CORN YIELD FRONTIER AND TECHNICAL EFFICIENCY MEASURES IN THE NORTHERN UNITED STATES CORN BELT: APPLICATION OF STOCHASTIC FRONTIER ANALYSIS AND DATA ENVELOPMENT ANALYSIS

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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

DOCTOR OF PHILOSOPHY

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ABSTRACT

About 75% of human food in the 21st century consists of just 12 crops, though specific crops vary among nations. Modern technology has allowed development of innovative food and non-food uses for these commodities. For instance, corn (maize (Zea mays L.)) is produced for many purposes, including food, livestock feed, biofuels, fiber for clothing, *etcetera*.

Scientists project the human population will reach 9.2 billion in next 20 years—an 18% increase from the 2020 population of 7.8 billion—resulting in increased demand for corn and other crops. Hence, farmers must increase total crop production to meet demand; however, local agricultural resource endowments such as climate, land and water availability, and soil attributes constrain production. Perhaps the quickest yield and efficiency improvements will result from farm management practices that tailor input applications to match accurate seasonal weather forecasts. Regional seasonal weather forecasts would enable farmers to optimize yields by reducing yield risk from extreme weather events, as well as from less extreme inter-annual weather variability. Improved productive efficiency is also critical to reducing environmental harms, e.g. contaminated runoff from excessive agricultural input use.

The objective of this dissertation is to estimate the corn yield frontier and efficiency measures based on agricultural input management and weather. This research contributes to an enhanced understanding of how the corn yield frontier responds to inter-annual weather variations, and how it may shift with climate change.

The first chapter summarizes three main topics—farm technology, climate change and weather variability, and methods for evaluating production efficiency. The second presents estimated corn yield frontiers and efficiency measures based on stochastic frontier and data envelopment analyses for nine North Dakota Agricultural Statistics Districts from 1994 to 2018.

The third presents corn yield efficiency measures for five states: Minnesota, North Dakota, Nebraska, South Dakota, and Wisconsin from 1994 to 2018. The results reveal the major causes of inter-annual yield variation are variability of rainfall and temperature. Development of accurate growing-season weather forecasts is likely to result in high value-added for farmers and downstream agribusinesses. Federal, state, and private research funding in seasonal weather forecasting would probably be well invested.

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My appreciation to my academic advisor, Dr. David C. Roberts, and to my advisory committee, Dr. Shawn DeKeyser, Dr. Robert Hearne, and Dr. Jack Norland. Thank you for your support and guidance. I also am grateful for financial support for my work provided by the National Science Foundation and the North Dakota Established Program to Stimulate Competitive Research under Cooperative Agreement Award *OIA-1355466* to the Center for Regional Climate Studies.

DEDICATION

This dissertation is dedicated to my Father, Badarch Chultem.

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LIST OF ABBREVIATIONS

ASD	Agricultural Statistics District.
DEA	Data Envelopment Analysis.
DMU	Decision Making Unit.
FINBIN	Farm Financial and Production Benchmark Information Network.
LP	Linear Programming.
NASS	National Agricultural Statistics Service.
NDAWN	North Dakota Agriculture Weather Network.
OLS	Ordinary Least Squares.
PRISM	Planning Tool for Resource Integration, Synchronization and Management.
QLIM	Qualitative and Limited Dependent Variable model.
SBM	Slack Based Measure.
SE	Scale Efficiency.
SFA	Stochastic Frontier Analysis.
TE	Technical Efficiency.
TFP	Total Factor Productivity.
USDA	United States Department of Agriculture.
VIF	Variance Inflation Factor.

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CHAPTER 1. INTRODUCTION

1.1. Farm Technology

Agriculture in North Dakota uses over 90 percent of the state's total land area for farming and ranching (ND Department of Agriculture, 2011). Farming and ranching are constrained by the limited arable land supply, while the demand for food, feed, fuel and fiber are still increasing dramatically. Both agricultural activities are constrained by different pressures from society to promote policies, including natural resource conservation and preservation programs (Johnson, 2000), the development of urbanization and industrialization (Honeywell, 2011), and the recreational parks (Leitch et al., 1990). An accounting of all constraints, on top of limited resources and increasing the crop yield through efficient farm production, is a top priority for sustainable agriculture in North Dakota and throughout the world.

Before 1930s, the primary driver of increased crop production was expansion of the agricultural land base. However, land base expansion is no longer viable due to the constrained supply of arable land. Fortunately, the development and introduction of hybrid corn varieties in the 1930s has helped the production increase even further by increasing yields. According to Harvard Economist, Zvi Griliches, science-based technological advances such as hybrid corn seed continuously sustained higher growth of corn production since 1950s (Griliches, 1957). Thus, hybrid corn seed enabled farmers to produce more corn without adding any more arable land. On top of that, hybrid corn seeds reduced the yield variation substantially because of the uniform resistance to pests and disease. Based on the prediction by Griliches (1957), the returns from switching to hybrid corn varieties were significantly large enough to persuade farmers to adopt this new technology without any hesitation. Farmers took the risk and paid the higher seed prices, which were offset by the resulting yield increases. While hybrid corn seed has been (and continues to be) essential to increased agricultural production in North Dakota and the nation as a whole, this has not been the only technological advance to increase corn yield during same period.

The United States corn yield was also increased by widespread use of commercial fertilizers: nitrogen, phosphate, and potassium. According to Ruddy et al. (2006), the nitrogen and phosphorus fertilizer inputs increased by 14.0 percent and 10.6 percent, respectively from 1987 to 1997, in the US alone. Increases in fertilizer inputs are mainly due to increases in farm input application. Based on the estimation by Gro Intelligence (2018), total fertilizer application rate in the United States increased from 46 lbs. per acre in 1960 to 146 lbs. per acre in 2004. Among the three categories, nitrogen fertilizer has the highest application rate of 82.5 lbs. per acre in 2007, and the nutrient accounts almost 60 percent of total fertilizer weight. Interestingly, about 40 percent of total commercially applied fertilizers are put on corn fields in the Midwestern United States.

Increased fertilizer use and application rate management over several decades enabled farmers to maintain or increase corn yield. Stewart et al. (2005), estimated the overall crop yield effect from commercial fertilizers. They found at least 30 to 50 percent of crop yield is attributable to commercial fertilizer nutrient inputs. Specifically, about 40 to 60 percent of corn yield is now attributable to fertilizer, especially nitrogen. Thus, the current level of yield is highly dependent on fertilizer use, and this state of affairs is likely to continue in the future (Stewart et al., 2005). Another managed farm input is pesticide, which not only increases crop yield but also plays an important role in maintaining yield improvements by reducing pest damage.

Pesticide, now an essential input that sustains increased crop yields, has been used increasingly in agriculture to address evolving crop pest pressures. According to the Gro Intelligence (2018), the United States currently spends about $15 billion on pesticides annually, and approximately 80 percent of total pesticide treatment is used for corn, soybeans, wheat and cotton. Corn dominates pesticide usage with a share of 39 percent, followed by soybean (22 percent). In the state of North Dakota, it is estimated that pesticide-treated corn seed accounted for 93 percent of all corn planted in 2008. Additionally, herbicide application on North Dakota's cropland increased from 17.5 million to 21.4 million acres, from 1984 to 2008 (Zollinger et al., 2018). According to the estimation by Zollinger et al. (2018) total applied insecticides and fungicides increased from 2.5 million to 4 million acres, and 0.5 million to 5.9 million acres, respectively, during the same period .

In the 1940s and 50s, North Dakota farmers were late adopters of new agricultural technologies such as hybrid corn seed, commercial fertilizer and other agrichemicals relative to the farmers in other Corn Belt states such as Iowa, Illinois, Indiana, and Minnesota (Griliches, 1957). They have caught up with modern technologies today. In fact, the State is ranked as the 11th leading corn producer in the nation. According to US Department of Agriculture historical data, corn yield in North Dakota has increased by 146 percent in the last three decades, which is the third highest percentage yield improvement among the Corn Belt states, just behind Missouri (230 percent increase) and South Dakota (189 percent increase). In 2018, the state's average yield was about 153 bushels per acre, and the state's total corn production was 448.2 million (USDA-NASS, 2019).

While farmers have seen the adopted technology as a major driver of the State's increased corn yield and production, there is also inter-annual variation of weather each growing season that leads to yield and financial risk for farmers, along with inter-annual variation of the crop's ability to use applied inputs. Ameliorating these risks by developing accurate predictive models for seasonal weather forecasting will help farmers set appropriate yield goals and select optimal input application rates early in the growing season.

1.2. Climate and Weather Variation

A pilot study by Badh et al. (2009) used air temperature data from six weather station in the North Dakota Agriculture Weather Network (NDAWN) from 1879 to 2008 to assess the average annual rate of changes in growing season length. Their results indicated the average growing season lengthened by 1.2 days per decade. Which means the expected duration of the state's growing season in 2008 was nearly 16 days longer than in 1879. This long-term increasing trend in the length of North Dakota's annual growing season has certainly played a role in increasing the state's crop yields for the past several decades by providing more time for crops to grow and mature, thus allowing farmers to plant late maturity corn hybrids (e.g. 120-day corn vs. 80-day corn). Moreover, the lengthening of the growing season may be one of the factors contributing to rising corn and soybean acreage in North Dakota since 1995 (USDA NASS, 2018). In short, the state's agricultural sector has evolved due, in part, to climate change's effects on the crop yields.

According to Simmer et al. (2015), inter-annual weather variations impact crop yields differently across geographical locations, particularly since each geographic location has its own baseline climate and natural resource endowment. Farmers have difficulty forecasting yield potential each year because the timing and intensity of precipitation and heat varies wildly. Wang et al. (2016) found drought is the strongest stress factor affecting inter-annual variability of corn yield in the Midwest region of the United States. However, this result does not apply equally throughout the Midwest. After all, different geographic locations have varied probabilities of diverse hazards, including drought, flood, hail, pests, and disease.

Liu et al. (2010), found corn yield changes in response to climate change using Vegetation Interface Processes (VIP) ecosystem model in two counties of the Huang-Huai-Hai Plain in China. Based on the crop yield simulation for two temperature change scenarios, the results showed that there is an impact of higher temperature on crop yield. They attribute the negative correlation of corn yield and temperature to the decreased length of the optimal growth period; however, they were uncertain whether temperature increases would affect corn yield equally throughout the study region. The results of the precipitation changes suggest corn yield has a positive correlation with the precipitation changes in the region. This suggests corn yield in this region is highly dependent on the precipitation level. If the precipitation is more than expected, then farmers will expect higher corn yield (Liu et al., 2010).

Moreover, Lobell et al. (2011) found that climate trends, which vary from region to region, have reduced global corn yield by 3.8 percent. However, impacts of temperature and precipitation trends on corn yield in the U.S. were not statistically detectable due to a lack of significant climate trends from 1980 to 2011, relative to other corn producing regions. In contrast, their research suggests no climate change-related global decline in yields of other crops, such as soybeans and rice yields, despite detectable positive and negative impacts in several nations, because the yield losses and gains of the major soy and rice producing countries balance each other out at the global scale (Lobell et al., 2011).

Given North Dakota and other states in the northern U.S. Corn Belt are distinct from not only the rest of the United States but also other parts of the world in that climate trends in the state are strongly evidenced (Badh et al., 2009), it is essential interest that farmers and policy makers, as well as agronomists and economists who advise them, understand how weather variables (e.g., temperature and precipitation) in the region may impact both the corn yield frontier and corn production efficiency. Improved understanding of systematic changes in climatic conditions will allow farmers to more efficiently manage their seed, fertilizer, and pesticides to maintain or increase yields and profitability in the presence of climate change and variation in inter-annual weather.

1.3. Efficiency Measures

1.3.1. Technical Efficiency Concept

Economists evaluate firm technical efficiency and productivity through time series and/or cross-sectional analysis (Fried et al., 2008). Efficiency is measured by the relationship between inputs and outputs. Efficiency improvements generally occur in three ways (Shaik et al., 2012): 1) total output increases without increasing total inputs, 2) total inputs decrease without decreasing total output, and/or 3) total output increases and total inputs decrease simultaneously.

According to Fried et al. (2008), the single firm production function is expressed as set of inputs: $\mathrm{x} = (x_1, \dots, x_N) \in R_+^N$ are used to produce an output(s): $\mathrm{y} = (y_1, \dots, y_N) \in R_+^N$. Thus, the production technology can be represented by the production set:

$$\mathrm{T} = \{(\mathrm{y}, \mathrm{x}): \mathrm{x\ can\ produce\ y}\} \qquad (1)$$

where T presents the production technology; y presents the firm's total output; x presents the firm's total input, and total inputs (x) is used to produce total output of (y). The conceptual framework of economic efficiency was initially developed by Koopmans (1957) and Shephard (1953) and has been well documented by Fried et al. (2008), upon which much of the discussion of technical efficiency in the present document is based.

Technical efficiency information can be conceptualized in three ways: 1) output-oriented technical efficiency, which is derived by maximizing radial expansion in all outputs that is feasible with given technology and inputs, 2) input-oriented technical efficiency, which is derived by maximizing radial reduction in all inputs that is feasible with given technology and fixed outputs, and 3) combined output- and input-oriented technical efficiency, which is derived by improving technical efficiency from both output- and input-oriented procedures applied at the same time.

To illustrate the concept of technical efficiency, Figure 1 presents a graph showing how firm A can improve technical efficiency and reach the efficiency frontier curve, T, or move from an interior, inefficient production level to the efficiency frontier by either increasing output while keeping inputs constant or by maintaining outputs while reducing input use. The horizontal distance implies firm A can increase its technical efficiency by reducing the given level of inputs, x. Thus, it represents input-oriented technical efficiency, which is mathematically expressed:

$$TE_I = (y^A, x^A) = \theta x^A / x^A = 1 \tag{2}$$

where TE_I is technical efficiency score from the input-oriented efficiency procedure; y^A is total output of firm A; x^A is total input of firm A; θ is total radial reduction (e.g. total input inefficiency) of firm A. On the other hand, the vertical distance implies the producer can also increase its technical efficiency without increasing input use. Thus, it represents output-oriented technical efficiency, which is mathematically expressed:

$$TE_O = (y^A, x^A) = \phi x^A / x^A = 1 \tag{3}$$

where TE_O is technical efficiency score from the output-oriented efficiency procedure; y^A is total output of firm A; x^A is total input of firm A; ϕ is total radial expansion (e.g., total output inefficiency) of firm A.

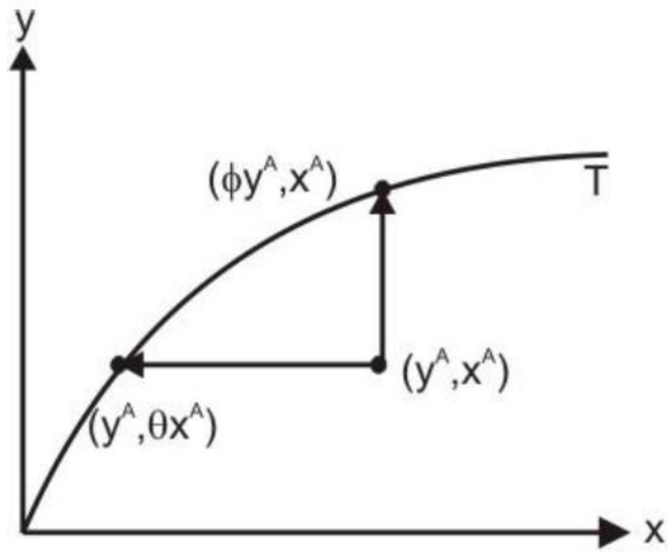

Figure 1. Technical efficiency frontier curve.
Fried et al. (2008).

Figure 2 presents the stochastic production frontier model (Coelli et al., 2005). The graph demonstrates two firms. Firm A uses the input level x_A to produce the output q_A, while firm B uses the input level x_B to produce the output q_B; these values are represented by the small (x). If both firms were efficient, then the outputs would be on the production frontier curve. The functional forms for each firm are presented below:

$$q_A^* = exp(\beta_0 + \beta_1 \ln x_A + v_A), \text{ and} \tag{4}$$

$$q_B^* \equiv exp(\beta_0 + \beta_1 \ln x_B + v_B) \tag{5}$$

where q_A^* and q_B^* are the optimal levels of total output for firms A and B, respectively; β_0 is an intercept of the model; β_1 is the parameter estimated to quantify the relation between inputs and the optimal output at various levels of input use; x_A and x_B are total inputs used by firms A and B, respectively; and v_A and v_B represent the statistical error terms. q_B^* β_0 $\beta_1 x_B$ v_B.

Firm A lies above the deterministic production frontier because the noise effect is positive, whereas firm B lies below the frontier because the noise effect is negative. The observed output for firm A lies below the frontier, because the sum of the noise effect, and the inefficiency effect 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, which is represented:

$$q_i^* > \exp(X_i'\beta)\; iff\, \varepsilon_i = v_i - u_i > 0 \tag{6}$$

where $q_i^*$is the optimal level of total output of firm *i*; $X_i'$is the vector of firms' inputs; β is the vector of unknown parameters to be estimated; ε_i is error terms of firm i; v_i is the statistical error terms of firm *i*; and u_i is error terms represents *i*th firm's technical inefficiency.

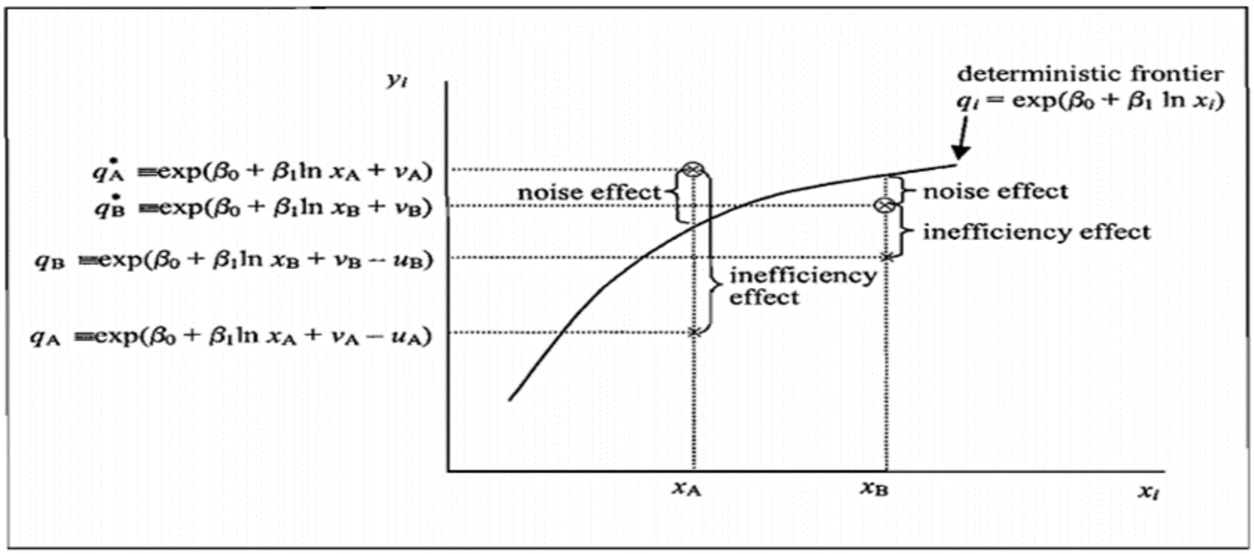

Figure 2. Stochastic production frontier technical efficiency.
Coelli et al.(2005).

1.3.2. Efficiency Approaches

Two popular approaches: Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) are commonly used in an analysis of technical efficiency and productivity (Fried et al., 2008). SFA is a statistical approach that simultaneously investigates the issues of input use efficiency and the effects of unusual events like extreme weather and climate variables on yields and maximum yield potential. The stochastic production frontier model was initially proposed by Aigner et al. (1977), and Meeusen and Van Den Broeck (1977). The stochastic frontier production model collects the error structure via a two-sided, symmetric error component and a one-sided error component. The one-sided component captures inefficiency, while the two-sided component accounts for statistical noise.

On the other hand, DEA is a non-parametric approach for modeling technical and allocative efficiency in the production, cost, revenue, and profit data (Fried et al., 2008). DEA is fundamentally based on a comparison among observed Decision Making Units (DMUs), and it does not require assumptions about the functional form, the distribution of the one-sided error term (inefficiency), or the technology employed by producers, which can be problematic (Seiford, 1996). The paper by Seiford (1996) briefly summarized the development of DEA based on the broad-brush description of incremental growth, enhancement, and improvement of the methodology between 1980 and 1995. More importantly, the paper discussed potential issues regards to the DEA modelling, such as the validation of the results obtained by DEA, and measures of DEA's goodness of fit in the variety of complex applications. The paper suggested some ways to validate the DEA results as well as the goodness of fit. For instance, the validation can be done by comparing published articles that used DEA or testing the sensitivity of the results with respect to the data. The paper pointed out that the biggest disadvantage of DEA is DEA omits or ignores statistical error (i.e. measurement error) in the underlying data. Thus, stochastic DEA will be the biggest challenge for DEA literature in the future (Seiford, 1996).

Banker et al. (1989) proposed a linear "rule of thumb", which indicates that the sample size (n) should satisfy this formula: $n \geq \max[\, p * q, 3(p+q)]$, where, p is the total number of inputs and q is the total of outputs. However, Dyson et al. (2001) argued that the "rule of thumb" should focus on the number of DMUs that should be at least twice the total number of inputs and output variables. Cooper et al. (2007) defined that an appropriate sample size should be up to 160

DMUs in order to have bias-free performance estimates, or a sample size adjusted due to the number inputs and outputs variables. Their findings were conforming the result found by Alirezaee et al. (1998), where DMUs should be at least few hundred to expect reasonably accurate estimation of efficiency scores from DEA. Nevertheless, the “rule of thumb” suggested that DEA estimation with a large sample size (i.e. n >160) would most likely provide an unbiased estimation of efficiency.

However, according to Pedraja-Chaparro et al. (1999), even though the “rule of thumb” accounts some of the key elements (e.g., sample size and number of factors), it does not capture other key elements such as distribution of efficiency, and covariance structure of factors (i.e. inputs). Pedraja-Chaparro et al. (1999) explored that four basic objectives in using DEA model, and each objective is reflected by following four performance measures: 1) the proportion of DMUs deemed inefficiency using DEA, 2) Spearman rank correlation coefficient between DEA and true efficiency, 3) the proportion of DMUs whose DEA efficiency is within 20% of their true efficiency, and 4) the percentage by which DEA efficiency exceeds true efficiency. All four performance measures were compared with the linear “rule of thumb” based on their isoperformance paths. The comparison suggested that the sample size should not be the main reason for choosing DEA analysis. Because the accuracy of DEA efficiency compare to true efficiency does not significantly changes in response to changes in the sample size. Their final conclusion was there is no simple way to determine what’s the best rules of thumb to offer the DEA users, whose are seeking guidance on the reliability of the results obtained. (Pedraja-Chaparro et al., 1999).

Various empirical studies have focused on the comparison of SFA and DEA using different sectors' data (Murwirapachena et al., 2019; Silva et al., 2017). Moreover, choosing one method over another is still controversial (Coelli, 1995; Bravo-Ureta and Pinheiro, 1993). Sharma et al. (1997) investigated the results from SFA and DEA and found technical efficiency scores from both methods are slightly different; specifically, the mean technical efficiency score of 0.64 from the Constant Returns to Scale (CRS) DEA model is significantly lower than mean technical efficiency of 0.75 from SFA model. The research data was collected from 60 swine farms in Hawaii in 1994. The research concluded that DEA efficiency measures have a significantly higher variability than the SFA efficiency scores. Moreover, based on Spearman's rank correlation coefficient, technical efficiency scores from both methods are correlated positively, and it's significant. The strongest correlation was achieved between SFA and CRS DEA (0.88), even though the means of technical efficiency were significantly different from each other.

Another comparison study was done by Madau (2015), who collected data from a sample of 107 Italian citrus farms. The study used gross revenue as the response variable in the model, which is different output data then crop yield or Total Factor Productivity. The study found the mean technical efficiency from SFA and Variable Returns to Scale (VRS) DEA are not significantly different from each other. However, there is significant difference between SFA and CRS DEA, which differed from the results found by Sharma et al. (1997).

Moreover, Kalaitzandonakes and Dunn (1995) measured technical efficiency scores from SFA and DEA on Guatemalan corn production using a sample of 82 family farms. The study found the mean technical efficiency of 0.93 from DEA-CRS is significantly greater than mean technical efficiency of 0.74 from SFA. While SFA-derived technical efficiency scores for corn production in Guatemala were higher than DEA-based scores, DEA-derived scores were higher than SFA-based scores in the case of swine production in Hawaii (Sharma et al., 1997; Kalaitzandonakes and Dunn, 1995). The present document presents similar analysis of results obtained from SFA, DEA-VRS and DEA-CRS for corn production in the northern United States Corn Belt.

A meta-analysis of scholarly technical efficiency literature by Odeck and Bråthen (2012) found the following: 1) the random-effect model seems to be a better estimator than the fixed-effect model based on the explanatory power and capability of accounting specific effects of each individual study, 2) modern studies tended to reveal lower mean technical efficiency scores than older studies, 3) studies with DEA models tended to have higher mean technical efficiency scores than those with SFA models, and 4) studies with panel data tended to have lower technical scores than those with cross-sectional data, which conflicts with findings from the meta-analysis by Bravo-Ureta and Pinheiro (1993). Lastly, studies using European seaport data provided lower mean technical efficiency scores than the rest of the studies. Thus, to capture individual-specific effects, the study favored the use of the random-effects regression model in the meta-analysis.

Efficiency studies were developed to estimate farm technical efficiency (Bravo-Ureta and Pinheiro, 1993). Bravo-Ureta and Pinheiro (1993), analyzed a total of 30 different efficiency studies across 14 different countries. Their meta-analysis highlighted seven essential components for estimating the technical efficiency and efficiency frontiers from farm level data.

The first component is random variables in the frontier model – estimation performance on farm efficiency was certainly dependent on different sets of variables – a variation of variables will be different across the regions and time variant as well as socio-economic data.

