChIn	1	-0.00685	0.017759	-0.39	0.6997	
lnSWChFO	1	0.037081	0.024967	1.49	0.1375	
lnSWChRe	1	-0.00982	0.019645	-0.5	0.6172	
lnSWChHl	1	-0.02181	0.006375	-3.42	0.0006	***
lnSWChFi	1	0.002996	0.013705	0.22	0.8269	
lnSWInFO	1	-0.03996	0.019652	-2.03	0.042	**
lnSWInRe	1	0.015502	0.016006	0.97	0.3328	
lnSWInHl	1	-0.00645	0.006222	-1.04	0.3	
lnSWInFi	1	0.002871	0.013116	0.22	0.8268	
lnSWFORe	1	0.009832	0.021641	0.45	0.6496	
lnSWFOHl	1	0.005836	0.009101	0.64	0.5214	
lnSWFOFi	1	0.038942	0.017369	2.24	0.025	**
lnSWReHl	1	-0.00688	0.007387	-0.93	0.3517	
lnSWReFi	1	-0.05439	0.01387	-3.92	<.0001	***
lnSWHlFi	1	0.00447	0.005009	0.89	0.3722	
lnAvgTe	1	-1.07152	0.18764	-5.71	<.0001	***
lnToRaFa	1	-0.18381	0.1992	-0.92	0.3561	
lnToRaFasq	1	0.039622	0.023574	1.68	0.0928	*
_Sigma_v	1	0.142271	0.004896	29.06	<.0001	***
_Sigma_u	1	0.465745	0.009761	47.72	<.0001	***

*** Significant at 1% level (p<0.01).
** Significant at 5% level (p<0.05).
* Significant at 10% level (p<0.10).

APPENDIX C. STATISTICAL ANALYSIS SYSTEM CODES

Codes for Estimating Stochastic Yield Frontier Models for Each of the Three Crop Yields to Evaluate the Cumulative Elasticity Effects from the Selected Independent Variables in the Restricted Maximum Likelihood Estimator. In addition, Codes for Generating Technical Efficiency Scores for Each Observation from the Data Sample. Each of the Three Codes are Written in Statistical Analysis System.

Code for Estimating Stochastic Yield Frontier Model for Corn Yield

```
PROC IMPORT OUT= WORK.CornModel
DATAFILE= "C:\Users\bayarbat.badarch\Desktop\Thesis\Recent f
iles\GrandFinal.xlsx"
DBMS=EXCEL REPLACE;
RANGE="Corn3$";
GETNAMES=YES;
MIXED=NO;
SCANTEXT=YES;
USEDATE=YES;
SCANTIME=YES;
RUN;
data work.CornModel; set work.CornModel;
lnCoYie=log(CoYie);
lnCoSe=log(CoSe); lnCoFe=log(CoFe); lnCoCh=log(CoCh); lnCoIn=log(CoIn);
        lnCoFO=log(CoFO); lnCoRe=log(CoRe); lnCoHl=log(CoHl); lnCoFi=log(CoFi);
                lnToCoAc=log(ToCoAc);
lnCoSesq=lnCoSe**2; lnCoFesq=lnCoFe**2; lnCoChsq=lnCoCh**2; lnCoInsq=lnCoIn**2;
lnCoFOsq=lnCoFO**2; lnCoResq=lnCoRe**2; lnCoHlsq=lnCoHl**2;
        lnCoFisq=lnCoFi**2; lnToCoAcsq=lnToCoAc**2;
lnCoAcSe=lnToCoAc*lnCoSe; lnCoAcFe=lnToCoAc*lnCoFe; lnCoAcCh=lnToCoAc*lnCoCh;
lnCoAcIn=lnToCoAc*lnCoIn; lnCoAcFO=lnToCoAc*lnCoFO; lnCoAcRe=lnToCoAc*lnCoRe;
lnCoAcHl=lnToCoAc*lnCoHl; lnCoAcFi=lnToCoAc*lnCoFi;
lnCoSeFe=lnCoSe*lnCoFe; lnCoSeCh=lnCoSe*lnCoCh; lnCoSeIn=lnCoSe*lnCoIn;
lnCoSeFO=lnCoSe*lnCoFO; lnCoSeRe=lnCoSe*lnCoRe; lnCoSeHl=lnCoSe*lnCoHl;
lnCoSeFi=lnCoSe*lnCoFi;
lnCoFeCh=lnCoFe*lnCoCh; lnCoFeIn=lnCoFe*lnCoIn; lnCoFeFO=lnCoFe*lnCoFO;
lnCoFeRe=lnCoFe*lnCoRe; lnCoFeHl=lnCoFe*lnCoHl; lnCoFeFi=lnCoFe*lnCoFi;
lnCoChIn=lnCoCh*lnCoIn; lnCoChFO=lnCoCh*lnCoFO; lnCoChRe=lnCoCh*lnCoRe;
lnCoChHl=lnCoCh*lnCoHl; lnCoChFi=lnCoCh*lnCoFi;
lnCoInFO=lnCoIn*lnCoFO;  lnCoInRe=lnCoIn*lnCoRe; lnCoInHl=lnCoIn*lnCoHl;
lnCoInFi=lnCoIn*lnCoFi;
lnCoFORe=lnCoFO*lnCoRe; lnCoFOHl=lnCoFO*lnCoHl; lnCoFOFi=lnCoFO*lnCoFi;
```

```
lnCoReHl=lnCoRe*lnCoHl;  lnCoReFi=lnCoRe*lnCoFi;
lnCoHlFi=lnCoHl*lnCoFi;
lnAvgTe=log(AvgTe); lnToRaFa=log(ToRaFa); lnAvgTeRaFA=lnAvgTe*lnToRaFa;
run; quit;
proc qlim data=work.CornModel;
nloptions maxiter=1000000 tech=qn maxfunc=100000 hs=1;
model  lnCoYie = lnCoSe lnCoSesq lnCoCh lnCoChsq lnCoFe  lnCoFesq
lnCoRe lnCoResq lnCoHl lnCoHlsq lnCoFi lnCoFisq
lnCoSeRe lnCoSeHl lnCoFeRe lnCoInHl lnCoReFi
        lnCoReHl lnCoHlFi
lnToCoAc lnToCoAcsq lnAvgTe lnToRaFa lnToRaFasq;
endogenous lnCoYie ~ frontier (type=exponential production);
output out=work_out12 residual TE1 TE2 predicted;
run; quit;
proc print data=work_out12;
var id year lnCoYie P_lnCoYie TE1;
run; quit;
```