The second component is the selection of the modelling method: parametric modeling, non-parametric modeling, or both in the same study. The main distinction is that parametric requires underlying assumptions about the distribution of the population, while the non-parametric modelling techniques require no such assumptions.

The third component is the selection of functional form in the case of parametric modelling (e.g., linear, or nonlinear). Researchers still need to be cautious about the selection of functional form, although many studies concluded differences in functional form have only small effects on the efficiency analysis.

The fourth component is the underlying assumptions about the distribution of the one-sided error terms (i.e. inefficiency effect). Many proposed distributions for this error component, including half-normal, truncated-normal, exponential, and gamma-normal distributions, are an important for efficiency analysis. Thus, one needs thorough understanding of the distribution assumptions.

The fifth component is selection between one-step or two-step procedures. The main difference is the one-step procedure does not omit socioeconomic variables, incorporating such variables directly into the production frontier model, whereas the two-step procedure produces conventional (in)efficiency estimates in the first step, and then the effects of variables on efficiency are estimated in the second step of the procedure (see Greene (2004)).

The sixth component is cross-sectional versus panel data. Because a single production period might not be representative of most production periods due to period-specific exogenous shocks, the efficiency estimates might not be accurate and unbiased if the period-specific distortions are significant. Thus, they conclude, it is better to estimate the efficiency effects from multiple production periods without imposing an arbitrary assumption on the distribution of the efficiency term.

The last component is the selection of a single equation model or systems equation model. Both provided significantly different results. For instance, the systems equation model has better asymptotic efficiency than the single equation model. However, a single equation model may be a proper method when analyzing farm level productivity and technical efficiency (Bravo-Ureta and Pinheiro, 1993).

In consideration of these components, this dissertation investigates the corn yield frontier and efficiency measures for selected regions in the northern U.S. Corn Belt. The SFA (a parametric model) and DEA (a nonparametric technique) efficiency approaches are both applied to the same dataset. A parametric approach, the SFA estimation used as the primary econometric model under specification of stochastic translog yield frontier model. In addition, output-oriented DEA-VRS and DEA-CRS are applied as nonparametric estimations are used to compare their performances against the SFA model in estimation of the technical efficiency scores.

To data, little or no research has yet evaluated the changes in the corn yield frontier from both weather variables and farm input expenditures in the single model. Thus, the research findings from the following two studies advance the existing scholarly literature on stochastic frontier analysis by analyzing the effects of basic weather (e.g., precipitation, and temperatures) in which their effects will be separated from the other inefficiency effects on the frontier analysis.

Hopefully, seasonal weather forecasts will be developed to help farmers optimize input expenditures for productive efficiency as well as make better selection of seed varieties for interannual weather variation and also climate change. Furthermore, a better seasonal weather forecast could potentially reduce crop yield uncertainty and, by extension, inefficiency in crop production thus allowing farmers to more effectively target their input allocations to efficiently reach the yield frontier.

CHAPTER 2. NORTH DAKOTA CORN EFFICIENCY FRONTIER: STOCHASTIC FRONTIER ANALYSIS AND DATA ENVELOPMENT ANALYSIS

2.1. Abstract

Long-term increases in crop yields will be essential to satisfy surging global food demand over coming decades, and climate change is likely to play a major role in determining producers' ability to meet that demand. Changing temperature and precipitation patterns all over the world are likely to necessitate myriad changes in farm management. Some evidence from prior research indicates North Dakota's climate has changed over the last several decades; however, how state's corn yields and production efficiency has been affected by changes in the climate and weather has not previously been addressed. This paper presents corn yield frontiers, maximum yield potentials, and efficiency measures, based on agricultural input use and weather variables, for the nine North Dakota Agricultural Statistics Districts from 1994 to 2018. The findings of this study reveal a median technical efficiency score of 0.85, indicating that corn yield at the USDA Agricultural Statistics District level could increase substantially in North Dakota, potentially by reallocating production inputs to better match interannual weather variability and/or systematic climate change that shifts yield potential. Lastly, the effects of temperature and rainfall on the state's corn yield frontier were far greater than those of farm input variables, and average growing season temperature is found to be the factor with the largest effect on corn yield and the corn yield frontier. The implication of this finding is important: future warming is likely to increase corn yield in the northern region of the United States Corn Belt.

2.2. Introduction

North Dakota's annual growing season lengthened by an average of 1.2 days per decade between 1879 and 2008, as demonstrated by Badh et al. (2009) using air temperature data from six weather stations in the North Dakota Agricultural Weather Network, meaning the expected duration of the state's growing season in 2008 was nearly 16 days longer than in 1879. According to National Agricultural Statistics Service data, average reported corn yields in the state have increased by 595 percent, and corn is one of the dominant crops due to the acreage planted every year (USDA NASS, 2018).

A large proportion of corn yield and efficiency improvement could be attributed to technological advances in agriculture. According to Ruddy et al. (2006), annual nitrogen fertilizer applications in the U.S. have increased 1,000 percent since 1950. Stewart et al. (2005) found that 40 to 60 percent of corn yield is now attributable to commercially produced fertilizers, especially nitrogen. Another significant technological innovation in corn production was the introduction of high-yielding hybrid corn seed varieties in the early 1930s, which were adopted at varying rates as adapted seed lines were released for different production environments (Griliches, 1957). Other technological trends, such as mechanization and the development of herbicides and pesticides, have also improved yields of major crops in the United States.

However, while technological change has been a major driver of North Dakota's increased agricultural productivity, the increase in the length of North Dakota's annual growing season has undoubtedly played a role in boosting the state's crop yields for the past several decades by giving many crops more time to grow and mature. The lengthening of the growing season may be one of the drivers of rapidly increasing corn and soybean acreage in North Dakota since 1995. In short, the state's agricultural sector has evolved due, in part, to climate change's effects on commodity crop yields.

Five consecutive years of bullish commodity crop markets, from 2007 to 2012, caused farm sales in the United States to increase by $97 billion, or 33 percent (USDA NASS, 2012).

During the same timeframe, farm sales in North Dakota increased by $4.9 billion, or roughly 44% (USDA NASS, 2018). The Bakken crude oil boom in western North Dakota, brought not only rapid economic growth but also substantially increased the state budget (Weber et al., 2014). However, a recent price rout for both crude oil and agricultural commodities has caused economic growth to stall, decreasing the state's GDP and causing a one-billion-dollar shortfall in the state budget (Maness, 2017; Nowatzki, 2016). The recent commodity price collapse, along with high price and yield volatility for North Dakota's corn, places farmers amid significant financial instability (Good and Irwin, 2008).

Given low, volatile commodity prices and changing and unpredictable climatic conditions, farmers will benefit from an improved understanding of the processes that have been and will continue to be at play. Understanding historical weather fluctuations' effects on agricultural productivity will help corn producers be technically and financially efficient in the face of climate trends and volatile markets. Intense investigation of the combined effects of crop production inputs, including both those that are managed by producers (e.g., seed, and fertilizer) and those that are uncontrollable (e.g. rainfall and temperature), on the technical efficiency of crop yield is critically important. Besides, almost no research has addressed the effects of climatic change and farm input expenditures on the yield frontier and technical efficiency in corn production. This research is aimed to answer the following four questions:

1. How do interannual weather variations and agricultural input use affect corn yield potential (i.e. the yield frontier) throughout North Dakota's nine USDA Agricultural Statistics Districts?
2. How does corn production efficiency vary across the state's USDA Agricultural Statistics Districts and over time?

3. What will be the likely effects of systematic climate change on the corn yield frontier and the optimal levels of controlled agricultural inputs?
4. Do stochastic frontier analysis and data envelopment analysis provide similar corn production efficiency estimates?

The following section of this paper presents the methodology. Subsequent sections describe the statistical models used for the analysis, indicate the data sources and structure, present and explore numerical and graphical results, and discuss the inferences and conclusions of the analysis.

2.3. Literature Review

In 2019, North Dakota corn grain valued approximately $1.62 billion at the average price of $3.55 per bushel and provided the highest production value to the State's economy (USDA NASS, 2020). Detailed study of corn yield and production efficiency in the State could provide a strong insight into what we may expect nationally in corn yield and efficiency variations. Corn yield and efficiency analysis should be of particular interest to farmers, Cooperative Extension Educators, and state government officials for several reasons. According to Taylor and Koo (2013), corn planted acres have increased approximately 148% in the past couple of decades. Based on the USDA historical data, corn yield has increased about 146% in the last three decades, which is the third largest yield increase in the United States Midwestern region. Lastly, the total economic contribution from the State's corn production has increased from $626 million in 2009 (Taylor and Koo, 2013) to $1.616 billion in 2019 (USDA NASS, 2020).

Inter-annual and spatial crop yield variation is attributable to many factors. Farm production inputs such as seed, fertilizer, chemicals, labor, and machinery are directly managed by farmers to optimize crop yield, subject to constraints imposed by, e.g., climate and soil properties. Nitrogen and phosphorus fertilizers are used as agricultural nutrients in many countries, and use of these two nutrients in agriculture increased sevenfold (nitrogen) and 3.5-fold (phosphorus) between 1960 and1995 (Tilman et al., 2002). According to the forecast by Tilman et al. (2002), global agricultural use of both nitrogen and phosphorus are likely to increase threefold again by 2050 barring substantial improvement in fertilize efficiency. Though nitrogen fertilizer is highly effective in increasing yield whenever nitrogen is the limiting factor, unusual weather events such as heatwaves, cold snaps, excessive rainfall, and drought can reduce plants' ability to use nutrients and, thereby, cause customary nitrogen application rates to be inefficient Powell and Reinhard (2016). For efficiency's sake, farmers would prefer to use more nitrogen given favorable growing conditions, and less when the weather will stunt plant growth. A longer growing season in North Dakota, for example, would allow crops to use more nitrogen and, by doing so, increase the responsiveness of corn to nitrogen. Failing to calibrate nitrogen application rates to the changing climate conditions—generally becoming increasingly favorable to corn and soybean production in North Dakota—could mean lost opportunities for profit.

However, profit is not the only motive to improve efficiency of input use in agriculture. According to Tilman et al. (2002), efficiency of farm input use must improve substantially to reduce the harms of agricultural pollution. Their research indicates inefficient use of four farm inputs—nitrogen, phosphorus, pesticides, and water—is harmful to both humans and the environment and suggests these should be targeted for increased input-use efficiency to make agriculture more sustainable. Furthermore, Raun and Johnson (1999) found that increasing nitrogen use efficiency—i.e. increasing the share of total applied nitrogen incorporated into plant tissues—by 20 percent globally would save the world's farmers $4.7 billion per annum by reducing overall nitrogen applications. This may seem trivial on the global scale; however, improving nitrogen use efficiency will also prevent an imbalance in nutrient cycles and ameliorate harms to ecosystems and human health.

Agrochemicals besides fertilizers—i.e. pesticides, herbicides, fungicides—play an important role in preventing yield losses by averting approximately 37 percent of potential yield loss that would otherwise be caused by insects and plant diseases annually in the U.S. (Pimentel, 1995). However, pesticide and nutrient contamination are detected in surface waters more frequently than in groundwater, and most such pollution is attributable to contaminated surface runoff from agricultural fields, which harms aquatic ecosystems (Rosen and Lapham, 2008).

Contamination from fertilizers and other agrochemicals damages not only ecosystems but also human health. Indeed, the cost of treating human health problems associated with agrochemical exposure and contamination in the U.S. is approximately $786.5 million per year (Pimentel, 1995). Given current knowledge of the benefits and detriments of agrochemicals and fertilizers, it seems essential that farmers more efficiently manage the timing, placement, and quantities of such inputs to sustain or increase crop yields while reducing the harmful impacts on ecosystems, natural resources, and human health.

Inter-annual weather variations impact crop yields differently across geographical locations, particularly since each geographic location has its own baseline climate and natural resource endowment (Simmer et al., 2015). Farmers have difficulty forecasting yield potential each year largely because the timing and intensity of precipitation and heat varies substantially by year. According to Wang et al. (2016), drought is the strongest stress factor affecting inter-annual variability of corn yield in the Midwest region of the U.S. However, this result does not apply equally throughout the Midwest. After all, different geographic locations have varied probabilities of diverse hazards—drought, flood, hail, pests, disease, etc. Moreover, Lobell et al. (2011) found that climate trends, which vary from region to region, have reduced global corn and wheat yields by 3.8 percent and 5.5 percent, respectively. The impacts of temperature and precipitation trends on corn and wheat yields in the U.S. were not statistically detectable due to a lack of significant climate trends from 1980 to 2011, relative to other corn and wheat producers. In contrast, their research suggests no climate change-related global decline in soybean and rice yields, despite detectable positive and negative impacts in several nations, because the yield losses and gains of the major soy and rice producing countries balance each other out at the global scale. Given North Dakota is distinct from the U.S. as a whole, in that climate trends in the state are strongly evidenced (Badh et al., 2009), it is of essential interest to farmers to understand how future temperature and precipitation trends in the state may impact maximum corn yield potential and production efficiency measures for North Dakota. Improved understanding of systematic changes in climatic conditions will allow farmers to more efficiently manage their fertilizer and agrochemical inputs to maintain or increase yields and profitability as the climate changes.

2.4. Methodology

2.4.1. Theoretical Model

The main concept is that managed agricultural inputs, along with uncontrollable factors such as weather, determine a crop's maximum yield potential (the yield frontier) in a particular location. Each producer is then able to realize a yield on the frontier only if managed inputs are matched to the crop's agronomic needs given weather patterns during the growing season, which vary by year. Any unexpected weather pattern, such as rainfall being above or below average during the growing season, may lead to a gap between maximum potential yield and the yield realized in the field, which can be attributed to inefficiency. Therefore, we have to specify the model carefully in terms of data restrictions and the choice of random variables in the model.

The stochastic production frontier initially proposed by Aigner et al. (1977) to address these unknown factors by composing two different error terms. Thus, a generic form of the stochastic production frontier model is represented as:

$$\ln y_i = f(X_i; \beta) + \varepsilon_i \tag{7}$$

$$\varepsilon_i = v_i - u_i \tag{8}$$

where $\ln y_i$ is the natural log of output of the ith firm; X_i is the vector of inputs used by the i^{th} firm; β is the vector of unknown parameters to be estimated; ε_i is an overall random error, which includes both v_i and u_i; v_i is a two-sided error term that represents the level of uncertainty about the yield frontier, and u_i is a non-negative one-sided random error term that captures the deviations from the frontier, which represents inefficiency effects of i^{th} production unit. The following distribution assumptions are made on these two error components in the stochastic production frontier model according to Kumbhakar and Knox Lovell (2003): 1) $v_i \sim iid\ N(0, \sigma_v^2)$, and 2) $u_i \sim iid\ N^+(0, \sigma_u^2)$, where v_i and u_i are assumed to be uncorrelated.

Thus, the stochastic yield frontier model for panel data is defined as:

$$lny_{it} = f(X_{it}; \beta) + v_{it} - u_{it} \tag{9}$$

where lny_{it} is the natural log of corn yield of the i^{th} Agricultural Statistics District (ASD) in t^{th} year from 1994 to 2018; X_{it} is farm inputs of the i^{th} ASD in t^{th} year; β is the vector of unknown parameters to be estimated; v_{it} is a two-sided error term representing uncertainty about the estimated yield frontier for i^{th} ASD in the t^{th} year, which is assumed to be independently and identically distributed $N(0, \sigma_v^2)$; and u_{it} is the non-negative one-sided error term that represents the yield gap, or yield inefficiency, for the i^{th} ASD in the t^{th} year, and it is assumed to be independently and identically distributed $N^{+}(0, \sigma_u^2)$. Additionally, v_{it} and u_{it} are assumed to be uncorrelated over time and across ASDs.

Based on the concept of the stochastic yield frontier model with panel data, we can compute the Technical Efficiency (TE) scores for i^{th} ASD in the t^{th} year as follows:

$$TE_{it} = \frac{q_{it}}{exp(X_{it}'\beta + v_{it})} = \frac{exp(X_{it}'\beta + v_{it} - u_{it})}{exp(X_{it}'\beta + v_{it})} = \exp(-u_{it}) \tag{10}$$

If $TE_{it} = 1$, then ASD *i* efficiently produced its corn output in year *t*—i.e. there was no statistically significant gap between the estimated frontier yield potential and the yield realized. On the other hand, if $TE_{it} < 1$ the ASD's yield fell short of its potential that year, potentially indicating that a superior allocation of controlled agricultural inputs such as fertilizer and chemicals might have ameliorated the yield gap.

2.4.2. Empirical Model for Stochastic Frontier Model

The empirical model of stochastic translog yield frontier is presented:

$$\begin{aligned} lny_{it} = \beta_0 + \sum_{j=1}^{7} \beta_{1,j}\, lnx_{ijt} + \frac{1}{2}\sum_{i=1}^{7}\sum_{i=1}^{7} \beta_{2,j}\, lnx_{ijt} lnx_{ijt} \\ + \sum_{j=1}^{6}\sum_{k=1}^{6} \beta_{3,j,k}\, lnx_{ijt} lnx_{ikt} + v_{it} - u_{it} \end{aligned} \tag{11}$$

where lny_{it} is the natural log of corn yield in ASD *i* in year *t*; β_0 is the estimated intercept; $\beta_{1,1} \cdots \beta_{1,7}$ are the estimated first-degree parameters relating natural logs of *J* = 7 farm input variables to the frontier yield; $\beta_{2,1}, \beta_{2,2}, \cdots, \beta_{2,7}$ are the estimated parameters relating the squared natural logs of the seven farm input variables to the yield frontier; the $\beta_{3,j,k}$ are the estimated parameters relating the products of the natural logs of farm input variables *j* and *k* (for all $j \neq k$)

to the yield frontier; v_{it} is the statistical random error term; and u_{it} is the technical inefficiency error term.

A log likelihood ratio test is used to assess the goodness of fit of the model by jointly testing the statistical significance of the parameters relating each independent variable to the yield frontier. Let β_j be the vector of parameters relating farm input *j* to the yield frontier, including first-degree, second-degree, and interaction parameters. The null hypothesis is then $H_0: \beta_j = 0$, meaning farm input *j* has no statistically discernible relation to corn yield or to the corn yield frontier. The test statistic is:

$$\chi^2_{LRT} = -2\{LLF_R - LLF_U\} \qquad (12)$$

where χ^2_{LRT} is the log likelihood test statistic, LLF_R is the value of the log likelihood function when the restrictions are imposed according to H_0, and LLF_U is the log likelihood function value when the restrictions are lifted. The statistic is distributed chi-square with degrees of freedom equal to the number of parameters restricted by H_0. If the test statistic exceeds the chi-square critical value the null hypothesis is rejected, revealing a statistically discernible relation between the yield frontier and farm input *j* through direct first- and/or second-degree effects and/or interactions with other farm inputs. Thus, the tested variable should be included in the regression, even if none of the individual parameters in β_j are statistically significant per *t*-testing. The intention of using log-likelihood ratio test is to improve the goodness of fit of the stochastic translog yield frontier model, hopefully, which leads to be a parsimonious model and provide robust estimation for corn yield technical efficiencies for each ASD. The Variance Inflation Factor (VIF) test is used to detect the presence of multicollinearity among the independent variables[1] (Joshi et al., 2012). In addition, it is appropriate to estimate the elasticity of mean production with respect to the independent variables for the stochastic translog yield frontier model. The formula is given by Battese and Broca (1997):

$$\vartheta_k = \beta_k + 2\beta_{kk}x_{ki} + \sum_{j \neq k} \beta_{kj}x_{ji} \tag{13}$$

where ϑ_k is the mean output elasticity of the corn yield frontier for independent variable *k*; β_k is the parameter estimates of the k^{th} independent variable; $2\beta_{kk}$ is the squared parameter estimates of the k^{th} independent variable; x_{ki} is the recent five year averages (e.g., 2014 – 2018) of the k^{th} independent variable in the i^{th} ASD; β_{kj} is the parameter estimates of the interaction among the independent variables; and x_{ji} is the recent five year averages (e.g., 2014 – 2018) of the j^{th} independent variable in the i^{th} ASD.

2.4.3. Empirical Model for Data Envelopment Analysis

According to Sharma et al. (1997), the output-oriented DEA model for a single output is generalized based on work by Ali and Seiford (1993), presented below. We have *n* number of DMUs (ASDs), and each produces single output (e.g., corn) by using *m* different inputs. The i^{th} ASD uses x_{ki} units of k^{th} input in the production of y_i unit of output. Thus, the Linear Programming (LP) problem will be separately solved for each ASD in the year *t* is presented with the assumption of Variable Returns to Scale (VRS) of DEA:

$$\underset{\phi_{it}\lambda_{it}}{\text{Maximize}}\ \phi_{it}$$

Subject to:

$$\sum_{j=1}^{n} \lambda_{jt}y_{jt} - \phi_{it}y_{it} - s = 0$$
$$\sum_{j=1}^{n} \lambda_{jt}x_{kjt} + e_{kt} = x_{kit} \qquad k = 1,\ldots, m \text{ inputs;}$$
$$\sum_{j=1}^{n} \lambda_{jt} = 1 \qquad j = 1,\ldots, n \text{ DMUs;}$$
$$\lambda_j \geq 0;\ s \geq 0;\ e_k \geq 0; \qquad t = 1,\ldots, t \text{ years;} \tag{14}$$

[1] The Variance Inflation formula is $VIF_i = \frac{1}{1-R_i^2}$

where ϕ_{it} is the proportional increase in output for the i^{th} ASD in the year t; s is the output slack; e_{kt} is the k^{th} input slack in the year t; and λ_{jt} is the weight of j^{th} ASD in the year t.

The analysis of the output-oriented DEA frontier model is to maximize the proportional increase in output while the current level of inputs stays constant. The output maximization of i^{th} ASD requires the output slack, s, to be zero; therefore, i^{th} ASD will be fully efficient in the year t. In other words, that ASD lies on the DEA frontier when ϕ_{it} = 1, λ_{it} = 1, and λ_{jt} = 0 for $j \neq i \neq t$. If $\phi_{it} > 1$, λ_{it} = 0, and $\lambda_{it} \neq 0$ for $j \neq i \neq t$, then i^{th} ASD is inefficient in the year t, implying that the current level of inputs can be used to achieve more output levels. The frontier production level for the i^{th} ASD is given by Sharma et al. (1997):

$$\hat{y}_{it} = \sum_{j=1}^{n} \lambda_{jt} y_{jt} = \phi_{it} y_{it} \qquad (14)$$

where $\hat{y}_{it}$ is the projected. Based on the $\hat{y}_{it}$, we can calculate the TE of i^{th} ASD by the ratio between the observed output level of i^{th} ASD and projected production frontier level for the i^{th} ASD in the same year t, which is same as the ratio between one and the proportional increase in output for the i^{th} ASD in the year t (Sharma et al., 1997):

$$TE_{it} = \frac{y_{it}}{\hat{y}_{it}} = \frac{1}{\phi_{it}} \qquad (15)$$

The ratio between TE_{it} of CRS and TE_{it} of VRS provides the scale efficiency (SE_{it}) for the i^{th} ASD in the t^{th} year (Wadud and White, 2010):

$$SE_{it} = \frac{TE_{it}\ \text{(CRS)}}{TE_{it}\ \text{(VRS)}} \qquad (16)$$

If the SE_{it} = 1 for i^{th} ASD in the year t, then the corn production in the i^{th} ASD is at the most productive scale size (MPSS), which indicates CRS in the year t. If SE <1 for the i^{th} ASD in the year t, then the corn production in i^{th} ASD has locally decreasing returns to scale (DRS), whereas if SE >1 for the i^{th} ASD in the year t, then corn production in the i^{th} ASD has locally increasing returns to scale (IRS) (Fried et al., 2008).

2.4.4. Data Description

This research provides estimates and analysis of the corn yield frontiers and efficiency components (e.g., technical efficiencies and scale efficiencies) by analyzing a panel data set of the nine ASDs in the state of North Dakota from 1994 to 2018. Figure 3 presents a North Dakota map with ASDs and counties labeled.

The primarily reason of using the ASDs as our research DMUs is twofold: 1) ASDs are intended to provide timely, accurate and useful statistical information to United States' agricultural service; therefore, the variety of crops' input and output data are available spatially as well as timely at the ASD level, and 2) ASDs are defined groupings of counties in each state, by geography, climate, and cropping practices that have similarities on the geographic attributes (e.g., soil type, terrain, and elevation), climate components (e.g., mean temperature, precipitation and length of growing season) and cropping practices (e.g., use of irrigation, crop rotation and specialty crops).

Each ASD has a number and corresponds to a geographic region within the state. For instance, North Dakota's district ND10 is the Northwest region of North Dakota, district ND20 is the North-central region, ND30 is the Northeast region, and so forth.

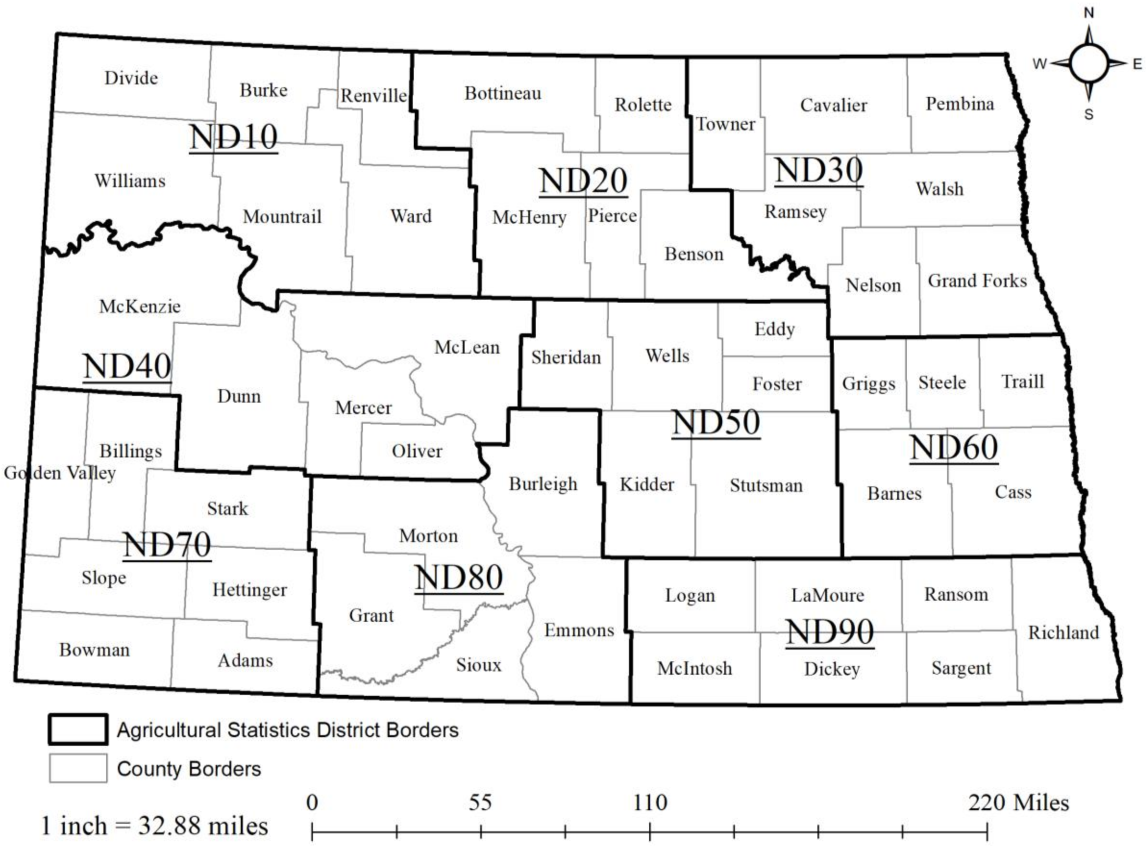

Figure 3. Agricultural Statistics Districts of the state of North Dakota.

The data sample includes corn yield as a dependent variable. Independent variables include per acre expenditures on seed, fertilizer, labor, and used in corn production. Additional independent variables include average corn land area, total growing season rainfall, average temperature, maximum temperature as independent variables. For each ASD each year, average corn yield per acre, average corn land area per farmer, and average per acre expenditures on seed, fertilizer, and labor were retrieved from the Farm Financial Management Database[2] (FINBIN). Data for total growing season rainfall and annual growing season averages of daily average temperature, and daily maximum temperature were collected from the PRISM Climate Database[3]

[2] Farm data sources: https://finbin.umn.edu/.
[3] Weather data sources: http://www.prism.oregonstate.edu/.

for each ASD each year. The sources and definitions of the variables are presented in Table 1. The descriptive statistics for each variable are presented in Table 2.

Table 1. Descriptions of input and output variables and data sources.

Variables	Unit descriptions	Sources
Yield	Average corn yield by ASD (bushels per acre)	FINBIN
Land	Average corn acreage by ASD (acres per farmer)	FINBIN
Seed	Average seed expenditure by ASD ($ per acre)	FINBIN
Fertilizer	Average fertilizer expenditure by ASD ($ per acre)	FINBIN
Labor	Average labor expenditure by ASD ($ per acre)	FINBIN
Rainfall	Total growing season rainfall by ASD (inches per year)	PRISM
Mean Temperature	Growing season average daily mean temperature by ASD (°F)	PRISM
Max Temperature	Growing season average maximum daily temperature by ASD (°F)	PRISM

According to the descriptive statistics in Table 2, the average corn yield in North Dakota from 1994 to 2018 is 113.61 bushel per acre, with a standard deviation of 26.01. One standard deviation is approximately 23% of the statewide average (26.01/113.61 ≈ 0.23). The average cornfield is 316.71 acres, with a standard deviation of 154.52. Acres of corn per operation vary substantially across ASDs and within most ASDs over time. Farmers in the south and eastern regions usually plant relatively more corn per operator than the farmers in the north and western regions. The overall share of agricultural land planted to corn has increased in recent decades due to increasing domestic and international corn demand (Taylor and Koo, 2013). Fertilizer was used extensively, averaging $75.18 per acre statewide with a standard deviation of $38.46. Thus, for 68% of observations, fertilizer expenditures are between $39.99 and $116.31 per acre. The variation in expenditures on fertilizer can be attributed to increasing application rates over the study period and to variability of crop fertilizer needs across the ASDs. The average corn seed expenditure $60.49 per acre with a standard deviation of $25.63; thus, a strong majority (84%) of observations had average seed expenditures greater than $34.86 per acre. Real expenditures on corn seed increased during the study period, potentially reflecting (1) production value-added from development of improved varieties for the Northern Great Plains and (2) generally decreasing row spacing (i.e. increasing plant population) (Henderson et al., 2000). The average expenditure on labor is $19.28 per acre of corn, and average expenditure for 84% of observations exceeding $12.39 per acre ($12.39 = 19.28 – 6.89).

Table 2. State-level descriptive statistics of input and output variables, North Dakota 1994-2018.

Variable	Unit	N	Mean	Std Dev	Minimum	Maximum
Yield	Bu./acre	225	113.61	26.01	13.96	184.34
Land	Acres	225	316.71	154.52	61.13	794.92
Seed	$/acre	225	60.94	25.63	19.84	110.61
Fertilizer	$/acre	225	75.18	38.46	24.00	172.22
Labor	$/acre	225	19.28	6.89	2.76	37.02
Rainfall	Inches	225	14.97	3.75	6.92	24.34
Temperature	°F	225	59.55	1.49	54.58	62.85
Max Temperature	°F	225	82.72	3.86	74.20	93.30

All corn input expenditure variables are adjusted for inflation and presented in 2018 USD per acre ($/ac.). The deflation is based on the Gross Domestic Product (GDP) deflator, and the formula is used as:

$$GDP\ deflator = \frac{Nominal\ GDP}{Real\ GDP} * 100 \tag{17}$$

The statewide growing season average of daily mean temperature (“average temperature”) is 59.55 °F, with a very small standard deviation of 1.49 °F. Higher average temperature values were recorded in the south and southeast, while lower values in the north and northwest. The growing season average daily high temperature (“maximum temperature”) is 82.72 °F, with a standard deviation of 3.86 °F. Maximum temperature shows the same spatial pattern as average temperature—warmer in the South and Southeast and cooler in the North and Northwest—and exhibits about 2.6 times as much variability as the average temperature. Total rainfall varied substantially over the study period, with a standard deviation 3.75 inches per season (about 25%

of the sample average, 14.97 inches). Rainfall values are higher in the eastern half of the state, with the highest growing season rainfall occurring in the southern Red River Valley.

Figure 4 presents corn yield descriptive statistics for each ASD over the study period. In the past 25 years, farmers in the Southeast ASD had an average corn yield of 127.14 bushels per acre with standard deviation of 25.36 bu./ac. Farmers in the East-central ASD had average corn yields of about 125.22 bushels per acre with standard deviation of 25.04 (not statistically different from the Southeast ASD). For Northeast ASD farmers, the mean corn yield was 118.27 bu./ac., with standard deviation 23.17—again, not statistically different from the farmers of the Southeast and East-central ASDs. In fact, every ASD's mean yield was within one or two standard deviations of every other ASD's mean yield during the study period. However, the mean yields have not been stationary over time; corn yield increased in every ASD throughout the study period.

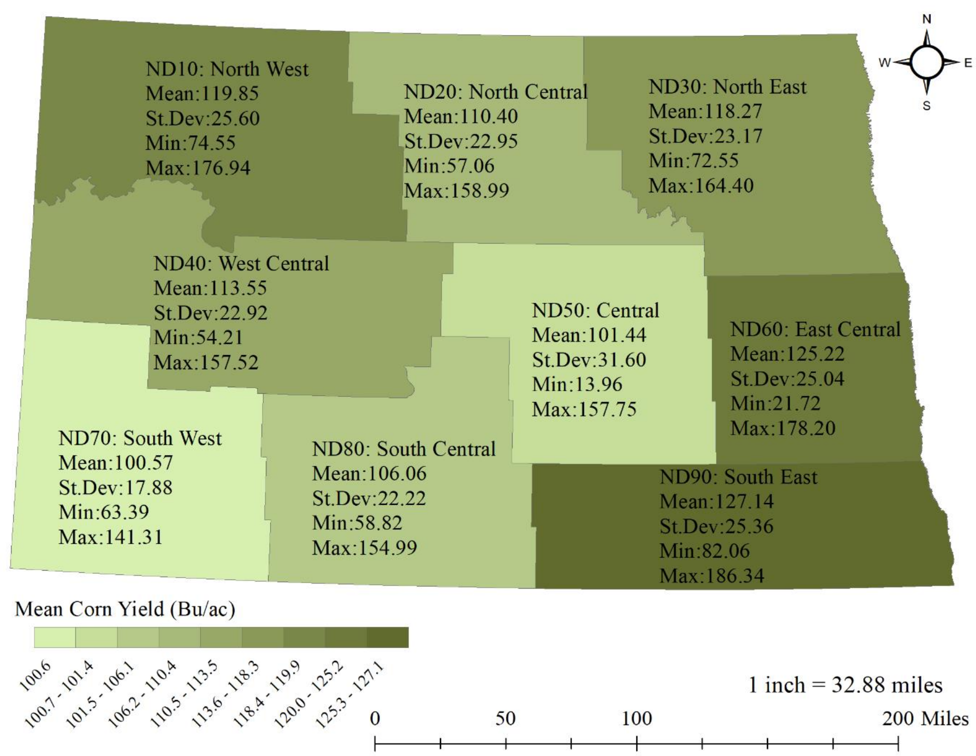

Figure 4. Corn yield summary statistics by Agricultural Statistics District, 1994-2018.

Qualitative and Limited Dependent Variable model (QLIM) of the Statistical Analysis System (SAS) is used for the estimation of the stochastic yield frontier model to provide SFA technical efficiency scores for each ASD in each year. In addition, Stata 14 is used for Monte Carlo simulations to estimate the standard errors for each elasticity effect from the independent variables. The simulated standard error for each output elasticities enables us to determine the significant level of each elasticities by using t-test. Simply, our hypothesis test is the output elasticities are no different from zero. If we reject the null, then the elasticities are statistically significant from zero and we have sufficient evidence to make inference on the relationship between inputs and output variables. In addition, we also used STATA for estimating the DEA yield efficiency frontier under both VRS and CRS assumptions to compare their technical efficiency scores with SFA's technical efficiency scores.

2.5. Results and Discussion

2.5.1. Results from Stochastic Frontier Model

Table 3 shows the results of the log-likelihood ratio tests for the joint significance of the parameter estimates for each of the farm input expenditure and weather variables. We found the effects of almost all variables, except labor on the corn yield frontier are statistically determined as significant. All insignificant parameters are tested by the log-likelihood ratio test and their joint effects are also statistically determined as significant. In addition, the VIF test is used for investigating the presence of multicollinearity in the model by regressing the Ordinary Least Squares (OLS) estimation in SAS. VIF results indicate the coefficient of factor level from each variable is less than five, implying that no independent variable in the model is a linear function of one or more other independent variables. Therefore, all independent variables are included in the model, including their terms of multiplication and interactions, to estimate the technical efficiency scores for each of the ASDs.

Table 3. Log likelihood ratio and variance inflation factor test results.

Variable	Null Hypothesis	Degrees of freedom	Log Likelihood Ratio Test Statistic	VIF
Land	$H_0: \beta_{\text{land}} = 0$	4	73.60***[a,b]	2.59
Seed	$H_0: \beta_{\text{seed}} = 0$	5	47.76***	4.81
Fertilizer	$H_0: \beta_{\text{fert.}} = 0$	4	47.96***	3.91
Labor	$H_0: \beta_{\text{labor}} = 0$	5	6.88	3.89
Rainfall	$H_0: \beta_{\text{rain}} = 0$	4	8.04**	1.72
Temperature	$H_0: \beta_{\mu\text{temp}} = 0$	5	29.48***	3.44
Max Temp	$H_0: \beta_{\mu\text{maxtemp}} = 0$	5	19.44***	4.25
Insignificant Parameters	$H_0: \beta_{\text{insignificant}} = 0$	15	45.80***	N/A

[a] The test statistics are distributed chi-square with the indicated degrees of freedom equal to the number of restricted parameters.
[b] Asterisks indicate exceedance of the chi-square critical value at significance levels 0.01 (***), 0.05 (**), and 0.10 (*).

The maximum likelihood parameter estimates of the stochastic semi-translog yield frontier model, specified in equation (11), are in Table 4. A total of 26 parameters, of which eight are statistically non-zero (for $\alpha \leq 0.10$).

The variance component gamma indicates the proportion of the total variance attributable to inefficiencies—about 80.9%—related to unexpected shifts in the corn yield frontier caused by favorable or unfavorable temperature and rainfall variations each year, as well as to any extreme weather events, crop disease, and accidents that may have contributed to yield gaps. This result is conforming other research done in the past (Asmara et al., 2016; Wadud and White, 2010; Odeck, 2007; Sharma et al., 1997). Thus, the variance parameters indicate that the stochastic frontier model is an appropriate modelling technique for the error structure present in the data (as opposed to ordinary least squares). Other parameters are not individually significant; however, the combined parameter estimates for each variable are significant in the model based on the results of log-likelihood ratio test.

Table 4. Stochastic semi-translog yield frontier model of estimation.

Variables	Parameter	Estimate	St. Error	p-value
Stochastic Yield Frontier				
Constant	β_0	13.98	200.71	0.944
Land	β_L	0.94	0.51	0.065
Land Square	β_{LL}	-0.08	0.04	0.058
Seed	β_S	-1.28	8.11	0.875
Seed Square	β_{SS}	-0.06	0.09	0.508
Fertilizer	β_F	5.41	6.61	0.413
Fertilizer Square	β_{FF}	-0.06	0.04	0.150
Labor	β_{La}	-0.07	0.58	0.908
Labor Square	β_{LaLa}	0.02	0.07	0.775
Rainfall	β_R	1.23	0.59	0.039
Rainfall Square	β_{RR}	-0.02	0.09	0.863
Temperature	β_T	-125.41	83.90	0.135
Temperature Square	β_{TT}	33.28	11.91	0.005
Maximum Temp	β_{Mt}	105.97	41.49	0.011
Max Temp Square	β_{MtMt}	4.92	4.07	0.226
Land x Labor	β_{LLa}	0.23	0.11	0.042
Land x Rainfall	β_{LR}	-0.15	0.12	0.213
Seed x Labor	β_{SLa}	-0.29	0.16	0.066
Seed x Temperature	β_{ST}	1.04	2.06	0.616
Seed x Max Temp	β_{SMt}	-0.32	1.27	0.801
Fertilizer x Temperature	β_{FT}	0.54	1.82	0.765
Fertilizer x Max Temp	β_{FMt}	-1.62	1.12	0.149
Labor x Rainfall	β_{LR}	-0.09	1.11	0.571
Temperature x Max Temp	β_{LaT}	-34.67	12.55	0.006
Variance Parameters				
Sigma2_v	σ_v^2	0.005		
Sigma2_u	σ_u^2	0.020		
Sigma2	$\sigma^2 = \sigma_v^2 + \sigma_u^2$	0.025		
Gamma	$\gamma = \sigma_u^2/\sigma^2$	0.809		
Log-likelihood	$\mathcal{L}$	124.61		
Observations		225		

Table 5. presents the output elasticities of the stochastic semi-translog yield frontier model, specified in equation (13). Almost all the output elasticities are discernibly different from zero ($\alpha \leq 0.10$), except the elasticity for labor. We estimated the elasticities of the corn yield frontier for the average temperature, for the maximum temperature, and for the combined average and maximum temperatures. The combined elasticity estimate indicates how corn yield may

respond to a uniform increase in temperature in which the distribution of temperatures increases by one percent. The elasticity of output for temperatures is positive, as expected, and is statistically significant level at $\alpha = 0.01$. A general interpretation of this combined temperature is that a general temperature increase of 1% will increase expected maximum yield potential (i.e. the frontier) by 52.3%, an increase of 59 bu./ac. This large elasticity indicates interannual variability of temperature has an outsize impact on the frontier yield and that climate warming is likely to substantially improve corn yield potential, especially as North Dakota producers re-optimize their managed agricultural inputs as climatic conditions change over decades to come.

The elasticity of the yield frontier to total growing season rainfall is 4.97%, and it is highly significant($\alpha = 0.01$). This implies 1% more precipitation in the growing season—an increase of just 0.15 inches—will increase maximum yield potential by nearly 17 bu./ac. The output elasticities for farm input expenditures are all statistically significant and positive, with the exception of the labor expenditure elasticity which is negative and not statistically significant. The elasticity response of the yield frontier to seed expenditure is 3.63% ($\alpha = 0.05$). This indicates that the corn yield frontier rose substantially during the study period in response to increasing expenditures on seed, probably because North Dakota farmers adopted narrower row spacing and because improved seed varieties developed and released since 1994 are much higher yielding but also more expensive as a proportion of total variable costs. Additional seed line improvements in coming decades will likely have similar effects. The yield frontier is also significantly responsive ($\alpha = 0.10$) to fertilizer expenditure, with the elasticity estimate indicating that a 1% increase in fertilizer expenditure (about $0.75 per acre) can raise the frontier yield by 2.54% (nearly 3 bu./ac.) if other factors such as rainfall and temperature are not limiting plant growth. The average farmer's land area planted to corn also has a statistically significant and positive relation to yield, with the elasticity estimate indicating a 1% increase in the average area planted per farmer is correlated with a 1.47% increase in yield ($\alpha = 0.05$). This relation does not necessarily imply causality; it is possible that planting more acreage to corn allows for economies of scale, but it is also possible that farmers who attain higher yields for other reasons simply plant more corn acres.

The elasticity estimates for each variable are approximately the same for every ASD, despite variations in temperature, precipitation levels, and input expenditures among the nine ASDs. The uniformity of such elasticity estimates at the ASD level conflict with the results of Simmer et al. (2015), who found corn yield responses to interannual weather variations were different across geographic locations. On the other hand, the results of the present work may simply suggest that the marginal factor productivity is similar in every ASD given local temperature and precipitation regimes and current local input management practices. After all, experienced farmers typically have reasonable expectations about weather and crop input needs for their farms and manage their factors of production accordingly. In fact, the equal marginal principle indicates producers should all be producing such that the expectation of the marginal revenue product of each input is equalized across all producers. In the context of the corn yield frontier, then, it should not be surprising that these elasticities vary little from one ASD to the next. It is possible, however, that expanding the study region to encompass more heterogeneity would affect this result.

Table 5. Output elasticities of the corn yield in each Agricultural Statistics District.

Variables	ND50	ND60	ND20	ND30	ND10	ND80	ND90	ND70	ND40	State
Land	1.48**	1.48**	1.48**	1.48**	1.48**	1.48**	1.48**	1.48**	1.48**	1.48**
	(0.61)	(0.61)	(0.61)	(0.61)	(0.61)	(0.61)	(0.61)	(0.61)	(0.61)	(0.61)
Seed	3.63**	3.63**	3.63**	3.63**	3.63**	3.64**	3.63**	3.64**	3.63**	3.63**
	(1.56)	(1.56)	(1.56)	(1.56)	(1.56)	(1.56)	(1.56)	(1.56)	(1.56)	(1.56)
Fertilizer	2.54*	2.54*	2.54*	2.54*	2.54*	2.54*	2.54*	2.54*	2.54*	2.54*
	(1.47)	(1.47)	(1.47)	(1.47)	(1.47)	(1.47)	(1.47)	(1.47)	(1.47)	(1.47)
Labor	-1.36	-1.36	-1.36	-1.35	-1.35	-1.36	-1.35	-1.36	-1.36	-1.36
	(0.96)	(0.96)	(0.96)	(0.96)	(0.96)	(0.96)	(0.96)	(0.96)	(0.96)	(0.96)
Rainfall	4.99***	4.97***	4.97***	4.97***	4.95***	4.97***	4.97***	4.96***	4.97***	4.97***
	(1.39)	(1.39)	(1.39)	(1.39)	(1.39)	(1.39)	(1.39)	(1.39)	(1.39)	(1.39)
Temperature	39.28**	39.28**	39.27**	39.27**	39.23**	39.28**	39.29**	39.28**	39.27**	39.27***
	(15.95)	(15.95)	(15.95)	(15.95)	(15.95)	(15.95)	(15.95)	(15.95)	(15.95)	(15.95)
Max Temp	13.06*	13.04*	13.06*	13.06*	13.05*	13.06*	13.05*	13.05*	13.05*	13.06*
	(6.36)	(6.36)	(6.36)	(6.36)	(6.36)	(6.36)	(6.36)	(6.36)	(6.36)	(6.36)
MtemTemp	52.33***	52.32***	52.33***	52.33***	52.28***	52.33***	52.35***	52.33***	52.32***	52.32***
	(18.03)	(18.03)	(18.03)	(18.03)	(18.03)	(18.03)	(18.03)	(18.03)	(18.03)	(18.03)

***, **, and * indicate significance at $\alpha = 0.01$, $\alpha = 0.05$, and $\alpha = 0.10$, respectively. Max Temp represents the maximum temperature in growing season. MtemTemp represents the combined elasticities of maximum temperature and average temperature.

Figure 5 presents corn yield technical efficiency scores from the semi-translog stochastic yield frontier model for each ASD from 1994 to 2018. The black line represents the annual median of the technical efficiency scores for all ASDs. The median technical efficiency score exceeds 0.80 every year, indicating corn production in the majority of ASDs are very technically efficient, producing 80% or more of the estimated maximum corn yield potential for the year. The only technical efficiency scores lower than 0.72 is for the Central ASD in 2004, with a score of only 0.49, indicating this district was shy of its frontier yield by 51%. The 2004 growing season corresponds to the coolest North Dakota summer from 1994 to 2018. The growing season statewide average temperature that year was 2.36 °F below the study period average. The low efficiency score for the Central ASD that year may indicate corn yield (but not the yield frontier) in this ASD is more sensitive to unexpectedly cool weather than yield in the other ASDs. Overall, there is no discernible time trend in the efficiency scores; they do not seem to be increasing or decreasing over time.

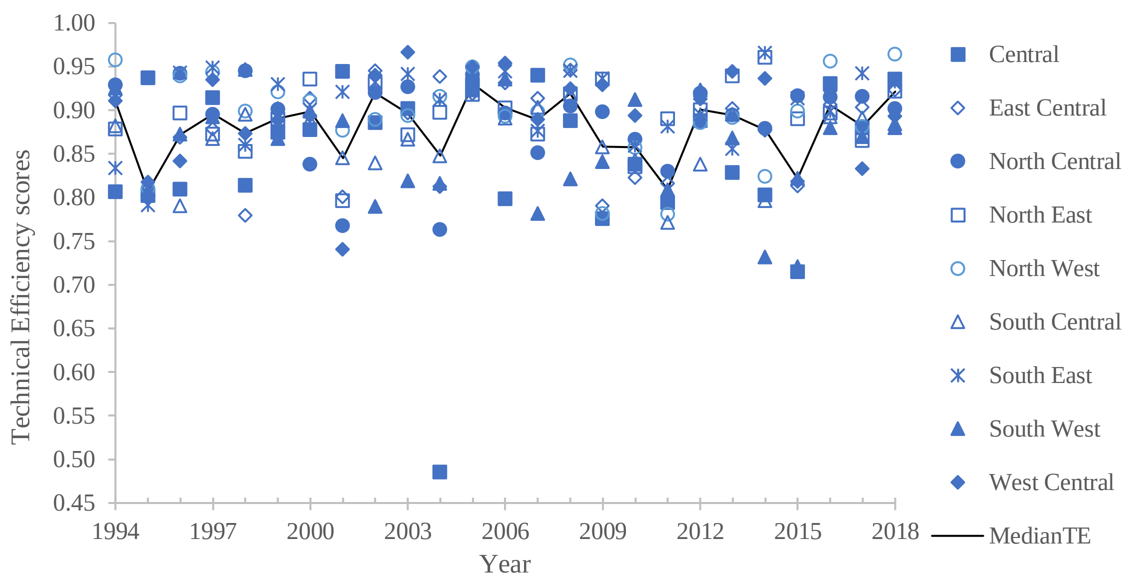

Figure 5. Technical efficiency scores from Stochastic Frontier Model, 1994-2018.

Figure 6 presents some descriptive statistics for each ASD’s estimated technical efficiency scores over the study period. The stochastic semi-translog yield frontier-based estimates of corn technical efficiency scores for the South East region have a mean of 0.908 and standard deviation of 0.041. The Southeast region in the state is where corn production has been most efficient, on average, from 1994 to 2018. The second highest average technical efficiency score is that of the Northwest region with average score of 0.893. This is somewhat surprising, as very little corn is produced in this ASD. It’s possible that much of the corn grain produced there is irrigated (see Figure A1), unlike corn acreage in the rest of the state. The lowest efficiency score belongs to the Central region, with a score of 0.848; however, the mean efficiency scores for all the ASDs are statistically indistinguishable from one another, as all ASDs’ average scores are within one standard deviation of the Central ASD’s average score. This result means the efficiency scores do not discernibly differ in any systematic way across ASDs. These average technical efficiency scores indicate each corn producing ASD could substantially increase its average corn yield by improving its technical efficiency, possibly by reallocating expenditures on managed inputs to address the evolving weather-related risks.