Code for Estimating Stochastic Yield Frontier Model for Soybean Yield

```
PROC IMPORT OUT= WORK.SoybeanModel
DATAFILE= "C:\Users\bayarbat.badarch\Desktop\Thesis\Recent f
iles\GrandFinal.xlsx"
DBMS=EXCEL REPLACE;
RANGE="Soybean3$";
GETNAMES=YES;
MIXED=NO;
SCANTEXT=YES;
USEDATE=YES;
SCANTIME=YES;
RUN;
data work.SoybeanModel; set work.SoybeanModel;
lnSoYie=log(SoYie);
lnSoSe=log(SoSe); lnSoFe=log(SoFe); lnSoCh=log(SoCh); lnSoIn=log(SoIn);
lnSoFO=log(SoFO); lnSoRe=log(SoRe);      lnSoHl=log(SoHl);
lnSoFi=log(SoFi); lnToSoAc=log(ToSoAc);
lnSoSesq=lnSoSe**2; lnSoFesq=lnSoFe**2; lnSoChsq=lnSoCh**2;
lnSoInsq=lnSoIn**2; lnSoFOsq=lnSoFO**2; lnSoResq=lnSoRe**2;
lnSoHlsq=lnSoHl**2; lnSoFisq=lnSoFi**2; lnToSoAcsq=lnToSoAc**2;
lnSoSeFe=lnSoSe*lnSoFe; lnSoSeCh=lnSoSe*lnSoCh; lnSoSeIn=lnSoSe*lnSoIn;
lnSoSeFO=lnSoSe*lnSoFO; lnSoSeRe=lnSoSe*lnSoRe; lnSoSeHl=lnSoSe*lnSoHl;
lnSoSeFi=lnSoSe*lnSoFi;
lnSoFeCh=lnSoFe*lnSoCh; lnSoFeIn=lnSoFe*lnSoIn; lnSoFeFO=lnSoFe*lnSoFO;
lnSoFeRe=lnSoFe*lnSoRe; lnSoFeHl=lnSoFe*lnSoHl; lnSoFeFi=lnSoFe*lnSoFi;
lnSoChIn=lnSoCh*lnSoIn; lnSoChFO=lnSoCh*lnSoFO; lnSoChRe=lnSoCh*lnSoRe;
```

```
lnSoChHl=lnSoCh*lnSoHl;  lnSoChFi=lnSoCh*lnSoFi;
lnSoInFO=lnSoIn*lnSoFO;    lnSoInRe=lnSoIn*lnSoRe; lnSoInHl=lnSoIn*lnSoHl;
lnSoInFi=lnSoIn*lnSoFi;
lnSoFORe=lnSoFO*lnSoRe; lnSoFOHl=lnSoFO*lnSoHl; lnSoFOFi=lnSoFO*lnSoFi;
lnSoReHl=lnSoRe*lnSoHl; lnSoReFi=lnSoRe*lnSoFi;
lnSoHlFi=lnSoHl*lnSoFi;
lnAvgTe=log(AvgTe); lnToRaFa=log(ToRaFa); lnAvgTeRaFA=lnAvgTe*lnToRaFa;
run; quit;
proc qlim data=work.SoybeanModel;
nloptions maxiter=1000000000 tech=nrr maxfunc=1000000 hs=1;
model  lnSoYie = lnSoSe lnSoSesq lnSoFe lnSoFesq  lnSoIn lnSoInsq
lnSoRe lnSoResq lnSoHl lnSoHlsq lnSoFi lnSoFisq
lnSoSeIn  lnSoSeRe lnSoFeCh lnSoFeIn  lnSoFeRe
          lnSoFeFi lnSoChFO lnSoChRe lnSoChHl lnSoReFi
lnToSoAc lnToSoAcsq lnAvgTe lnToRaFa lnToRaFasq;
endogenous lnSoYie ~ frontier (type=exponential production);
output out=work_out22 residual TE1 TE2 predicted;
run; quit;
proc print data=work_out22;
var id year lnSoYie P_lnSoYie TE1;
run; quit;
```