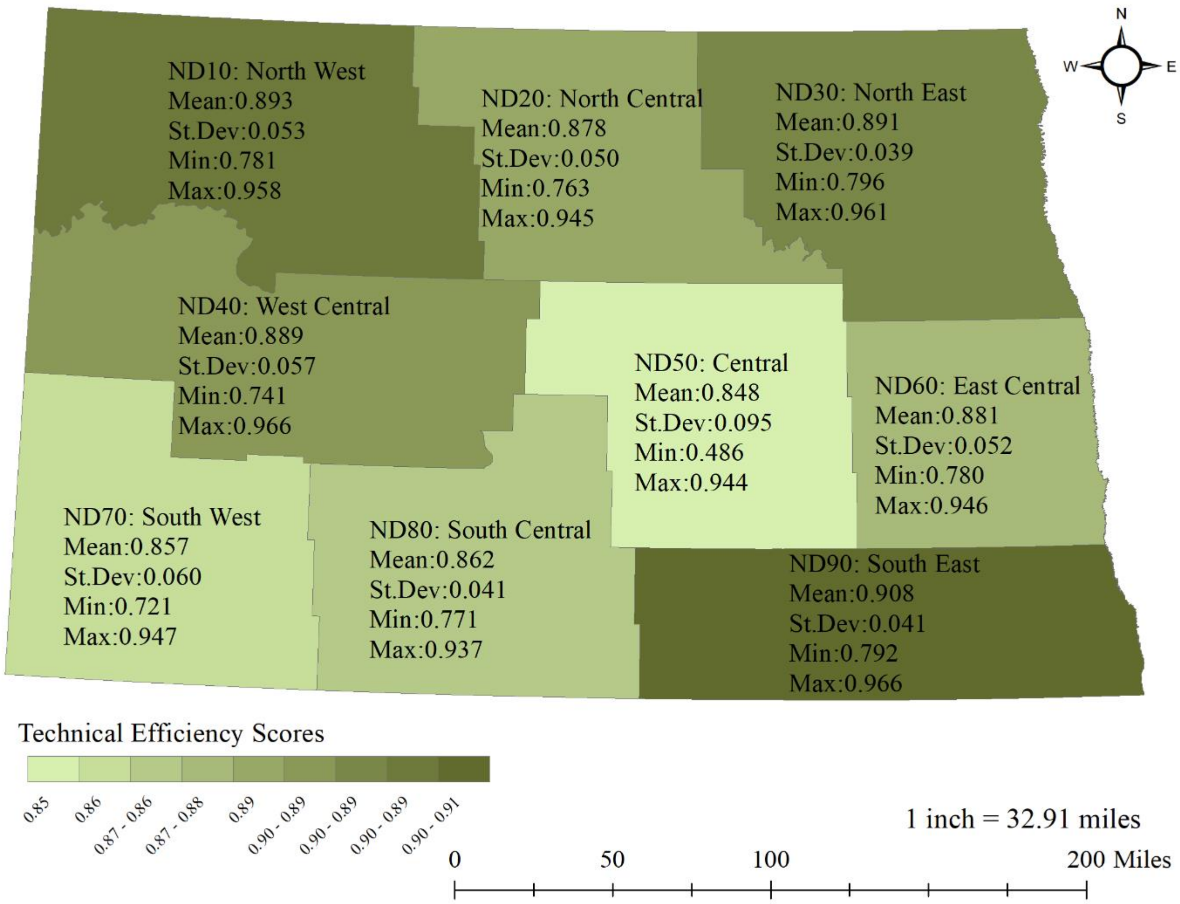

Figure 6. Technical efficiency score from Stochastic Frontier Model in each Agricultural Statistics District, 1994-2018.

2.5.2. Results from Data Envelopment Analysis

We also applied the output-oriented DEA model under both technological assumptions: VRS and CRS to estimate the corn yield frontier and technical efficiency for each ASD. Figure 7 presents corn yield technical efficiency scores from the DEA-VRS model for each ASD from 1994 to 2018. The black line is the median of the annual technical efficiency scores. Based on the technical efficiency scores from the DEA-VRS model, the median technical efficiency score varies wildly by year, relative to the scores from the stochastic yield frontier model.

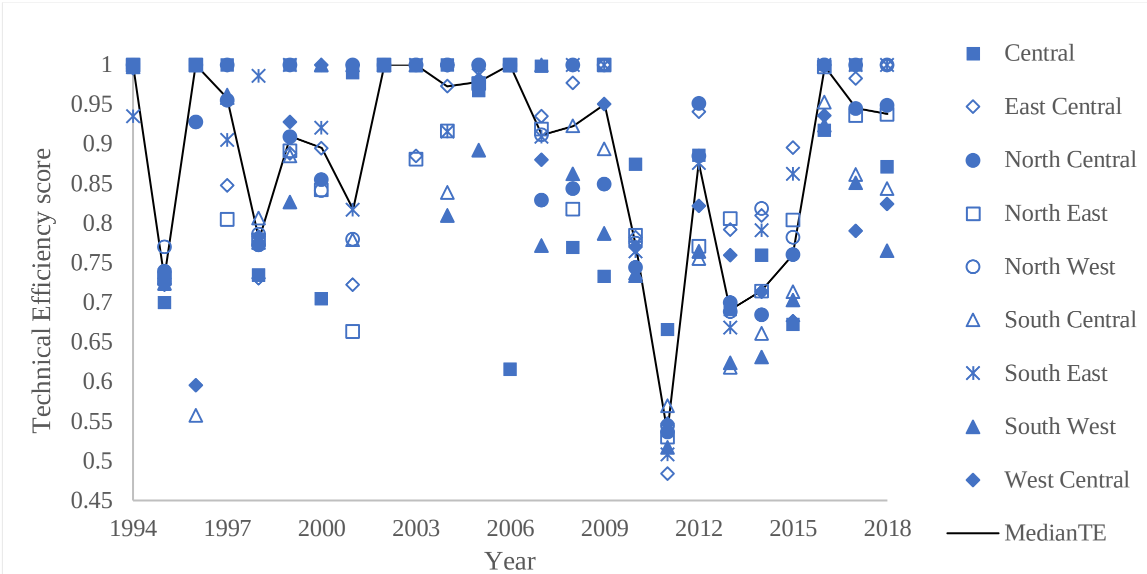

Figure 7. Technical efficiency scores from the Data Envelopment Analysis with Variable Returns to Scale, 1994-2018.

The wide range in the technical efficiency scores from the DEA-VRS model may suggest that the corn yield frontier changes substantially from year to year in ways farmers cannot predict. However, the stochastic frontier estimates suggest that weather variables shift the yield frontier in ways that linear programming methods like DEA cannot capture. The DEA-VRS model results in technical efficiency scores that range from 0.55 to 1.00, which is much greater than range of scores estimated by stochastic yield frontier model (Figure 5). The high variability of technical efficiency scores based on DEA-VRS relative to the stochastic yield frontier efficiency estimates is consistent with results of other research (Wadud and White, 2010; Kurkalova and Carriquiry, 2003). In addition, higher variability of technical efficiency scores might be due to the sample size in the study. For instance, Alirezaee et al. (1998) studied samples of various sizes under DEA method, and found that smaller sample size often leads to biased efficiency estimation using DEA. They concluded that the number of DMUs should be at least a few hundred to expect reasonably accurate estimation of efficiency if the assumption of technology is CRS. For VRS, DMUs should be roughly doubled to have unbiased estimation. Thus, due to our sample size of

225 observations, it may not be the most accurate technical efficiency estimation under the DEA-CRS.

A paired differences t-test—in which the differences between the stochastic frontier efficiency score and the DEA-VRS efficiency score for each ASD in each year are tested against the null hypothesis that the average difference is zero—shows the mean efficiency scores from the two estimation techniques are not discernibly different at any significance level ($p \leq 0.10$), primarily because the variation in the DEA-VRS technical efficiency scores is very large relative to that of the stochastic frontier estimates.

Figure 8 presents basic summary statistics for each ASD's technical efficiency scores over the study period. The DEA-VRS estimates of technical efficiency scores for the Northwest region have a mean of 0.912 with standard deviation of 0.129, which is the highest average technical efficiency score amongst others. The second highest average technical efficiency score is estimated in the Southeast region with average score of 0.903. The third highest average technical efficiency score is estimated in the East-central region with average score of 0.890 and the followed by North-central (0.878), West-central (0.867), Central (0.862), Northeast (0.860), South-central (0.843), and Southwest (0.837). These average technical efficiency scores indicate each corn producing ASD could substantially increase the corn yield by improving its technical efficiency. For instance, the average technical efficiency can improve by 0.088 in the Northwest region, the average technical efficiency can improve by 0.097 in the Southeast region, the average technical efficiency can improve by 0.11 in the East-central region, the average technical efficiency can improve by 0.122 in the North-central region, the average technical efficiency score can improve by 0.133 in the West-central region, the average technical efficiency score can improve by 0.138 in the Central region, the average techincal efficiency score can improve by

0.140 in the Northeast region, the average techincal efficiency score can improve by 0.157 in the South-central region, and the average techincal efficiency score can improve by 0.163 in the South-west region. The lowest efficiency score belongs to the Southwest region, with a score of 0.837, but the mean efficiency scores for all the ASDs are statistically indistinguishable from one another, as all ASDs' average scores are within one standard deviation of the Central ASD's average score. This result seemed to be consistent with what we found in Figure 6, where the efficiency scores do not discernibly differ in any systematic way across ASDs.

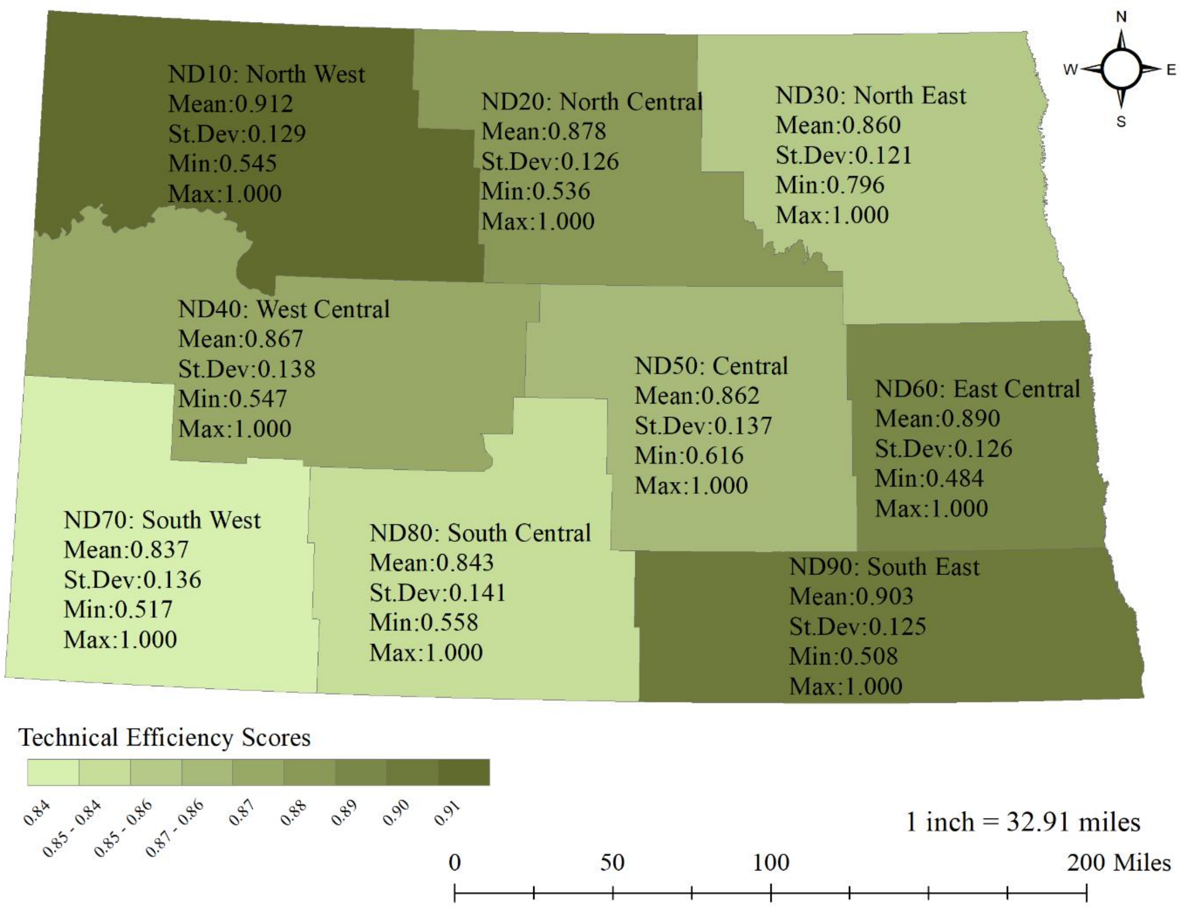

Figure 8. Technical efficiency score from Data Envelopment Analysis with Variable Returns to Scale in each Agricultural Statistics District, 1994-2018.

Figure 9 presents corn yield technical efficiency scores from the DEA-CRS model for each ASD from 1994 to 2018. The black line represents the median of the annual technical efficiency scores. The median technical efficiency score changed substantially from one year to another, which looks very similar to Figure 7, but some years are slightly different. For example, we can see the median technical efficiency scores in 1997, 2004, 2012, 2017, and 2018 are estimated much lower than the median estimated of DEA-VRS. DEA-CRS model results in technical efficiency scores that range from 0.55 to 1.00, which is about the same range of scores estimated by DEA-VRS, in contrast to the range of scores estimated by SFA (Figure 5). The wide range of technical efficiency scores from the DEA-CRS model may be suggesting the corn yield frontier changes dramatically over the years in ways farmers cannot predict. Moreover, it may be suggesting that CRS is likely inappropriate and unrealistic technology assumption for estimating the efficiency in crop production at the ASD level or based on the size of the sample (Alirezaee et at., 1998). Moreover, the higher variability of technical efficiency scores from DEA-VRS and CRS relative to the stochastic yield frontier efficiency estimates is consistent with some research results (Madau, 2015; Sharma et al., 1997), but contrasts with other research (Asmara et al., 2016).

Figure 9. Technical efficiency scores from the Data Envelopment Analysis with Constant Returns to Scale, 1994-2018.

Figure 10 presents the important summary statistics for each ASD's technical efficiency scores over the study period. Based on the corn technical efficiency scores from DEA-CRS, the average technical efficiency score in the Northwest region is predicted as 0.860 with standard deviation of 0.120, which is also the highest average scores amongst others, same as Figure 10. The second highest technical efficiency score of 0.847 is predicted in the Southeast region and the followed by the other technical efficiency scores corresponding their regions: 0.823 in the East-central region, 0.816 in the Northeast region, 0.791 in the West-central region, 0.789 in the North-central region, 0.787 in the Central region, 0.769 in the South-central region, and 0.748 in the Southwest region.

These average technical efficiency scores imply that corn producing ASDs: Northwest, Southeast, East-central, Northeast, West-central, North-central, Central, South-central, and Southwest, could potentially increase their corn yield with the improvement of their technical efficiencies by 0.140, 0.153, 0.177, 0.184, 0.209, 0.211, 0.213, 0.231, and 0.252, respectively. Efficiency gains could be achieved by re-optimizing the levels of managed agricultural inputs based on accurate seasonal weather forecasts, should such forecasts be available.

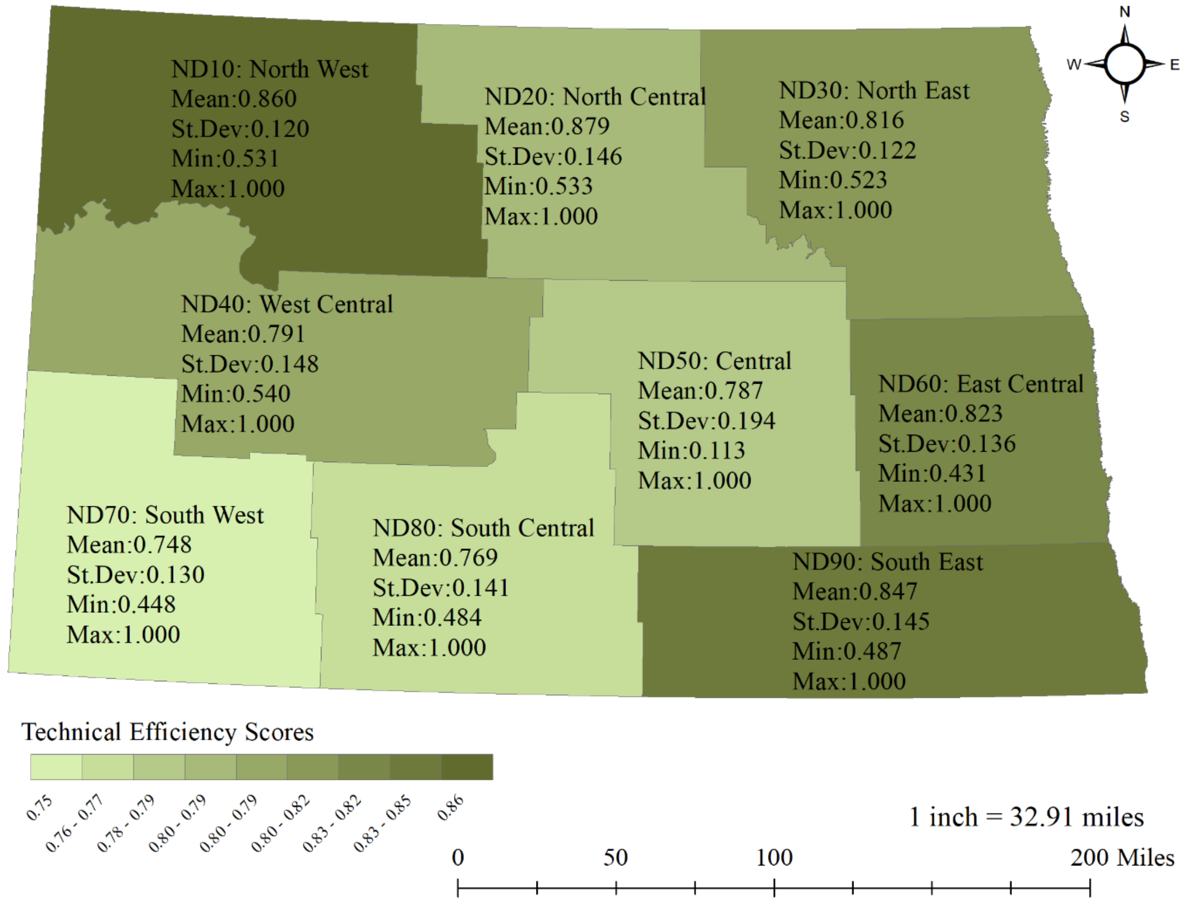

Figure 10. Technical efficiency score from Data Envelopment Analysis with Constant Returns to Scale in each Agricultural Statistics District, 1994-2018.

2.5.3. Comparison of the Efficiency Results

The descriptive statistics for technical efficiency scores from SFA, DEA-VRS and DEA-CRS are reported in Table 6. The DEA-VRS estimates of technical efficiency scores for the Northwest region have a mean of 0.912 with standard deviation of 0.129, The statewide average of technical efficiency score from SFA is 0.89, from DEA-VRS is 0.91, and from DEA-CRS is 0.81. These medians mean at least half of the corn yield technical efficiency scores were performed above 0.89, 0.91, and 0.81 under the estimations of SFA, DEA-VRS, and DEA-CRS, respectively, in the past years from 1994 to 2018.

Table 6. Descriptive statistics of technical efficiency scores.

	SFA	DEA-VRS	DEA-CRS	DEA-SE
Median	0.89	0.91	0.81	0.95
Mean	0.88	0.87	0.80	0.95
Std Dev	0.06	0.13	0.15	0.10
Minimum	0.49	0.48	0.11	0.11
Maximum	0.97	1.00	1.00	1.28

The mean technical efficiency scores estimated from SFA, DEA-VRS, and DEA-CRS are about 0.88, 0.87, and 0.80, with their standard deviation of 0.06, 0.13, and 0.15, respectively. Interestingly, the mean of SFA and DEA-VRS estimated very close, but the standard deviation of DEA-VRS is twice as large than the standard deviation of SFA. The mean of DEA-CRS estimated relatively lower than SFA and DEA-VRS, with a higher standard deviation than both. Thus, technical efficiency scores from DEA should be carefully compared with the scores from SFA in this study since their variances are significantly large in all ASDs. These differences between two approaches are in accord with the efficiency study done by Madau (2015), and Theodoridis and Anwar (2011), where the means of SFA and DEA-VRS were estimated about same but means of SFA and DEA-CRS were estimated significantly different. In addition, our efficiency results are conforming to other research (Sharma et al., 1997) in which the means of DEA-CRS were estimated much lower than the means of SFA and DEA-VRS in the study of swine efficiency study in Hawaii. In contrast, our findings are not conformed with other studies that compared these two approaches (Asmara et al., 2016; Hassan et al., 2014; Kalaitzandonakes and Dunn, 1995). The coefficients of variances are considerably small, but the variance of SFA is even smaller than the others.

We calculated scale efficiency using equation (17). The wide range of scale efficiencies from minimum of 0.11 to maximum of 1.28 with the mean of 0.95 and the standard deviation of

0.10. The median of scale efficiency is equal to 0.95, meaning that at least half of these corn producing ASDs were at decreasing returns to scale. This basically suggests corn operations in North Dakota have a potential to expand some degree until scale efficiency reaches to 1.

Figure 11 presents the descriptive summary for each ASD's scale efficiency scores over the study period. Based on the corn scale efficiency scores, the average scale efficiency score for the Northeast region is determined as 0.950, and this is the highest average amongst others. The second highest scale efficiency score is estimated as 0.945 for the Northwest region and the following scale efficiency scores are estimated as 0.937 for the Southeast region, 0.925 for the East-central region, 0.921 for the Central region, 0.914 for the West-central region, 0.913 for the South-central region, 0.902 for the North-central and 0.898 for the Southwest region.

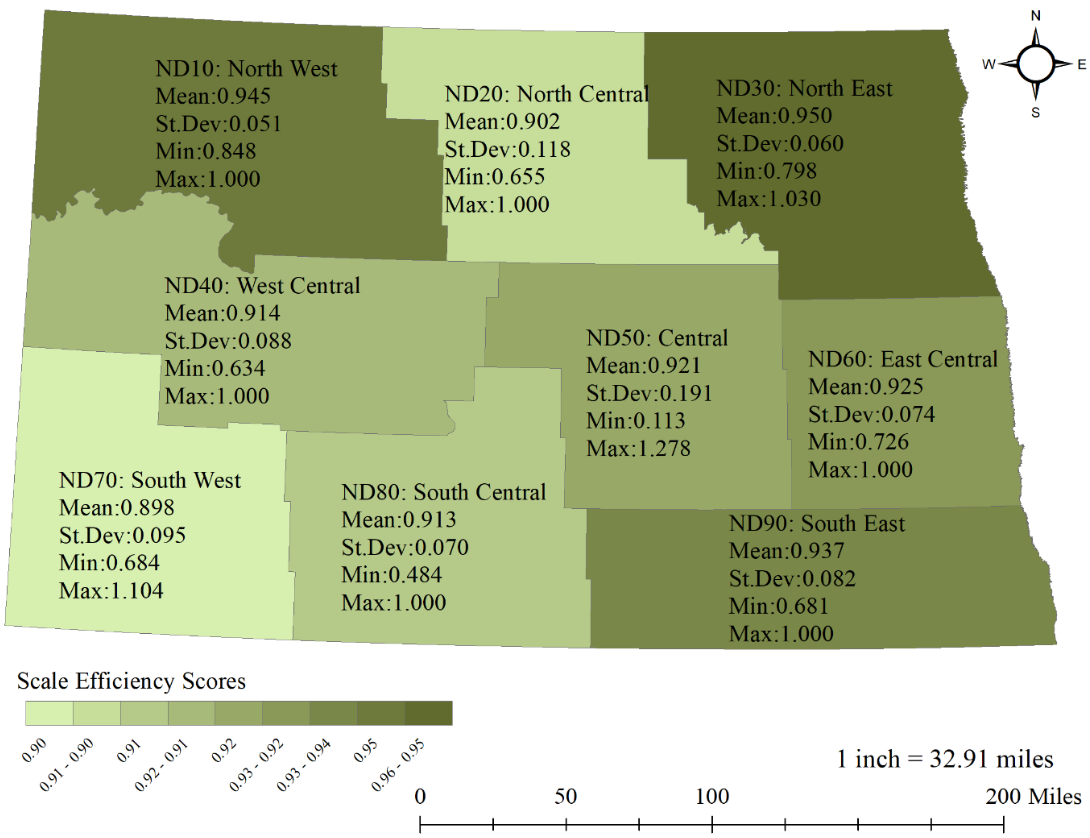

Figure 11. Scale efficiency scores from Data Envelopment Analysis in each Agricultural Statistics District, 1994-2018.

Table 7 presents the correlation coefficients among the efficiency approaches. In order to contribute to better understanding of the distinction between two different approaches: SFA (parametric) and DEA (non-parametric), many researches use the Spearman correlation matrix to estimate the relationships between technical efficiencies generated from these two approaches. In this study, we found all correlations have a positive relationship, and they are performed with a strong significance level ($\alpha = 0.01$). Our rankings indicate a weak correlation between SFA and DEA-VRS with coefficient of 0.44, whereas a stronger correlation between SFA and DEA-CRS (0.54). Furthermore, the strongest correlation (0.78) is between DEA-VRS and DEA-CRS as we anticipated during the discussion of Figures 7 and 9.

Table 7. Spearman correlation coefficients.

	SFA (TE)	VRS (TE)	CRS (TE)
SFA (TE)	1.000		
VRS (TE)	0.438^{***}	1.000	
CRS (TE)	0.537^{***}	0.776^{***}	1.000

Prob > |r| under H0: Rho=0

Even though the finding for the means of technical efficiency scores from SFA and DEA were consistent with Madau (2015), our correlation results between SFA and DEA did not conform to the results found by Madau (2015). Interestingly, the correlation coefficients found in other research (Sharma et al., 1997) are a little bit higher, but the correlation between SFA and DEA-VRS was weaker than the correlation between SFA and DEA-CRS and is consistent with our results.

Table 8 presents the ASD ranking based on the technical efficiency, scale efficiency, and average yield. We found the highest average yield was estimated in the Southeast region. The highest average corn yield technical efficiency score is also estimated in the Southeast region under SFA. But under the DEA estimations, the highest average corn yield technical efficiency score is in the Northwest region under both VRS and CRS, even though the average corn yield in the Northwest region was recorded as the third highest amongst others. This is quite interesting to see two efficiency methods' technical efficiency scores that are different by ASD. However, according to Chen et al. (2016), SFA is more appropriate for estimating DMU's under a variety of sizes, but DEA seemed to under-estimated due to the estimation of relative efficiency amongst DMUs in the dataset. Thus, some regions with smaller inputs and output are considered as efficient in DEA, and efficiency scores are estimated as close to 1 or even 1. This interpretation might possibly make sense to our findings. Corn producers in the Northwest region may not be quite as big as corn producers in the South and East region in terms of size of operation (e.g., land, capital). That maybe the case why we had higher efficiency scores for the Northwest region from DEA method. But one can also argue that the Northwest ASD is ranked second-highest in technical efficiency under the SFA method, thus there may be some other managed variables (e.g. irrigation (see the Figure A1 in the appendix section)) that reduces the variability of the corn yield frontier and technical efficiency in the Northwest region.

Table 8. Agricultural Statistics Districts ranking for efficiency estimates.

Rank	SFA	DEA-VRS	DEA-CRS	DEA-SE	Mean corn yield
1	Southeast	Northwest	Northwest	Northeast	Southeast
2	Northwest	Southeast	Southeast	Northwest	East-central
3	Northeast	East-central	East-central	Southeast	Northwest
4	West-central	North-central	Northeast	East-central	Northeast
5	East-central	West-central	West-central	Central	West-central
6	North-central	Central	North-central	West-central	North-central
7	South-central	Northeast	Central	South-central	South-central
8	Southwest	Southcentral	South-central	North-central	Central
9	Central	Southwest	Southwest	Southwest	Southwest

2.6. Summary and Conclusion

Long-term increases in crop yields will be essential to satisfy surging global food demand over coming decades, and climate change is likely to play a major role in determining producers' ability to meet that demand. Prior research indicates North Dakota's climate has changed over the last several decades such that the state's suitability for corn production has improved. However, no studies have holistically estimated corn yield frontier and technical efficiency for the whole state. Therefore, this research presents corn production efficiency measures and estimates of corn yield frontiers, based on agricultural input use and weather variables, for the nine North Dakota Agricultural Statistics Districts from 1994 to 2018. The research uses the stochastic semi-translog yield model to estimate the corn yield technical efficiency scores and to approximate the yield variation in response to the different yield attributes. In addition, we estimate the output-oriented DEA model to estimate the corn yield efficiency scores to compare the efficiency results from two different approaches.

According to the SFA model, average temperature, maximum temperature, and total rainfall in the growing season are the crucial attributes to increase corn yield. Precisely, warmer growing condition with more rainfall in each North Dakota ASD is predicted to increase yield from an average of 113.16 to 172.34 bushels per acre, while current farm technology and better weather forecast continue to improve the in the future. The coefficient of elasticity for independent variables reveal the farm input expenditures (e.g., seed, land, and fertilizer), excluding labor expenditure, are positive to the corn yield with strong significant levels. However, their effects are much smaller than the effects of uncontrollable inputs (e.g., temperature and rainfall).

Furthermore, SFA indicates the proportion of the total variance attributable to inefficiencies—about 80.9%—related to unexpected shifts in the corn yield frontier caused by favorable or unfavorable temperature and rainfall variations each year, as well as to any extreme weather events, crop disease, and accidents that may have contributed to yield gaps. The overall findings of this study reveal a median technical efficiency score of 0.85, indicating that corn yield at the ASD level could increase substantially in North Dakota, potentially by reallocating production inputs to better match weather variability that shifts yield potential.

Our study features the following highlighted findings:

1) The corn yield will increase in all ASDs of the state when there will be higher temperature with more rainfall in the growing season.
2) The elasticity estimates for each variable are approximately the same for every ASD, implying the marginal factor productivity is similar in every ASD given local heterogeneities.
3) The variation of efficiency scores of SFA is significantly smaller than DEAs, which seems familiar with other efficiency studies.
4) The mean of SFA (0.88) is estimated about same as DEA-VRS (0.87), but higher than the mean of DEA-CRS (0.80).
5) The coefficient correlations between SFA and DEA-CRS is better than SFA and DEA-VRS.
6) At least half of the corn producing ASDs were technically efficient at 0.85 or above in the past couple of decades.

Based on the different efficiency approaches, the estimated technical efficiency scores from DEA model varied much wider range than the scores from SFA model. Thus, the prediction of yield frontier and technical efficiency by the SFA model will be a better estimate than compared to the linear programming methods like DEA. The final conclusion is corn production in each North Dakota's ASD is technically efficient levels (0.85 to 1), but there can be improvements on the yield gap and technical inefficiencies. The output elasticities from SFA indicated that increase in farm input expenditures will increase corn yield; however, better interannual weather forecasting and weather risk management practices will certainly bring higher corn yields in the future for North Dakota farmers.

CHAPTER 3. CORN YIELD EFFICIENCY MEASURES IN MULTISTATES: STOCHASTIC FRONTIER ANALYSIS AND DATA ENVELOPMENT ANALYSIS

3.1. Abstract

Climate is changing both globally and regionally, and partly in response to climate change, major commodity crop yields have been changing substantially as cold regions become warmer and warm places become hotter. As a result of these climatic changes, farmers in the northern region of the U.S. Corn Belt might be able to attain higher yield from warm-season crops than has historically been possible. Since 1990, for instance, North Dakota corn yield has increased by 146%, which is the third-highest yield increase amongst the Corn Belt states. In 2019, about 3.5 million acres of corn (up from 770,000 acres in 1994) were planted in the state, accounting for 9% of North Dakota's total farmland. In this research, both stochastic frontier and data envelopment analyses are used to quantify the corn yield responses in the different U.S. Corn Belt states by analyzing data from 775 USDA Agricultural Statistics Districts in Minnesota, North Dakota, Nebraska, South Dakota and Wisconsin from 1994 to 2018. Results indicate weather variables (e.g., rainfall, and temperatures) account for most of the interannual variability of maximum corn yield potential. Further temperature increases resulting from global climate change are likely to increase the yield frontier at a much higher rate in the north than in the south. We conclude that the corn yield in each state has the potential to increase a certain degree, but the yield increases will differ regionally as a result of regional differences in climate — e.g. baseline regional differences in growing season length. It is impossible to determine how far will the U.S. Corn Belt shift to the northwestern region, but our finding suggests that the higher corn yield and increasing corn plantings will shift in that direction if the cold regions continue to warm in the future.

3.2. Introduction

In the early 20th century, about half of the population in the United States was involved in farming because traditional farming required an intensive labor force (Dimitri et al., 2005). U.S. agricultural productivity increased by 1.9% annually from 1948 to 1999 as farming became increasingly industrialized, starting shortly after World War II (Dimitri et al., 2005).

According to Grassini et al. (2015), the annual total corn supply from the United States accounted for about 38% of the total global corn supply between 2007 and 2011. Therefore, U.S. corn suppliers play an essential role in the corn market not only nationally but also globally. The majority of U.S. corn is grown in the region known as the Corn Belt. There is no formal definition that describes the Corn Belt, but it often refers to regions or states that consistently produce a large proportion of U.S. corn output every year.

According to the United States Department of Agriculture, the U.S. farmers produced approximately 15.1 billion bushels of corn in 2016. Iowa's farmers produced about 18.1% of total corn in 2016. About 14.9% was produced in Illinois, 11.22% in Nebraska, 10.19% in Minnesota, 6.25% in Indiana, 5.45% in South Dakota, 4.61% in Kansas, 3.78% in Wisconsin, 3.77% in Missouri, 3.41% in North Dakota, 2.11% in Michigan, and 1.47% in Kentucky. All of these states, including others not mentioned above, contribute to the total corn supply in the United States.

These previously named states are variously considered part of the Corn Belt (see appendix Figure A2 to A10). Figure A11 in the appendix is an animated clip showing how total plated corn acreage has changed from 2010 to 2018 at the Agricultural Statistics District (ASD) level within each state. Based on this animation, the state of Iowa is undoubtedly the center of corn production in the U.S. Corn Belt. The surrounding states: Illinois, Indiana, Minnesota, Nebraska, South Dakota, and Missouri plant a considerable amount of corn acres, but their acreages are vary substantially from year to year.

Reilly et al. (2001) stated corn producers in these states recognize the substantial corn yield variability caused by inter-annual weather variation and, potentially, global climate change. Many types of research have acknowledged and tried to better understand the yield variability attributable to weather variation (Bhattarai et al., 2017; Westcott and Jewison, 2014). Due to climate change, cooler locations are transitioning toward warmer, longer growing seasons, while warmer states are becoming hotter than they have historically been. As a result, farmers in the northern region of the U.S. Corn Belt may benefit more than southern farmers as northern states become more suitable for warm season crops such as corn, soybean, and sorghum (Hoffman et al., 2018). In contrast, the warmer areas in more southerly locations may not be able to attain the yield that they used to expect due to temperature thresholds of certain crops (Meerburg et al., 2009).

Figure A12 to A20 present the average corn yield at the ASD level within each state from 2010 to 2018 in the appendix section. Figure A21 in the appendix is an animated clip showing how the average corn yield of each ASD has varied from 2010 to 2018 in the Corn Belt region. According to Figure A21, the average corn yield has trended upward substantially over the years in each state, but each ASD does not provide a consistent high yield every year from 2010 to 2018. Thus, it is clear that higher corn acreage does not necessarily mean higher corn yields. In other words, states with less corn acreage can also expect to achieve high corn yields in the areas where corn is grown.

Various crop modeling and simulation techniques have been developed to quantify the impacts of managed inputs (e.g. fertilizer) and exogenous inputs (e.g., rainfall and temperature) on crop yields (Bhattarai et al., 2017). Bhattarai et al. (2017) investigate the corn and soybean yields repsonse simulated from Enronmntal Policy Integrated Climate (EPIC) by using the down-scaled weather data for the period from 2015 to 2099. Based on the different carbon scenarios, they found corn and soybeans yields will increase by the end of the century. In addition, they found that the yields variablity increases substantally due to the impact of climate change after middle of the century. According to Reilly et al. (2001), the Canadian and Hadley crop yield simulation showed the average corn yields will increase by 15% to 40% by the end of the 21st century in the U.S. Corn Belt. However, these corn yield increases will not be equally distributed throughout the nation, as can also be discerned from Figure A21. Their simulations have predicted that the most significant yield increases will most likely be realized in regions like the Northern Great Plain and the Northern Lakes Region, where the corn production might increase due to the warmer temperature and more rainfall under both climate scenarios (Reilly et al., 2001). Therefore, the research presented in the present dissertation has objectives that focus on analyzing corn yield in the northern region of the U.S. Corn Belt. More specifically, the research addresses the following questions:

1. How do interannual weather variations and agricultural input use affect corn yield potential (i.e. the yield frontier) in the northern region of the U.S. Corn Belt?
2. How does corn production efficiency vary across the study region’s USDA Agricultural Statistics Districts and over time?
3. What will be the likely effects of systematic climate change on the corn yield frontier and the optimal levels of controlled agricultural inputs?
4. Do stochastic frontier analysis and data envelopment analysis provide similar corn production efficiency estimates?

5. Do output elasticities vary by state when the geographic extent is increased to include more observations?
6. Do technical efficiency results vary for different approaches (i.e. stochastic frontier, and data envelopment analysis) at the state level?

The rest of this paper is organized as follows: Section 3.3 reviews the scholarly literature explores the research methodologies typically used to measure technical efficiency in production. Section 3.4 outlines the methodology applied in this research and provides descriptions of the data used; Section 3.5 presents the results and discussion; lastly, Section 3.6 summarizes the research and presents conclusions.

3.3. Literature Review

One statistical approach that can be used to simultaneously investigate the issues of input use efficiency and the effects of climate change on the corn yield is Stochastic Frontier Analysis (SFA), first empirically applied by Farrell (1957) to estimate production efficiency. The SFA model separates the error structure into components—a two-sided, symmetric error component and a one-sided error component. The one-sided component captures inefficiency, while the two-sided component accounts statistical noise. SFA has been used to evaluate economic efficiency, especially technical efficiency in developing and developed countries. Due to capital constraints in many developing countries, increasing productive efficiency by reallocating variable inputs has historically been a more viable means of increasing agricultural output than adopting new, costly technologies (Baten and Hossain, 2014; Naqvi and Ashfaq, 2013; Coelli et al., 2003). A case study by Bravo-Ureta and Pinheiro (1993) highlighted the fact the most farmers in developing countries have a potential to increase their efficiency to maximize farm output without increasing total input use or purchasing costly technological upgrades. Coelli et al. (2003) evaluated the profit efficiency of modern rice farmers in Bangladesh by determining the impacts of farm inputs on technical efficiency. The purpose of their research was to investigate how changing input combinations and adoption of new, modern rice varieties led to increasing yields on Bangladesh's rice farms. Despite increasing rice yields and acreage following the adoption of modern varieties, farm income in Bangladesh has declined. Their results indicate a mean technical efficiency score of 0.77 for the sample, implying modern rice farmers in Bangladesh have the potential to increase profit by improving economic efficiency, which is likely to happen autonomously as they gain more experience with modern rice varieties and improved access to input markets (Coelli et al., 2003).

Many researchers have studied productivity and efficiency measures using SFA (Njuki et al., 2019). The fundamental assumption of SFA is that uncontrollable events (e.g., cold snaps, droughts, flooding, and crop disease) will appear as inefficiency effects on agricultural productivity. Thus, it is common to see farm efficiency analysis tend to omit basic information about weather and environmental heterogeneity (e.g., temperature, and precipitation) (Lachaud et al., 2017). According to Lachaud et al. (2017), the combined effect of temperature and precipitation patterns had an adverse impact on agricultural output and farm productivity in the Latin American and Caribbean countries from 1961 to 2012. Specifically, the farm productivity across the region was reduced an average between 0.02% and 22.7%, attributable to weather variables. The output reductions varied considerably across the countries, where 20 out of 28 countries' agricultural output was negatively impacted by weather variability.

Other research by Njuki et al. (2018) analyzed the changes in Total Factor Productivity (TFP) from the weather variables by using the stochastic production frontier model. Their study concludes that accounting for environmental variables is an essential part of explaining changes in agricultural TFP. They found that technological change has had a positive effect on agricultural output and is the primary engine to improve TFP. In addition, advanced farming technologies have improved farm level efficiency, which directly helps farmers to be more adaptive to the local environment. Their research concluded additional efforts to learn the best management practices will allow farmers to be more resilient to spatial weather variation as well as agricultural ecological factors (Njuki et al., 2018).

The absence of extreme weather and other catastrophic data in the analysis of crop productivity and efficiency seems to be a common constraint in most related research, unless crops were grown in the greenhouse environment (Bournaris et al., 2019). The study by Bournaris et al. (2019) used the Data Envelopment Analysis (DEA) model to evaluate the productive efficiency of four different greenhouse vegetables (e.g., cucumber, eggplant, pepper, and tomato) in southern Greece. They analyzed the farm level efficiency by using the input-oriented DEA model with the technological assumption of variable return to scale (VRS). However, Cooper et al. (2004) suggested the input-oriented radial efficiency should be used carefully because it neglects slack variables in the inputs and output. To help farmers make better decisions on crop rotations as well as agricultural input allocations, it might be more appropriate to use the multiple-output or single output of DEA model with both technological assumptions (e.g., VRS and CRS) as suggested by Cooper et al. (2004), or multiple input-output frontier analysis, which is proposed by Dellnitz and Kleine (2019).

Ullah et al. (2019) analyzed the efficiency of sugarcane production in Thailand. Their data was gathered via face-to-face interviews with 1,366 farmers in six different sugarcane production regions in Thailand. The research used a Slack Based Measure (SBM) to evaluate the percentage reduction in each input in the input-oriented DEA model. They assumed farming has VRS due to the law of diminishing returns[4]. The main findings of their study are as follows: 1) most of the production inefficiency is associated with farm-level decision-makers (farmers) in general, but inefficiency varies by regional size of scale such as sugarcane production efficiency are significantly lower in the Northeast, Central, and West regions, 2) profit maximization will be more attainable if farmers reduce the quantity of physical inputs through better, or more precise, management practices, and 3) labor intensive farming practices might be possible solutions to increase efficiency and reduce the environmental costs. One interesting aspect of their research was the analysis of the heterogeneity in both intra-regional and inter-regional efficiency of Decision Making Units (DMUs). One drawback of the study was the lack of accounting for the heterogeneity of environmental effects on sugarcane production in the study region.

Various studies have focused on comparing SFA and DEA using data from different industrial sectors (Murwirapachena et al., 2019; Silva et al., 2017; Kaitelidou et al., 2016). In the efficiency literature, choosing one method over another is still controversial (Coelli, 1995; Bravo-Ureta and Pinheiro, 1993). Thus, many studies compare these two methods using the same data (Mathur and Ramnath, 2018). Research by Sharma et al. (1997) compared the results from SFA and DEA. Their analysis indicated technical efficiencies from both methods are slightly different. Specifically, the mean technical efficiency of 0.64 form the DEA-CRS model is lower than the mean technical efficiency of 0.75 from the SFA model. Data for their research was collected from 60 swine farms in Hawaii in 1994, thus it is a cross-sectional dataset. Moreover, DEA efficiency measures indicate a significantly higher variability than the SFA efficiency scores. The researchers used Spearman's rank correlation coefficient to examine the technical efficiencies from both methods. The correlation results indicated the technical efficiencies from both SFA,

[4] According to Basu & Fernald (1997), the law of diminishing returns to scale states that adding more input in the production will increase the output at a diminishing rate until additional input can no longer increase the output.

and DEA are positively correlated, and that these correlations are statistically significant. But the strongest correlation was between SFA and DEA-CRS (e.g., 0.88), even though the means of technical efficiencies are significantly different from each other (Sharma et al., 1997).

Similar research was done by Kalaitzandonakes and Dunn (1995) to measure technical efficiency from SFA and DEA on Guatemala corn production using a sample of 82 family farms. The study provides different results where the mean technical efficiency of 0.74 from SFA is significantly smaller than the mean technical efficiency of 0.93 from DEA-CRS. Technical efficiency scores derived from non-parametric methods (i.e. DEA or deterministic frontier) are higher, relative to stochastic frontier-derived efficiency scores, in the case of corn production in Guatemala. A similar study by Madau, (2015) compared the technical efficiency results from SFA and DEA. This research used the cross-sectional data set of 107 Italian citrus farms. The output data (i.e. the response variable) is gross revenue, which is slightly different from crop yield or TFP. The study found that the strong correlation between SFA-derived technical efficiency scores and DEA-VRS-derived technical efficiency scores, whereas slightly weak correlation is found between SFA-derived technical efficiency scores and DEA-CRS-derived technical efficiency scores based on the Spearman's rank. This result conflict with some findings of Sharma et al. (1997). The existing literature seems to provide mixed results about SFA and DEA and the accuracy of their efficiency measures; therefore, more research is needed to explore the accuracy of the technical efficiency estimation from SFA and DEA methods.

3.4. Methodology

3.4.1. Conceptual Framework

SFA and DEA will be used in the present research. Under SFA, corn yield frontiers and technical efficiency scores are estimated, and output elasticities of corn yield frontiers are derived for each independent variable. The critical component of the SFA focuses on the deviations from the production frontier, which is the corn yield frontier. Each DMU has a unique yield frontier, which varies randomly according to a collection of stochastic elements not controlled by the DMUs. In our research, each corn producing Agricultural Statistics District (ASD) is a DMU with its own production frontier, randomly varying with uncontrolled elements that appear as an inefficiency. Therefore, our methodology focuses on the following two crucial aspects of modeling: 1) functional form of the production (yield) function, and 2) appropriate selection of independent variables.

The study performed the log-likelihood ratio test to assess the goodness of fit of the model by jointly testing the statistical significance of the parameters relating each independent variable to the yield frontier. Let β_j be the vector of parameters relating farm input *j* to the yield frontier, including first-degree, second-degree, and interaction parameters. The null hypothesis is then $H_0\colon \beta_j = 0$, meaning farm input *j* has no statistically discernible relation to corn yield or to the corn yield frontier. The test statistic is:

$$\chi^2_{LRT} = -2\{LLF_R - LLF_U\} \tag{18}$$

where χ^2_{LRT} is the log-likelihood ratio test statistic, LLF_R is the value of the log likelihood function when the restrictions are imposed according to H_0, and LLF_U is the log likelihood function value when the restrictions are lifted. The statistic is distributed chi-square with degrees of freedom equal to the number of parameters restricted by H_0. If the test statistic exceeds the chi-square critical value the null hypothesis is rejected, revealing a statistically discernible relation between the yield frontier and farm input *j* through direct first- and/or second-degree effects and/or interactions with other farm inputs. Thus, the tested variable should be included in the regression, even if none of the individual parameters in β_j are statistically significant per *t*-testing.

The intention of using log-likelihood ratio test is to improve the goodness of fit of the stochastic translog yield frontier model, hopefully, which leads to be a parsimonious model and provide robust estimation for corn yield technical efficiencies for each ASD. In addition, we will perform the Variance Inflation Factor (VIF) test to detect the presence of collinearity among the independent variables[5] (Joshi et al., 2012).

The pioneers of stochastic frontier analysis include Farrell (1977), Aigner et al. (1977), and Meeusen and Van Den Broeck (1977). There are different functional forms (e.g., Cobb-Douglas, a log-linear, or translog) are assumed in the parametric efficiency. In the research, stochastic translog yield frontier model is specified and the theoretical model for this frontier model is expressed as:

$$lny_{it} = f(X_{it}; \beta) + v_{it} - u_{it} \tag{19}$$

where lny_{it} is the natural log of corn yield of the i^{th} ASD within each state in t^{th} year from 1994 to 2018; X_{it} is farm inputs of the i^{th} ASD within each state in t^{th} year; β is the vector of unknown parameters to be estimated; v_{it} is a two-sided error term representing uncertainty about the estimated yield frontier for i^{th} ASD in the t^{th} year, which is assumed to be independently and identically distributed $N(0, \sigma_v^2)$; and u_{it} is the non-negative one-sided error term that represents the yield gap, or yield inefficiency, for the i^{th} ASD in the t^{th} year, and it is assumed to be independently and identically distributed $N^+(0, \sigma_u^2)$. $v_{it}\ and\ u_{it}$ are assumed to be uncorrelated over time and across ASDs.

Based on the concept of the stochastic yield frontier model with panel data, a technical efficiency score is computed for i^{th} ASD in the t^{th} year as follows:

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[5] The Variance Inflation formula is $VIF_i = \frac{1}{1-R_i^2}$

$$TE_{it} = \frac{q_{it}}{exp(X'_{it}\beta + v_{it})} = \frac{exp(X'_{it}\beta + v_{it} - u_{it})}{exp(X'_{it}\beta + v_{it})} = \exp(-u_{it}) \tag{20}$$

where if $TE_{it} = 1$, then ASD *i* efficiently produced its corn output in year *t*—i.e. there was no statistically significant gap between the estimated frontier yield potential and the yield realized. On the other hand, if $TE_{it} < 1$ the ASD's yield fell short of its potential that year, potentially indicating that a superior allocation of controlled agricultural inputs such as fertilizer and chemicals might have ameliorated the yield gap.

3.4.2. Empirical Model for Stochastic Frontier Model

The empirical model of stochastic translog yield frontier is written as follows:

$$\begin{aligned} lny_{it} = \beta_0 + \sum_{j=1}^{10} \beta_{1,j}\, lnx_{ijt} + \frac{1}{2}\sum_{i=1}^{10}\sum_{i=1}^{10} \beta_{2,j}\, lnx_{ijt}lnx_{ijt} \\ + \sum_{j=1}^{9}\sum_{k=1}^{9} \beta_{3,j,k}\, lnx_{ijt}lnx_{ikt} + v_{it} - u_{it} \end{aligned} \tag{21}$$

where lny_{it} is the natural log of corn yield in ASD *i* of the state in year *t*; β_0 is the estimated intercept; $\beta_{1,1} \cdots \beta_{1,10}$ are the estimated first-degree parameters relating natural logs of *J* = 10 farm input variables to the frontier yield; $\beta_{2,1}, \beta_{2,2}, \cdots, \beta_{2,10}$ are the estimated parameters relating the squared natural logs of the ten farm input variables to the yield frontier; the $\beta_{3,j,k}$ are the estimated parameters relating the products of the natural logs of farm input variables *j* and *k* (for all $j \neq k$) to the yield frontier; v_{it} is the statistical random error term; and u_{it} is the technical inefficiency error term. In addition, we estimate the elasticity of mean production with respect to the independent variables for the stochastic translog yield frontier model. According to Battese and Broca (1997), the output elasticity calculation is given as:

$$\vartheta_k = \beta_k + 2\beta_{kk}x_{ki} + \textstyle\sum_{j\neq k} \beta_{kj}x_{ji} \tag{22}$$

where ϑ_k is the mean output elasticity of the corn yield frontier for independent variable k; β_k is the parameter estimates of the k^{th} independent variable; $2\beta_{kk}$ is the squared parameter estimates of the k^{th} independent variable; x_{ki} is the recent five year averages (e.g., 2014 – 2018) of the k^{th} independent variable in the i^{th} state; β_{kj} is the parameter estimates of the interaction among the independent variables; and x_{ji} is the recent five year averages (e.g., 2014 – 2018) of the j^{th} independent variable in the i^{th} state.

3.4.3. Empirical Model for Data Envelopment Analysis

According to Sharma et al. (1997), the output-oriented DEA model for a single output is generalized based on the research by Ali and Seiford (1993), presented below. We have n number of DMUs (ASDs), and each produces single output (e.g., corn) by using m different inputs. The i^{th} ASD uses x_{ki} units of k^{th} input in the production of y_i unit of output. Thus, the linear programming (LP) problem will be separately solved for each ASD in the year t, which is presented in the following formulas (Equation 24), based on the assumption of Variable Returns to Scale (VRS) of DEA:

$$\begin{aligned} &\underset{\phi_{it}\lambda_{it}}{\text{Maximize}}\, \phi_{it} \\ &\text{Subject to:} \\ &\textstyle\sum_{j=1}^{n} \lambda_{jt} y_{jt} - \phi_{it} y_{it} - s = 0 \\ &\textstyle\sum_{j=1}^{n} \lambda_{jt} x_{kjt} + e_{kt} = x_{kit} && k = 1, \ldots, m \text{ inputs;} \\ &\textstyle\sum_{j=1}^{n} \lambda_{jt} = 1 && j = 1, \ldots, n \text{ DMUs;} \\ &\lambda_j \geq 0;\ s \geq 0;\ e_k \geq 0; && t = 1, \ldots, t \text{ years;} \end{aligned} \qquad (23)$$

where ϕ_{it} is the proportional increase in output for the i^{th} ASD in year t; s is the output slack; e_{kt} is the k^{th} input slack in year t; and λ_{jt} is the weight of j^{th} ASD in year t.