Code for Estimating Stochastic Yield Frontier Model for HRS Wheat Yield

```
PROC IMPORT OUT= WORK.WheatModel
DATAFILE= "C:\Users\bayarbat.badarch\Desktop\Thesis\Recent f
iles\GrandFinal.xlsx"
DBMS=EXCEL REPLACE;
RANGE="Wheat3$";
GETNAMES=YES;
MIXED=NO;
SCANTEXT=YES;
USEDATE=YES;
SCANTIME=YES;
RUN;
data work.WheatModel; set work.WheatModel;
lnSWYie=log(SWYie);
lnSWSe=log(SWSe); lnSWFe=log(SWFe); lnSWCh=log(SWCh); lnSWIn=log(SWIn);
lnSWFO=log(SWFO); lnSWRe=log(SWRe); lnSWHl=log(SWHl); lnSWFi=log(SWFi);
lnToSWAc=log(ToSWAc);
lnSWSesq=lnSWSe**2; lnSWFesq=lnSWFe**2; lnSWChsq=lnSWCh**2;
lnSWInsq=lnSWIn**2;
lnSWFOsq=lnSWFO**2; lnSWResq=lnSWRe**2; lnSWHlsq=lnSWHl**2;
lnSWMlsq=lnSWMl**2; lnSWFisq=lnSWFi**2; lnToSWAcsq=lnToSWAc**2;
lnSWSeFe=lnSWSe*lnSWFe; lnSWSeCh=lnSWSe*lnSWCh; lnSWSeIn=lnSWSe*lnSWIn;
```

```
lnSWSeFO=lnSWSe*lnSWFO; lnSWSeRe=lnSWSe*lnSWRe; lnSWSeHl=lnSWSe*lnSWHl;
lnSWSeFi=lnSWSe*lnSWFi;
lnSWFeCh=lnSWFe*lnSWCh; lnSWFeIn=lnSWFe*lnSWIn; lnSWFeFO=lnSWFe*lnSWFO;
lnSWFeRe=lnSWFe*lnSWRe; lnSWFeHl=lnSWFe*lnSWHl; lnSWFeFi=lnSWFe*lnSWFi;
lnSWChIn=lnSWCh*lnSWIn; lnSWChFO=lnSWCh*lnSWFO; lnSWChRe=lnSWCh*lnSWRe;
lnSWChHl=lnSWCh*lnSWHl; lnSWChFi=lnSWCh*lnSWFi;
lnSWInFO=lnSWIn*lnSWFO;         lnSWInRe=lnSWIn*lnSWRe;
lnSWInHl=lnSWIn*lnSWHl;
lnSWInFi=lnSWIn*lnSWFi;
lnSWFORe=lnSWFO*lnSWRe; lnSWFOHl=lnSWFO*lnSWHl; lnSWFOFi=lnSWFO*lnSWFi;
lnSWReHl=lnSWRe*lnSWHl; lnSWReFi=lnSWRe*lnSWFi;
lnSWHlFi=lnSWHl*lnSWFi;
lnAvgTe=log(AvgTe); lnToRaFa=log(ToRaFa); lnAvgTeRaFA=lnAvgTe*lnToRaFa;
run; quit;
proc qlim data=work.WheatModel;
nloptions maxiter=1000000 tech=qn maxfunc=1000000 hs=1;
model  lnSWYie =  lnSWFe lnSWFesq lnSWCh lnSWChsq lnSWIn lnSWInsq
lnSWHl lnSWHlsq lnSWFi lnSWFisq
lnSWChHl lnSWInFO lnSWFOFi lnSWReFi
lnAvgTe lnToRaFa lnToRaFasq ;
endogenous lnSWYie ~ frontier (type=exponential production);
output out=work_out32 residual TE1 TE2 predicted;
run; quit;
proc print data=work_out32;
var id year lnSWYie P_lnSWYie TE1;
run; quit;
```