The analysis of the output-oriented DEA frontier model is to maximize the proportional increase in output while the current level of inputs stays constant. The output maximization of i^{th}

ASD requires the output slack, *s*, to be zero; therefore, the *i*^th^ ASD will be fully efficient in year *t*. In other words, that ASD lies on the DEA frontier when ϕ_{it} = 1, λ_{it} = 1, and λ_{jt} = 0 for $j \neq i \neq t$. If $\phi_{it} > 1$, λ_{it} = 0, and $\lambda_{it} \neq 0$ for $j \neq i \neq t$, then i^{th} ASD is inefficient in year *t*, implying that the current level of inputs can be used to achieve a higher output level. The frontier production level for the i^{th} ASD is given by Sharma et al. (1997):

$$\hat{y}_{it} = \sum_{j=1}^{n} \lambda_{jt} y_{jt} = \phi_{it} y_{it} \tag{24}$$

where $\hat{y}_{it}$ is the projected production yield frontier. Based on $\hat{y}_{it}$, the TE of the i^{th} ASD is calculated as the ratio of the observed output level of the i^{th} ASD and the projected production frontier level for the i^{th} ASD in the same year *t*, which is same as the ratio between one and the proportional increase in output for the i^{th} ASD in the year *t* (Sharma et al., 1997):

$$TE_{it} = \frac{y_{it}}{\hat{y}_{it}} = \frac{1}{\phi_{it}} \tag{25}$$

The ratio between TE_{it} of CRS and TE_{it} of VRS provides the scale efficiency (SE_{it}) for the i^{th} ASD in the t^{th} year (Wadud and White, 2010):

$$SE_{it} = \frac{TE_{it}\ (\text{CRS})}{TE_{it}\ (VRS)} \tag{26}$$

If the SE_{it} = 1 for i^{th} ASD in the year *t*, then the corn production in the i^{th} ASD is at the most productive scale size (MPSS), which indicates CRS in the year *t*. If SE <1 for the i^{th} ASD in the year *t*, then the corn production in i^{th} ASD has locally decreasing returns to scale (DRS), whereas if SE >1 for the i^{th} ASD in the year *t*, then corn production in the i^{th} ASD has locally increasing returns to scale (IRS) (Fried et al., 2008).

3.4.4. Data Description

This research analyzes a panel data set of the 31 ASDs in five different states: Minnesota, North Dakota, Nebraska, South Dakota and Wisconsin, from 1994 to 2018. The following two reasons are why our research used ASDs as our research DMUs (USDA NASS, 2018): 1) ASDs are intended to provide timely, accurate and useful statistical information to United States' Agricultural Service; therefore, the variety of crops' input and output data are available spatially as well as historically at the ASD level, and 2) ASDs are defined groupings of counties in each state, by geography, climate, and cropping practices that have similarities on the geographic attributes (e.g., soil type, terrain, and elevation), climate components (e.g., mean temperature, precipitation and length of growing season) and cropping practices (e.g., use of irrigation, crop rotation and specialty crops).

Figure 12 presents the map with ASD and states are labeled with underline. Due to the data availability and limitation, we are able to organize and collect data of all nine ASDs for only the state of North Dakota. However, for other states, we are not able to collect data of all ASDs. Thus, we only have data of eight ASDs for the state of Minnesota, data of five ASDs for the state of South Dakota, data of six ASDs for the state of Nebraska, and three ASDs for the state Wisconsin. Each ASD has a number and corresponds to a geographic region within the state. For instance, Minnesota's district MN10 is the Northwest region, district MN20 is the North-central region, MN90 is the Southeast region, and so forth.

The response variable for this research is corn yield at the ASD level. Independent variables include land area planted to corn, expenditures on seed, fertilizer, pesticide, labor, and machinery, as well as rainfall and temperature variables (average daily minimum and maximum temperatures and average daily mean temperature for the growing season). Data for corn yield, corn area planted, and expenditures on seed, pesticide, fertilizer, labor, and machinery were collected from the Farm Financial Management Database[6] (FINBIN). Data for rainfall and temperatures were collected from PRISM Climate Database[7]. The data descriptions are provided in Table 9. The descriptive statistics associated with the response and explanatory variables are presented in Table 10.

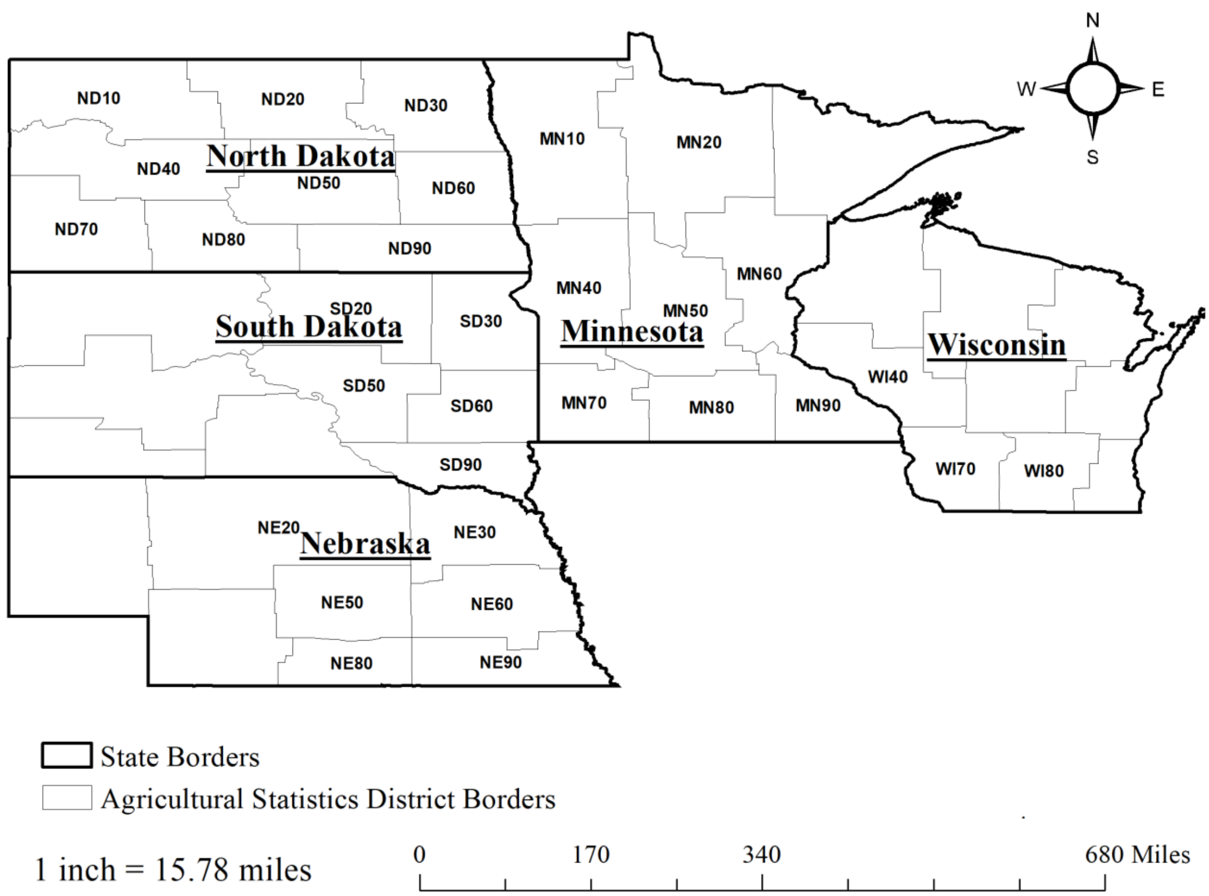

Figure 12. Agricultural Statistics Districts of five state.

[6] Farm data sources: https://finbin.umn.edu/.
[7] Weather data sources: http://www.prism.oregonstate.edu/.

Table 9. Descriptions of input and output variables and data sources.

Variables	Unit descriptions	Sources
Yield	Average corn yield by ASD (bushels per acre)	FINBIN
Land	Average corn acreage by ASD (acres per farmer)	FINBIN
Seed	Average seed expenditure by ASD ($ per acre)	FINBIN
Fertilizer	Average fertilizer expenditure by ASD ($ per acre)	FINBIN
Pesticide	Average pesticide expenditure by ASD ($ per acre)	FINBIN
Labor	Average labor expenditure by ASD ($ per acre)	FINBIN
Machinery	Average machinery expenditure by ASD ($ per acre)	FINBIN
Rainfall	Total growing season rainfall by ASD (inches per year)	PRISM
Mean Temperature	Growing season average daily mean temperature by ASD (°F)	PRISM
Min Temperature	Growing season average minimum daily temperature by ASD (°F)	PRISM
Max Temperature	Growing season average maximum daily temperature by ASD (°F)	PRISM

Table 10 presents the multistate-level descriptive statistics for all inputs and output used in the research. In addition, we also report descriptive statistics for all inputs and output of each state in Appendix A from Table A1 through A5.

Table 10. Multistate-level descriptive statistics of input and output variables, 1994-2018.

Variable	Unit	N	Mean	Std Dev	Minimum	Maximum
Yield	Bu./acre	775	127.06	34.12	13.96	220.16
Land	Acres	775	277.30	122.33	58.77	794.92
Seed	$/acre	775	64.59	28.06	19.24	144.73
Fertilizer	$/acre	775	80.66	40.82	21.40	224.16
Pesticide	$/acre	775	31.13	9.57	12.44	78.48
Labor	$/acre	775	17.96	11.27	2.76	96.77
Machinery	$/acre	775	6.24	3.38	0.00	22.84
Rainfall	Inches	775	20.57	6.60	6.92	43.64
Temperature	°F	775	61.40	4.06	45.63	70.05
Min Temperature	°F	775	37.30	5.93	22.70	61.05
Max Temperature	°F	775	83.48	4.16	73.30	96.20

Based on Table 10, the average corn yield in the study region from 1994 to 2018 is 127.06 bushel per acre, with a standard deviation of 34.01. The average cornfield was approximately 277.30 acres, with a standard deviation of 122.33. According to Table A1 through A5, cornfield size varies substantially across the states. For instance, the average corn acreage in North Dakota is 316.71, which is the largest average corn acreage amongst the states, whereas Nebraska's average corn acreage of 221.62 is the smallest in the data sample. In the past 25 years, acres of corn per operation varied substantially across each state's ASDs and within most ASDs over time. The standard deviation of the average corn acreage in North Dakota is 154.52, which is the largest amongst other states: standard deviations of 116.41 in Minnesota, 97.18 in Nebraska, 87.07 in South Dakota, and 50.92 in Wisconsin. This is indicating the farmers in North Dakota use crop rotations every year, so the total corn acreage changes substantially from year to year. Moreover, the average cropland size per farmer in North Dakota may also be relatively larger than others. On the other hand, the farmers in Wisconsin do not change corn acreage as much as other states. This may be due to the consistent quantity of corn demanded at the local level in every year; therefore, the total corn acreage per farmer will also be consistent over time.

For farm input expenditures, the aggregated seed expenditure from all states averages $64.59 per acre with a standard deviation of $28.06. The average corn seed expenditure in Nebraska is $53.92 per acre, which is the lowest seed expenditure of all states studied. Minnesota farmers' average spending on seed is much higher, at $72.71 per acre. The aggregated fertilizer expenditure from all five states is averaged as $80.66 per acre, with a standard deviation of $40.82. Surprisingly, the average fertilizer expenditures in each state have relatively wider variation. The fertilizer expenditure in Wisconsin is $99.77 per acre and followed by $97.02 in Minnesota, $75.18 in North Dakota, $68.49 in South Dakota, and $67.66 in Nebraska. The aggregated pesticide expenditure is averaged as $31.13 per acre, with a standard deviation of $9.57. By state, the average pesticide expenditure in Wisconsin is the highest amongst others. Noticeably, the pesticide expenditures in Wisconsin, Nebraska, and Minnesota are relatively higher than the expenditures in South Dakota and North Dakota. The aggregated expenditure of farm labor and machinery are averages as \$17.96 per acre and \$6.24 per acre, respectively. Both expenditures in each state are estimated fairly close (see Table A1 to A5). All corn input expenditure variables are adjusted for inflation and presented in 2018 USD per acre (\$/ac.). The deflation is based on the Gross Domestic Product (GDP) deflator, and the formula is used as:

$$GDP\ deflator = \frac{Nominal\ GDP}{Real\ GDP} * 100 \tag{27}$$

Based on the study region, total rainfall in the growing season is averaged approximately 20.57 inches over the study period, with a standard deviation of 6.60. Specifically, almost all states' total rainfall stayed around 20.57 range, except North Dakota's total rainfall. Because total rainfall in North Dakota is averaged as 14.97, which is considerably lower than the overall average. For growing season average daily mean temperature ("average temperature"), the study region's temperature is average of 61.40 °F with a standard deviation of 6.60 °F. The highest mean temperature of 66.22 °F is in Nebraska, whereas the lowest mean temperature is estimated in South Dakota with 58.37 °F. The temperature difference makes sense geographically, where Nebraska is located in the further south of the Northern Plains than South and North Dakota. Due to climate change, the growing season in the southern states is hotter compared to northern states (Allen et al., 2015). The growing season average daily high temperature ("maximum temperature") is 83.48 °F, with a standard deviation of 4.16°F. Maximum temperature in Nebraska is the highest of 87.99 °F and followed by 84.66 °F in South Dakota, 82.72 °F in North Dakota, 81.14 °F in Wisconsin, and 81.09 °F in Minnesota. The growing season average daily low temperature ("minimum temperature") is 37.30 °F, with a standard deviation of 5.93 °F. Minimum temperature in South Dakota is the highest of 44.54 °F and followed by 39.93 °F in Nebraska, 38.05°F in Wisconsin, 36.34 °F in Minnesota, 32.12 °F in North Dakota. To visually observe the corn yield variation across the study region, Figure 15 presents corn yield descriptive summary of each state over the study period from 1994 to 2018.

According to Figure 13, farmers in Minnesota, North Dakota, South Dakota, Nebraska, and Wisconsin had an average corn yield of 145.77 bushels per acre, 113.61 bushels per acre, 115.46 bushels per acre, 119.42 bushels per acre, and 152.10 bushels per acre, respectively. The average corn yields in Minnesota and Wisconsin are significantly higher than the other three states' corn yield averages. The highest corn yield was recorded in Minnesota with 220.16 bushels per acre, whereas the lowest corn yield was recorded in North Dakota with 13.96 bushels per acre in the past 25 years.

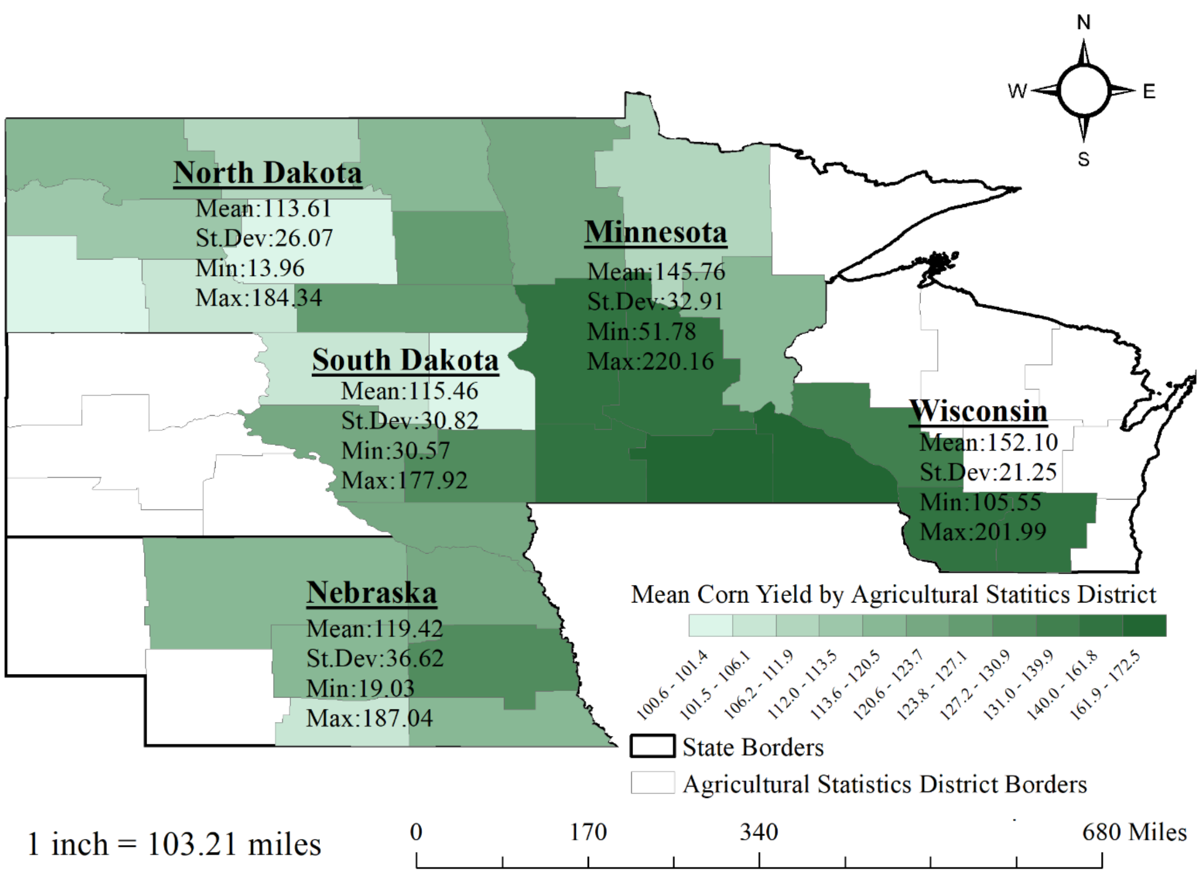

Figure 13. Corn yield summary statistics by state, 1994-2018.

Qualitative and Limited Dependent Variable model (QLIM) in the Statistical Analysis System (SAS) is used to estimate the stochastic yield frontier model. The estimation provides a coefficient for each parameter in the model and generates estimates for yield frontier as well as technical efficiency scores. Additionally, Stata 14 is used for Monte Carlo simulations to approximate the standard errors of the elasticity estimates for each explanatory variable. This process enables us to determine the significance level of each elasticity by using a t-test. Our null hypothesis for the test is that the output elasticities are no different from zero. If we reject the null hypothesis, the tested elasticities are statistically different from zero. Thus, we can conclude that there is sufficient evidence to make inferences about the relationships between inputs and output variables and economies of scale. We also used Stata to estimate the DEA yield efficiency frontier under two technological assumptions (VRS and CRS) to compare their technical efficiency scores with SFA's technical efficiency scores.

3.5. Results and Discussion

3.5.1. Results from Stochastic Frontier Model

Table 11 presents the log-likelihood ratio test results. The joint significance of the parameter estimates for each of the farm input expenditure and weather variables are tested comparing the log-likelihood ratio statistic calculated with equation (19) to the appropriate chi-square critical value. The test results indicate that the effects of all explanatory variables, including second-degree and interaction effects, on the corn yield frontier are all statistically significant. In addition, the Variance Inflation Factor (VIF) test indicates the coefficient of each variable is lower than six. Thus, VIF results indicates multicollinearity should not have substantial effects on the standard errors of the parameter estimates. Given the statistical results and discussion above, all the explanatory variables in the dataset can be included in the estimated translog stochastic frontier model of corn yield. The parameter estimates of this model are presented in Table 12.

Table 11. Multistate log likelihood ratio and Variance Inflation Factor test results.

Variables	Null Hypothesis	Degrees of freedom	Log Likelihood Ratio Test Statistic	VIF
Land	$H_0: \beta_{\text{land}} = 0$	8	145.44***[a, b]	1.75
Seed	$H_0: \beta_{\text{seed}} = 0$	7	46.02***	5.59
Fertilizer	$H_0: \beta_{\text{fert.}} = 0$	8	35.48***	4.79
Pesticide	$H_0: \beta_{\text{Pest.}} = 0$	11	57.56***	2.13
Labor	$H_0: \beta_{\text{Labor}} = 0$	9	55.08***	1.17
Machinery	$H_0: \beta_{\text{Mach.}} = 0$	11	46.46***	1.50
Rainfall	$H_0: \beta_{\text{rain}} = 0$	7	46.56***	2.55
Temperature	$H_0: \beta_{\mu\text{temp}} = 0$	7	113.42***	2.44
Min Temp	$H_0: \beta_{\mu\text{mintemp}} = 0$	7	77.54***	2.29
Max Temp	$H_0: \beta_{\mu\text{maxtemp}} = 0$	6	92.64***	1.67
Insignificant Parameters	$H_0: \beta_{\text{insignificant}} = 0$	26	205.84***	N/A

[a] The test statistics are distributed chi-square with the indicated degrees of freedom equal to the number of restricted parameters.
[b] Asterisks indicate exceedance of the chi-square critical value at significance levels 0.01 (***), 0.05 (**), and 0.10 (*).

The stochastic translog yield frontier model is specified in equation (22). Table 12 presents the maximum likelihood estimates of the model. The model estimated a total of 54 parameters, including sigma *v* and *u*. Almost half of 54 parameters are individually significant at $\alpha = 0.10$ or above. Moreover, the variance component gamma represents the proportion of the inefficiency from the total variance, and it is estimated at 0.918. This implies that about 91.8% of corn yield variation is caused by the technical inefficiency effects. In chapter 2, the gamma coefficient was 0.809 (80.9%) for the analysis of corn yield efficiency in North Dakota, which is little bit smaller than this coefficient for the multistate analysis.

Table 12. Multi-states stochastic translog yield frontier model of estimation.

Variables	Parameter	Estimate	t-statistic	p-value
Stochastic Yield Frontier				
Constant	β_0	-83.43	41.08	0.042
Land	β_L	7.01	1.22	<0.001
Land Square	β_{LL}	-0.01	0.03	0.671
Seed	β_S	0.93	0.49	0.060
Seed Square	β_{SS}	0.05	0.09	0.153
Fertilizer	β_F	-3.27	1.24	0.008
Fertilizer Square	β_{FF}	0.14	0.06	0.046
Pesticide	β_P	9.21	2.14	<0.001
Pesticide Square	β_{PP}	-0.06	0.06	0.380
Labor	β_{La}	-0.52	1.22	0.674
Labor Square	β_{LaLa}	0.04	0.02	0.021
Machinery	β_M	-0.76	0.77	0.328
Machinery Square	β_{MM}	-0.00	0.00	0.699
Rainfall	β_R	1.87	1.77	0.289
Rainfall Square	β_{RR}	-0.07	0.04	0.094
Temperature	β_T	-32.03	9.08	0.001
Temperature Square	β_{TT}	4.09	1.17	0.001
Minimum Temp	β_{Mi}	-6.29	1.54	0.080
Min Temp Square	β_{MiMi}	0.61	0.22	0.005
Maximum Temp	β_{Ma}	59.79	16.41	<0.001
Max Temp Square	β_{MaMa}	-5.35	1.82	0.003
Land x Seed	β_{LS}	0.04	0.05	0.463
Land x Pesticide	β_{LP}	-0.05	0.06	0.383
Land x Machinery	β_{LM}	0.02	0.02	0.244
Land x Rainfall	β_{LR}	-0.07	0.04	0.132
Land x Temperature	β_{LT}	-0.31	0.31	0.324
Land x Min Temp	β_{LMi}	0.04	0.12	0.726
Land x Max Temp	β_{LMa}	-1.23	0.31	0.001
Seed x Fertilizer	β_{SF}	-0.33	0.14	0.025
Seed x Pesticide	β_{SP}	0.04	0.11	0.735
Seed x Labor	β_{SL}	-0.06	0.03	0.044
Seed x Machinery	β_{SM}	0.06	0.04	0.139
Fertilizer x Pesticide	β_{FP}	-0.09	0.09	0.353
Fertilizer x Machinery	β_{FM}	-0.12	0.04	0.002
Fertilizer x Temperature	β_{FT}	-0.20	0.32	0.535
Fertilizer x Min Temp	β_{FMi}	0.33	0.12	0.005
Fertilizer x Max Temp	β_{FMa}	0.80	0.30	0.008
Pesticide x Labor	β_{PL}	0.15	0.05	0.001
Pesticide x Machinery	β_{PM}	0.02	0.03	0.409
Pesticide x Rainfall	β_{PR}	0.10	0.09	0.285
Pesticide x Temperature	β_{PT}	0.27	0.48	0.586
Pesticide x Min Temp	β_{PMi}	0.13	0.19	0.507
Pesticide x Max Temp	β_{PMa}	-2.36	0.40	<0.001
Labor x Machinery	β_{LM}	-0.04	0.02	0.066
Labor x Rainfall	β_{LR}	0.07	0.05	0.190
Labor x Temperature	β_{LT}	0.10	0.31	0.755
Labor x Min Temp	β_{LMi}	0.11	0.12	0.360
Labor x Max Temp	β_{LMa}	-0.22	0.26	0.408
Machinery x Rainfall	β_{MR}	0.07	0.03	0.007

Table 12. Multi-states stochastic translog yield frontier model of estimation (continued).

Variables	Parameter	Estimate	t-statistic	p-value
Machinery x Min Temp	β_{MMi}	-0.37	0.08	0.001
Machinery x Max Temp	β_{MMa}	-0.14	0.23	0.526
Rainfall x Max Temp	β_{RMa}	-0.36	0.36	0.321
Variance Parameters				
Sigma2_v	σ_v^2	0.003		
Sigma2_u	σ_u^2	0.028		
Sigma2	$\sigma^2 = \sigma_v^2 + \sigma_u^2$	0.031		
Gamma	$\gamma = \sigma_u^2/\sigma^2$	0.918		
Log-likelihood	$\mathcal{L}$	404.02		
Observations		775		

The higher gamma estimate for the larger geographic region in this chapter may simply reflect that larger geographic regions have greater heterogeneity of climate, as compared with smaller regions such as the state of North Dakota. This is possible that more observations in the dataset will definitely increase the inefficiency effects, where the prediction of the technical efficiency and the effect of yield frontier become more accurate under the SFA model.

One relatively simple way to assess the effects of the several input variables is to explore the output elasticity of the corn yield frontier's response to each explanatory variable. The elasticity estimates provide standardized, unit-free statistical quantifications of the percentage change in in the corn yield frontier resultant from a 1% increase in each of the individual explanatory variables, *ceteris paribus*.

Table 13 reports the output elasticities derived from equation (23). The output elasticities quantify the effects of changes in each explanatory variable on the corn yield frontier. A total of 14 output elasticities are derived from the SFA model and their standard errors are approximated using Monte Carlo simulation to determine each output elasticity's significance level.

To better assess how the yield would change in response to three daily temperatures: minimum temperature, maximum temperature, and mean temperature, we estimated the combined output elasticities. For instance, MiMatemTemp represents the combined output elasticity of a uniform shift in mean temperature, minimum temperature, and maximum temperature. The elasticities of MiMatemTemp in each state are statistically significant at $\alpha < 0.10$. In the multi-state study region, the corn yield frontier will increase by 31.12% when the entire growing season temperature distribution increases by 1%. In other words, if daily average temperature increases from 61.40 to 62.01, daily maximum temperature increases from 83.48 to 84.31, and daily minimum temperature increases from 37.30 to 37.67, the average corn yield frontier in the northern U.S. Corn Belt will increase to 166.37 bushels per acre (an increase of approximately 40 bushels per acre).

Notably, each MaMitemTemp elasticity varies by state. For instance, the North Dakota corn yield will increase by 48.25%, up to 168.42 bu./acre, the Minnesota corn yield will increase by 38.30%, up to 201.59 bu./acre, the South Dakota corn yield increase by 40.26%, 161.94 bu./acre, the Wisconsin corn yield will increase by 43.32%, up to 217.98 bu./acre, and Nebraska corn yield increase by 17.53%, up to 178.76 bu./acre. Among the states, North Dakota's corn yield will increase the most, whereas corn yield in Nebraska will increase the least. However, all states' average corn yields are predicted to increase from general temperature increases. Greater yield responses to temperature changes will occur at more northern latitudes because colder temperatures in the northern states are more constraining than the warmer temperatures in the southern portions of the study region.

Table 13. Output elasticities of the corn yield in each state.

Variables	MN	ND	NE	SD	WI	Pooled
Land	1.46***	1.66***	1.20***	1.78***	1.62***	1.54***
	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)
Seed	2.31	3.31**	3.13**	3.31**	3.32**	3.08**
	(1.53)	(1.53)	(1.53)	(1.53)	(1.53)	(1.53)
Fertilizer	2.51***	3.26***	3.51***	3.03***	2.26***	2.91***
	(0.92)	(0.92)	(0.92)	(0.92)	(0.92)	(0.92)
Pesticide	0.19	0.77*	0.09	0.88	0.59*	0.51
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Labor	2.16	3.15*	3.17*	2.48	3.50*	2.89*
	(1.83)	(1.83)	(1.83)	(1.83)	(1.83)	(1.83)
Machinery	3.51	2.52	3.49	3.55	5.62	3.74
	(4.42)	(4.42)	(4.42)	(4.42)	(4.42)	(4.42)
Rainfall	7.95*	7.98*	9.98**	8.95*	9.95**	8.96**
	(4.43)	(4.43)	(4.43)	(4.43)	(4.43)	(4.43)
Temperature	27.14**	34.08***	18.28*	24.09**	24.15**	18.24**
	(11.68)	(11.68)	(11.68)	(11.68)	(11.68)	(11.68)
Min Temp	5.27*	5.25*	7.30***	5.27*	5.29*	6.48*
	(2.94)	(2.94)	(2.94)	(2.94)	(2.94)	(2.94)
Max Temp	5.89	8.93	11.56	13.90*	13.88*	6.21*
	(7.54)	(7.54)	(7.54)	(7.54)	(7.54)	(7.54)
MiMatemTemp[a]	38.30**	48.25***	17.53*	40.26***	43.32***	31.12***
	(10.13)	(10.13)	(10.13)	(10.13)	(10.13)	(10.13)
MitemTemp[b]	32.41***	39.32***	5.98	20.36***	29.44**	24.91***
	(10.32)	(10.32)	(10.32)	(10.32)	(10.32)	(10.32)
MatemTemp[c]	33.03***	43.00***	10.83***	29.99***	38.03***	24.65***
	(10.91)	(10.91)	(10.91)	(10.91)	(10.91)	(10.91)
MiMatem[d]	11.16	14.17	0.25	19.17**	19.18**	12.68**
	(8.90)	(8.90)	(8.90)	(8.90)	(8.90)	(8.90)

***, **, and * indicate the significant level at $\alpha = 0.01$, $\alpha = 0.05$, and $\alpha = 0.10$, respectively.

[a] MiMatemTemp represents the combined elasticities of minimum temperature, maximum temperature, and average temperature.

[b] MitemTemp represents the combined elasticities of minimum temperature and average temperature.

[c] MatemTemp represents the combined elasticities of maximum temperature and average temperature.

[d] MiMatem represents the combined elasticities of minimum temperature and maximum temperature.

Under the assumption that average temperature and minimum temperature can shift together, while maximum temperature stays constant, the yield frontier will increase by approximately 25% for a 1% increase in mean temperature and minimum temperature in the same growing season in the northern region. Looking at each state alone, the effects of MitemTemp in North Dakota corn are the highest, at 39.32% ($\alpha = 0.01$) whereas Nebraska corn yield will increase least, at 5.98% (not statistically significant).

If mean temperature and maximum temperature shift simultaneously while minimum temperature remains constant, the elasticity of MatemTemp predicts the corn yield frontier would increase by 24.6%, (31.25 bu./ac), on average. If this happens, then we should expect the average corn yield in the northern U.S. Corn Belt to be approximately 158.50 bushels per acre, on average. These elasticity estimates vary from state-to-state, again, with the largest estimated elasticity in North Dakota, where the corn yield frontier will increase by 43.0% ($\alpha = 0.01$) whereas Nebraska's corn yield least, by 10.83% ($\alpha = 0.01$).

The MiMatem elasticity is estimated to assess how corn yield might respond to simultaneous changes in daily minimum temperature and daily maximum temperature coincide, while average temperature stays constant (admittedly, an unlikely scenario). MiMatem elasticity indicates that corn yield will increase by 12.68% when there is a 1% increase in both daily maximum and minimum temperatures in the northern region. By state, the elasticities of South Dakota (19.17%) and Wisconsin (19.18%) are statistically significant ($\alpha = 0.05$), while others are not. Generally, we can infer that corn yield in the northern region of the US Corn Belt is very responsive to increases in the general temperature level, especially in states north of Nebraska. More importantly, the yield frontier seems to depend on general, uniform increases in all three temperature variables in the model, this finding has not been reported in the related literature.

The mean temperature has the highest effect on the corn yield by 18.24% for the study region, 34.08% for North Dakota, 27.14% for Minnesota, 24.15% for Wisconsin, 24.09% for South Dakota, and 18.28% for Nebraska. The maximum temperature has the second highest effect on the corn yield, but not all elasticities are statistically significant.

In addition, the elasticities of minimum temperature in each state are significant at $\alpha = 0.10$ or above. If a 1% increase occurs in the minimum daily temperature, it is predicted to increase corn yield by 7.30% in Nebraska, 5.90% in South Dakota, 5.29% in Wisconsin, 5.27% in Minnesota, and 5.25% in North Dakota. The variation of the minimum temperature in the growing season is estimated to be another critical factor. Sources of average minimum daily temperature increases during the growing season would be earlier spring thaw, later first fall frost, and general warming. It seems obvious that when the minimum daily temperature during the early growing season is higher than the average, farmers may be able to plant their crops a bit earlier than usual, which provides more time for crops to grow and mature and allows farmers to select higher-yielding corn varieties that need more time for maturation. Similarly, a longer frost-free period in fall further increases the viable growth period. If farmers had better information about the weather in the crop growing season, especially in early spring and fall, then they would be able to better manage the timing of inputs and potentially find other ways to adaptively increase crop yield.

The elasticities of rainfall in each state are significant at $\alpha \leq 0.10$ or better. Thus, the corn yield frontier shifts with inter-annual and spatial variations in rainfall—increases of 8.96% in the pooled study region, 9.98% in Nebraska, 9.95% in Wisconsin, 8.95% in South Dakota, 7.98% in North Dakota, and 7.95% for Minnesota, when there is a 1% increase in total rainfall in the growing season. The variation of total rainfall has the second largest effect, after temperature, on the corn yield frontier in the pooled study region, as well as in the states individually.

In terms of farm input expenditure, machinery expenditure seems a vital factor for corn yield, but some state's elasticities are not statistically significant. Machinery expenditure is referring to agricultural machinery and equipment leases. Thus, farmers using newer, more advanced, and costlier farming machinery and equipment will have higher machinery expenditures. Because newer implements are designed to improve input use efficiency while increasing yield, it is expected that farmers with higher machinery expenditures can produce more output given the same level (or a lower level) of other inputs such as labor. In this case, an increase in expenditures on machinery and equipment leases may maintain the current level of corn yield, but it is not quite increasing the yield in the substantially.

The corn yield frontier is also highly responsive to seed expenditure. The estimated elasticity of yield’s response to seed expenditure for the pooled study region is 3.08, meaning a 1% increase in seed expenditure leads to a 3.08% increase in corn yield significant at $\alpha = 0.05$. All states in the study region have similarly elastic yield responses to seed expenditure: a 1% increase in seed expenditure should increase corn yield by 3.13% in Nebraska, 3.31% in South Dakota, 3.32% in Wisconsin, 3.31% in Minnesota, and 3.31% in North Dakota. Perhaps this elasticity indicates that increases in the real price of corn seed during the study period reflect the higher productivity of new (and costlier) seed lines during the study period, as well as simultaneously decreasing row spacing to allow higher plant populations. The output elasticities of seed expenditures imply that the price of new varieties is probably competitive, and that breeding effort have resulted increasing productivity that outweighs the increase in costs.

Fertilizer expenditure is the third essential expense for increasing the yield, and all fertilizer elasticities are statistically significant at $\alpha = 0.01$. This means a 1% increase in fertilizer expenditure is predicted to increase the yield by 3.51% in Nebraska, 3.03% in South Dakota, 2.91% in Wisconsin, 2.51% in Minnesota, and 3.26% in North Dakota.

The labor expenditure is the fourth essential expense in terms of increasing yield, but this expenditure is related to farm management, and one of the management goals is to increase or maintain the crop yield without increasing total inputs. In other words, labor expenditures may not directly increase the yield; however, it might have indirect effects that should be explored in the model. Based on the estimated elasticity of labor expenditure, corn yield would increase by 3.17% in Nebraska, 2.46% in South Dakota, 3.50% in Wisconsin, 2.16% in Minnesota, and 3.15% in North Dakota when the labor expenditure increases about 1%.

The last (and maybe least) essential farm input is land quantity (acreage of corn planted), but each elasticity of land in the states is statistically determined as significance at 1% level. The elasticities of yield response to land do not vary from state-to-state; that is to say the 90% confidence intervals for these estimates have substantial overlap. The general interpretation would be about a 1% increase in the average planted area per farmer would increase corn yield by 1.20% in Nebraska, 1.78% in South Dakota, 1.62% in Wisconsin, 1.46% in Minnesota, and 1.66% in North Dakota. This translates to an increase of 2.12 bu./ac. in Minnesota and Nebraska, 1.88 bu./ac. in North Dakota, 1.38 bu./ac. in South Dakota, , and 2.46 bu./ac. in Wisconsin.

According to the overall interpretation of the output elasticities, the study found that the variation of weather variables is the dominant factor affecting inter-annual corn yield variation in all five states, though farm input expenditures are also important factors of production. Unfortunately, the effects of managed inputs on yield are decidedly smaller than weather effects.

Most weather variable's elasticities are statistically significant at $\alpha = 0.10$ or better; however, their effects vary substantially at the state level, which implies that when the geographic scope of the study region increases, the effects of weather variables change substantially throughout the region. This may not be the case at ASD level because of the results found in chapter 2. In chapter 2, each variable's elasticities were not discernibly different across the ASDs in North Dakota. We conjecture that the different findings in chapters 2 and 3might be related to the various attributes of the study regions, such as location, size, and number of DMUs included in the study region, and a higher degree of weather variability when the geographic scope is extended. In this case, we used the state averages to estimate the elasticities of corn yield from each explanatory variable. Hence, differences between the state and ASD suggest each variable's elasticities would vary relatively more at the state level than at the ASD level. One may be interested in how the elasticity effects will be different at the county or country level if data for crop inputs and outputs are publicly available at these levels.

The state-level comparison provides more inferences about which variables account for the most and least yield variation in each state. We find that the yield frontier shifts much more in response to temperature variation in the more northern states, such as North Dakota and Minnesota, than in the southern-most state in the study region (Nebraska). The greater responsiveness of yield to temperature variation in the north (vs. in Nebraska) can likely be attributed primarily to lower baseline temperatures in the northern latitudes and corn yield's dose-response relation with heat. Therefore, northern states should be expected to experience greater yield gains in response to climate change than southern states. In fact, states far to the south of the study region may even see corn yields decline in response to higher temperatures

Figure 14 presents the corn yield efficiency scores derived from the stochastic translog yield frontier model for each of the five states from 1994 to 2018. The black line represents the median efficiency score each year. The median remains fairly constant from year to year, always between 0.80 and 0.95. This means that every year at least three states were 80% efficient or better; however, none of the states attained an efficiency score of 1 in any year, indicating that each state has some inefficient ASDs every year. In 2002 and 2012, the distribution of technical efficiency scores was negatively skewed, indicating the technical efficiency distribution has a long left tail. This means some states, Wisconsin, Minnesota, and North Dakota performed at an economically efficient level relative to Nebraska and South Dakota..

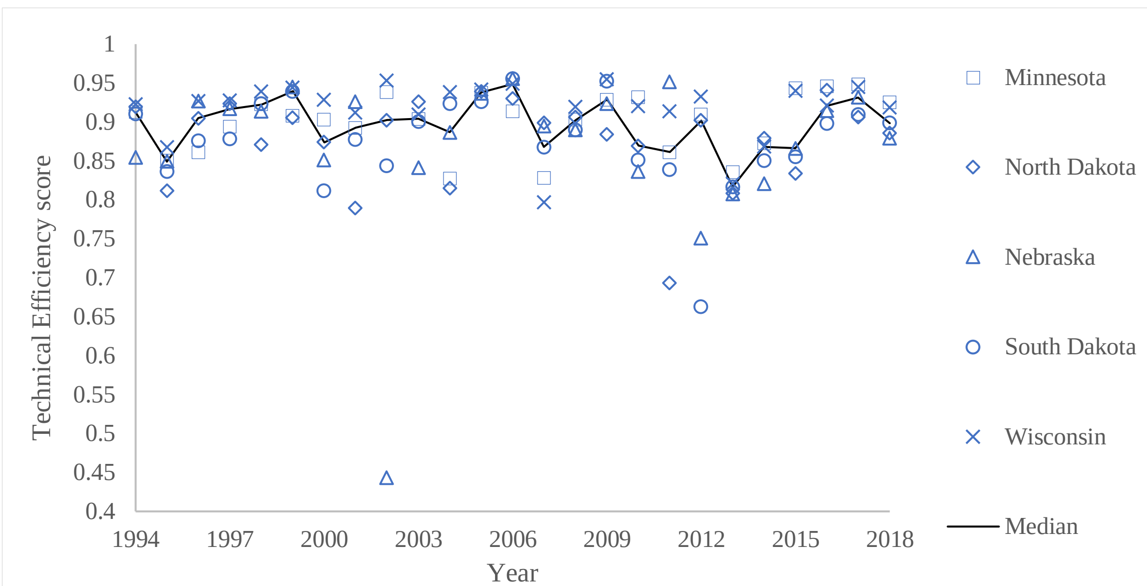

Figure 14. Technical efficiency scores from Stochastic Frontier Model, 1994-2018.

Corn producers from Nebraska in 2002, North Dakota in 2011, and South Dakota and Nebraska in 2012 had substantially lower technical efficiency scores than the other states. This may be due to abnormal weather patterns or crop disease outbreaks in these states during those years. Based on historical weather information, the more southern states in the study region had severe to extreme drought conditions during the summer of 2012. For North Dakota in 2011, the summer was much cooler than usual, and it was a rainy, excessively wet summer. For Nebraska in 2002, there was a severe drought all summer long and farmers had a poor crop yield. These abnormal effects could be the main disruption causing low technical efficiency in South Dakota and Nebraska in 2002 and 2012, and North Dakota in 2011. Overall corn technical efficiency scores in the study region haven’t fluctuated much over the study period according to the SFA model.

Figure 15 presents the descriptive summary for each state's technical efficiency scores at the ASD level. From 1994 to 2018, the average technical efficiency scores in Southern Minnesota and South Western Wisconsin had the highest average technical efficiency scores amongst all the ASDs analyzed. The average technical efficiency scores in the Central ASD in North Dakota, and the South-central ASD in Nebraska were as the lowest. Based on the aggregated ASDs' technical efficiency scores in each state, the technical efficiency score in Wisconsin averaged 0.916, which is the highest average comparatively. The second-highest average is in Minnesota, the third is in North Dakota, followed by South Dakota, and Nebraska. During the past 25 years, the lowest technical efficiency score in a North Dakota ASD was 0.128 (Central and 2004) for North Dakota, and the highest was 0.977 (Northeast and 2009), which implies technical efficiencies varied substantially in North Dakota compared to other states. This efficiency variation could be attributable to the following: 1) there are more observations (more of North Dakota’s DMUs) in the dataset than for the other states, and 2) North Dakota has substantial daily temperature variations, that are relatively more prominent than other state's daily temperature variations. Nevertheless, Nebraska's estimated standard deviation is the largest (0.123), indicating corn production technical efficiency varies much more in Nebraska than other states.

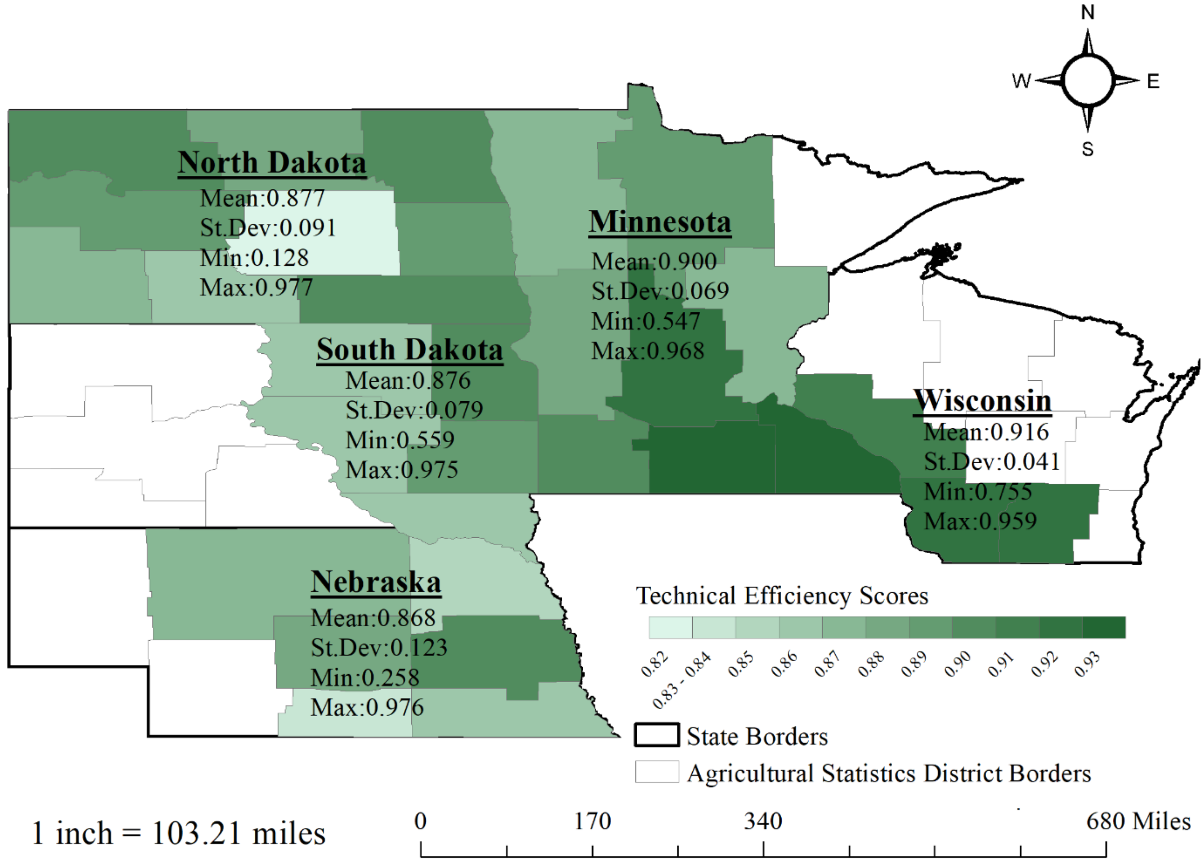

Figure 15. Technical efficiency score from Stochastic Frontier Model in each Agricultural Statistics District within states, 1994-2018.

3.5.2. Results from Data Envelopment Analysis

The output-oriented DEA model with the technology assumption of VRS and CRS are estimated to generate the corn yield technical efficiency scores for all ASDs within the five states. Figure 16 presents the technical efficiency scores generated by the DEA-VRS for all ASDs within the five states over 25 years from 1994 to 2018. The black line represents the overall median of the technical efficiency scores. The overall median technical efficiency score has peaks and troughs on the same timeline as the median score from SFA; however, the peaks and troughs of the DEA-derived scores are much more extreme by comparison. Nonetheless, the range of variability of technical efficiency scores seem to be reduced some if this one is compared to the one in Figure 7, which has smaller data sample (225 DMUs). In other words, the sample size of 775 DMUs clearly provides better efficiency estimates under the DEA-CRS by reducing the variance of estimated technical efficiency scores which is supporting the results found in some research (Clement et al., 2008; Sarkis, 2007; Alirezaee et al., 1998; Banker et al., 1989), but conflicts with some research (Pedraja-Chaparro et al., 1999).

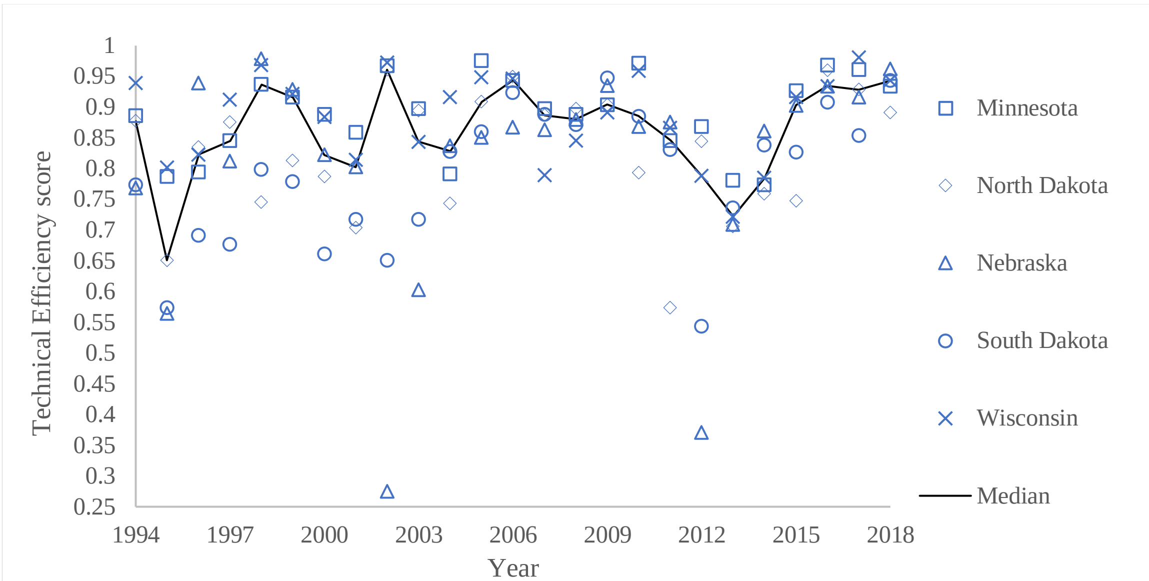

Figure 16. Multistate technical efficiency scores from the Data Envelopment Analysis with Variable Returns to Scale, 1994-2018

The year 1995 was a special one for corn because widespread wheat disease occurred in 1994, leading farmers to plant more corn acreage than usual in 1995. However, many of them were new and inexperienced at corn production in the northern region at that time, which might have caused them to have lower efficiency scores in Nebraska, South Dakota, and North Dakota. In 2002, Nebraska's average efficiency score was 0.28, which is the lowest among all states over the study period. In 2012, Nebraska's average efficiency score was about 0.37. Thus, it is evident that occasionally, technical efficiency scores in Nebraska are shocked by something very severe (e.g., drought, crop disease, water issue).

Figure 17 presents the descriptive summary of each state's technical efficiency score at the ASD level from 1994 to 2018. Based on the DEA-VRS, the average technical efficiency scores in Northwest of North Dakota, Northeast of South Dakota, Central and the whole South of Minnesota, and Southwest of Wisconsin are high relative to the study region as a whole. On the other hand, the average estimated technical efficiency scores for the North-central ASD of Nebraska, the Southeast and Central ASDs of South Dakota, and Northwest ASD of Minnesota are the lowest in the study region.

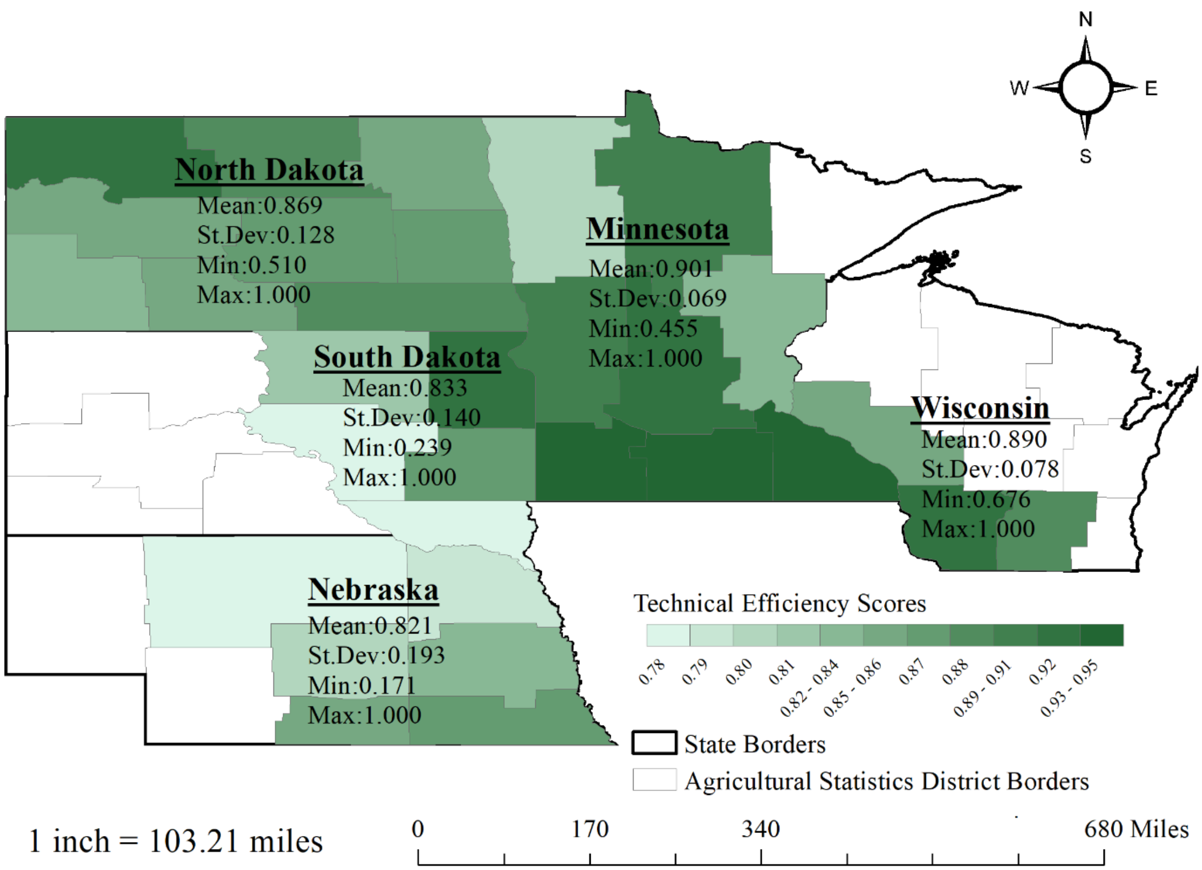

Figure 17. Technical efficiency score from Data Envelopment Analysis (VRS) in each Agricultural Statistics District within states, 1994-2018.

Based on the aggregated ASD's technical efficiency scores in each state, the technical efficiency score in Minnesota averaged 0.901, followed by Wisconsin (0.890), North Dakota

(0.869), South Dakota (0.833) and Nebraska (0.821). In the past 25 years, the lowest minimum technical efficiency was in Nebraska with a score of 0.171 (South-central and 2002). The standard deviation of Nebraska's technical efficiency scores is the largest (0.193) amongst all, and this is consistent with standard deviations from SFA (Figure 15).

Figure 18 presents the corn yield efficiency scores generated from the DEA-CRS for all ASDs within the five states over the study period. The black line represents the median of the efficiency scores. These efficiency scores look very similar to the one found from DEA-VRS (Figure 16). The medians from DEA-VRS and DEA-CRS covary closely to each other, except in 1998, 2002, and 2012. In these three years, the distribution of technical efficiency scores is negatively skewed significantly, which indicates some technical efficiency scores in some states are estimated significantly lower in the CRS model. Otherwise, one small difference between CRS and VRS is the range of variation of the scores over time. The state average of TE scores from DEA-CRS ranged between 0.70 and 1, but the range of the DEA-VRS scores was 0.65 to 0.98.

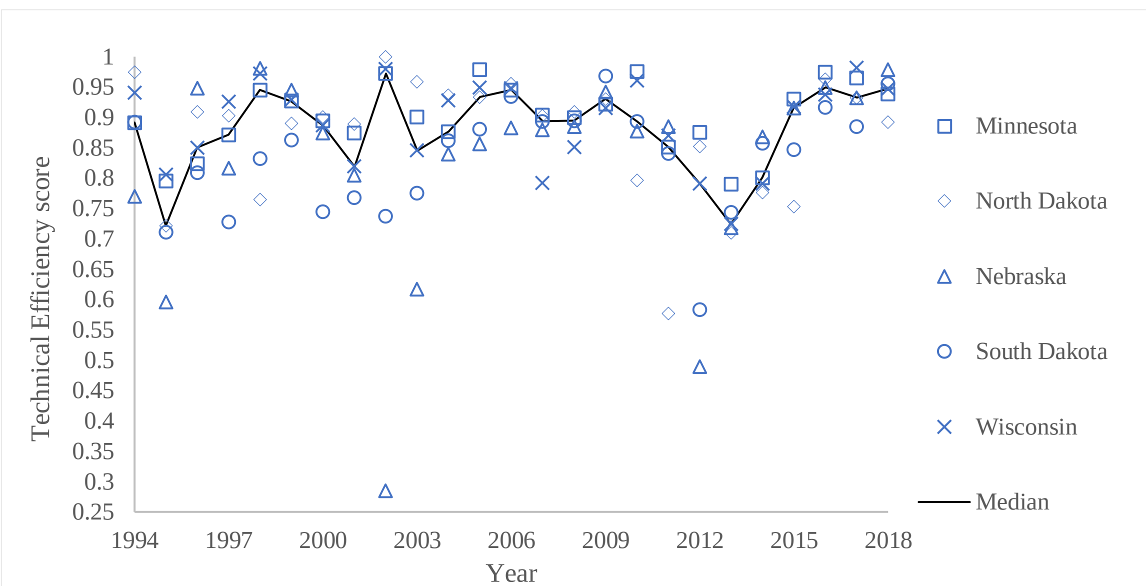

Figure 18. Multistate technical efficiency scores from the Data Envelopment Analysis with Constant Returns to Scale, 1994-2018

By state, Nebraska's technical efficiency scores in 1995, 2002, 2003, and 2012 were substantially lower than other states, but most years the average technical efficiency scores for Nebraska ranged between 0.75 and 1. The average technical efficiency score of North Dakota in 2011 and South Dakota in 2012 are also considerably lower. The DEA-CRS, excluding the years mentioned above, indicates the five states' corn producers were technically efficient between 0.70 and 0.99 in the past.

Figure 19 presents the descriptive summary for each state's technical efficiency scores at the ASD level. Based on DEA-CRS, the average technical efficiency scores in all South regions of Minnesota, and Southwest of Wisconsin is noticeably higher than other ASDs in the study region, whereas the average technical efficiency scores in the North-central and Southeast ASDs of South Dakota, the Southwest and Central ASDs of North Dakota, and the North-central ASD of Nebraska were the lowest scoring DMUs in the study area.

The average technical efficiency score in Minnesota is 0.888, followed by Wisconsin (0.884), North Dakota (0.825), Nebraska (0.805) and South Dakota (0.789). The lowest minimum technical efficiency score during the study period was in North Dakota, with a score of 0.106 (Central and 2004), whereas the highest maximum technical efficiency was 1 for each state during at least one year of the study period. The standard deviation of scores in Nebraska is the largest, at 0.195.

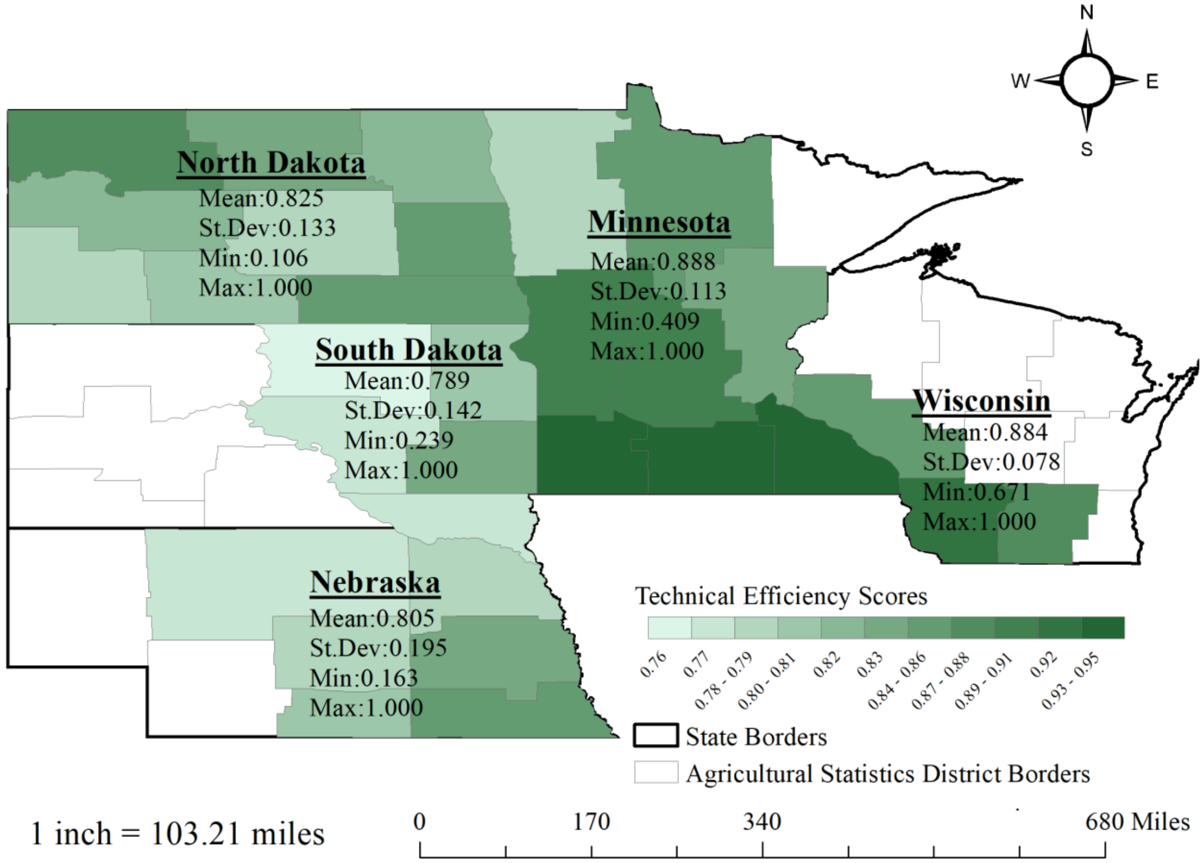

Figure 19. Technical efficiency score from Data Envelopment Analysis (CRS) in each Agricultural Statistics District within states, 1994-2018.

Figure 20 presents the descriptive summary for each ASD's scale efficiency scores over the study period. We found the best scale efficiency or (MPSS) is in South-central of Minnesota, suggesting no potential to increase the size of corn operation in terms of improving technical efficiency because it has already reached the optimal scale. Furthermore, the suboptimal scale efficiencies are found in Southeast of North Dakota, almost all regions in Minnesota, Wisconsin, and Nebraska and South-central and East of South Dakota. These results indicate there is no potential to improve scale efficiency because they are at decreasing returns to scale. Overall, the scale efficiencies in these regions are very close to the optimal scale level (close to 1). However, there are some regions such as the Central ASD of North Dakota, the North-central, Northeast, Central and Southeast ASDs of South Dakota, North-central, Northeast ASD of Nebraska, and the Northwest ASD of Minnesota that should not expand their corn operation size because their scale efficiencies are not at Increasing Returns to Scale.

According to the aggregated ASDs scale efficiencies in each state, the average scale efficiencies are estimated as 0.99, 0.98, 0.98, 0.95, and 0.95 for the state of Wisconsin, Minnesota, Nebraska, South Dakota, and North Dakota, respectively. The lowest scale efficiency is found in North Dakota with a score of 0.106, whereas the highest scale efficiency is found in Wisconsin with a score of 0.957.

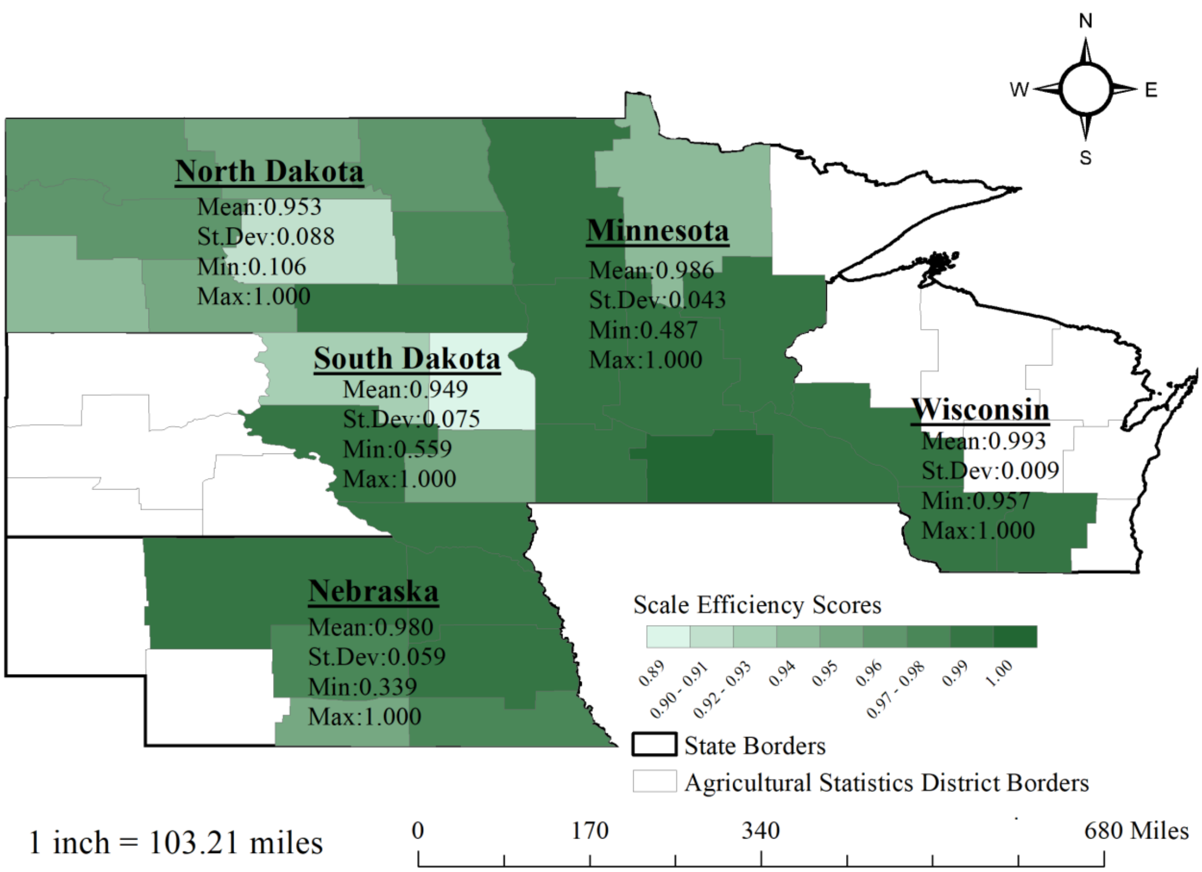

Figure 20. Scale efficiency scores from Data Envelopment Analysis in each Agricultural Statistics District within states, 1994-2018.

3.5.3. Comparison of the Efficiency Results

The descriptive statistics of technical efficiency scores derived from SFA and DEA are presented in Table 14. Based on the SFA efficiency scores, the most technically efficient corn-producing state is Wisconsin with a score of 0.92 and followed by Minnesota (0.90), South Dakota (0.88), North Dakota (0.88) and Nebraska (0.87). Based on the DEA-VRS, the most technically efficient corn-producing state is Minnesota, with a score of 0.90, followed by Wisconsin (0.89), North Dakota (0.87), South Dakota (0.83), and Nebraska (0.82). Based on the DEA-CRS, the most technically efficient corn-producing state is Minnesota with a score of 0.88 and followed by Wisconsin (0.88), North Dakota (0.82), Nebraska (0.80), and South Dakota (0.80).

Table 14. Descriptive statistics of technical efficiency scores.

	North Dakota				Minnesota			
	SFA	VRS	CRS	SE	SFA	VRS	CRS	SE
Mean	0.877	0.869	0.825	0.953	0.900	0.901	0.888	0.986
Std Dev	0.091	0.128	0.133	0.088	0.069	0.107	0.113	0.043
Min	0.128	0.510	0.106	0.106	0.547	0.455	0.409	0.487
Max	0.977	1.000	1.000	1.000	0.968	1.000	1.000	1.000
	South Dakota				Wisconsin			
	SFA	VRS	CRS	SE	SFA	VRS	CRS	SE
Mean	0.876	0.833	0.789	0.949	0.916	0.890	0.884	0.993
Std Dev	0.079	0.140	0.142	0.075	0.041	0.078	0.078	0.009
Min	0.559	0.239	0.233	0.559	0.755	0.676	0.671	0.957
Max	0.975	1.000	1.000	1.000	0.959	1.000	1.000	1.000
	Nebraska				Pooled			
	SFA	VRS	CRS	SE	SFA	VRS	CRS	SE
Mean	0.868	0.821	0.805	0.980	0.885	0.864	0.838	0.970
Std Dev	0.123	0.193	0.195	0.059	0.089	0.140	0.145	0.068
Min	0.258	0.171	0.163	0.339	0.128	0.171	0.106	0.106
Max	0.976	1.000	1.000	1.000	0.977	1.000	1.000	1.000

The two efficiency approaches found different states to be the most efficient. This also happens when we compare both approaches using North Dakota's ASDs in Chapter 2. This result may be attributable to the differences in the representation of each state in in the dataset; there are eight ASDs in Minnesota versus only three ASDs in Wisconsin. Other idiosyncrasies in the data may also contribute to the variant results from DEA and SFA.

Under the pooled estimates, the mean technical efficiency scores from SFA, DEA-VRS, and DEA-CRS are approximately 0.88, 0.86, and 0.84, with their standard deviations of 0.089, 0.140, and 0.145, respectively. These estimates imply that the corn yield in the northern region of U.S. Corn Belt, including Nebraska, is technically efficient at 88.0% by SFA, 86.0% by DEA-VRS, and 84% by DEA-CRS in the period from 1994 to 2018. On the other hand, the yield can potentially increase by 12% according to the SFA estimation, 14% according to the DEA-VRS estimation, and 16% according to the DEA-CRS, without changing the current level of total expenditure on inputs, and its production practices and technologies. All three means are considerably close to each other; however, one should be careful in comparing their means due to their substantively different standard deviations. The standard deviation from SFA is much smaller than the standard deviations from both DEA techniques, which implies that DEA might be possibly under-estimated the technical efficiency scores due to the assumptions of relative efficiency in data set in each year (see Alirezaee et al., 1998).

Table 15. Ranking based on technical efficiency, scale efficiency, and average yield.

Rank	SFA	DEA (VRS)	DEA (CRS)	DEA (SE)	Mean Corn Yield
1	Wisconsin	Minnesota	Minnesota	Wisconsin	Wisconsin
2	Minnesota	Wisconsin	Wisconsin	Minnesota	Minnesota
3	North Dakota	North Dakota	North Dakota	Nebraska	Nebraska
4	South Dakota	South Dakota	Nebraska	North Dakota	South Dakota
5	Nebraska	Nebraska	South Dakota	South Dakota	North Dakota

Table 15 presents the rankings based on the state level. These rankings are based on the means of the SFA and DEA (VRS and CRS) technical efficiency scores, the DEA-based scale efficiencies, and corn yield for each state in the study region. Wisconsin had the highest average corn yield. Based on the SFA efficiency scores, Wisconsin is also the most technically efficient corn producing state among the five. In addition, Wisconsin is ranked as number one corn producing state based on the scale efficiency derived from DEA. Though average corn yield in Minnesota was the second-highest in the region, the technical efficiency of Minnesota corn production is ranked the most technically efficient of all five states based on the results of both DEA models. Based on these first and second ranking, the study can conclude that a strong positive relation exists between high corn yield and high technical efficiency.

Table 16. Spearman correlation coefficients.

	SFA (TE)	VRS (TE)	CRS (TE)
SFA (TE)	1.000		
VRS (TE)	0.650***	1.000	
CRS (TE)	0.783***	0.872***	1.000

Prob > |r| under H0: Rho=0

Table 16 presents Spearman rank correlation coefficients between the technical efficiency scores derived from SFA, DEA-VRS and DEA-CRS. All correlations have a positive relationship with a strong significance level ($\alpha = 0.01$). The rankings indicate the slightly weak correlation is between SFA and VRS (0.650), whereas a slightly strong correlation is between SFA and CRS (0.783). These correlations are consistent with the correlation results found in Chapter 2. The strongest correlation is between DEA-VRS and DEA-CRS, which makes sense in light of the Figures 16 and 18. Overall, the correlation result supports the results of Sharma et al. (1997), where the correlation between SFA and DEA-VRS was a little bit weaker than the correlation between SFA and DEA-CRS.

3.6. Summary and Conclusion

Globally, about 38% of corn supply is dependent on corn producers in the United States (Grassini et al., 2015). The majority of corn is grown in the region known as the U.S. Corn Belt. The Corn Belt includes states with massive corn production, such as Illinois, Indiana, Iowa, Kansas, Kentucky, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin. The report by Courter (2018) stated that Taylor, climatologist at the Iowa State University Extension discussed about the Corn Belt shifts. Due to the climate shift, corn acres are rapidly increasing in the North-Western region of U.S. Corn Belt, specifically, in the states of North Dakota, South Dakota, and Minnesota. In addition, Hoffman et al. (2018) found that a northwestward shift of the U.S. Corn Belt is in progress, with gradual changes resulting from farmers' autonomous adaptation to a changing production environment. Their research concluded that a further investigation should focus on what region will provide a better yield for certain crops under its current and evolving weather conditions (Hoffman et at., 2018)

This dissertation research aimed to evaluate the corn yield frontier and technical efficiency measures based farm input management and weather variables at the ASD level within the following states in the northern U.S. Corn Belt: North Dakota, Minnesota, South Dakota, Wisconsin, and Nebraska. The stochastic semi-translog yield frontier model was developed to estimate the changes in corn yield frontier and technical efficiency scores for each ASD. In addition, the output-oriented DEA model to estimate the non-parametric technical efficiencies to compare the parametric technical efficiencies from SFA and to estimate the scale efficiencies for each ASD within each state. The research found all output elasticities of corn yield for each state are positive, suggesting that the corn yield has a positive relationship with all inputs included in the SFA model. The growing season temperatures are the variables that most restrict yield, especially in the states bordering Canada, and corn yield is highly and positively responsive to changes in temperature in such states. The second most constraining factor of production is rainfall. Farm input expenses are also important factors for increasing yield; however, their output elasticities are much smaller than the weather output elasticities.

Furthermore, we also found the estimated output elasticities of weather variables differ by the state. For instance, a 1% increase in the average growing season temperature in North Dakota will increase the corn yield by 34.08%, which is the highest percentage yield response to temperature amongst all states in the region. In contrast, a 1% increase in Nebraska's average growing season temperature will raise corn yield by only 18.28%, which is lower than in all other states in this study. This result likely indicates that an equivalent increase in average growing season temperature (1 °F, say) will increase corn yield much more in northern states than in southern states.

The difference in output elasticities among the states contrasts with the results we found in chapter 2. In Chapter 2, we found that the output elasticities did not differ among the ASDs of North Dakota. Therefore, further research is necessary to elucidate the effects of scale (geographic size of individual DMUs) and scope (the geographic extent of the entire study region) on differences in output elasticities and yield frontiers by region. Based on the findings, many of the output elasticities vary at the state level.

The technical efficiency performance in each state is estimated differently. The average corn yield technical efficiency in Wisconsin is the highest of all based on the SFA estimates, and Wisconsin is nearest of all the states to being scale-efficient under the DEA over the past 25 years from 1994 to 2018. However, Wisconsin did not rank as the most technically efficient under the DEA estimates. Based on the SFA estimates, the second most technically efficient corn-producing state is Minnesota, which also has the second highest rank by scale efficiency, but Minnesota ranked as the most technically efficient under the DEA estimates. In third place, the most technically efficient corn-producing state is North Dakota under both SFA and DEA estimates, but the scale efficiency for North Dakota is ranked very last. The fourth most technically efficient corn-producing state is South Dakota under SFA, and DEA-VRS, as well as South Dakota, is ranked as fourth in scale efficiency. Nebraska is the least technically efficient corn-producing state under the SFA and DEA-VRS, but Nebraska's scale efficiency is third highest.

Overall, we conclude that the corn yield frontier in each state has the potential to increase substantially in the selected study area in response to climate change, but the yield increases will differ among states and regions based on constraints imposed by current and historical weather patterns, which will become less constraining with anticipated global warming. In addition, the corn yield can be increased to some degree throughout this study region by improving technical efficiency, especially if meteorologists develop a seasonal weather forecast that can help farmers better anticipate the constraints that may (or may not) be imposed by inter-annual weather variation. An accurate seasonal forecast would have implications about the shifts in the yield frontier, allowing farmers to set reasonable yield goals and better manage their controlled inputs to attain those goals. This research does not predict the extent of the spatial shift of the U.S. Corn Belt, nor does it quantify the degree to which climate change has been a driver of shifting corn acreage, but it does provide evidence suggesting that corn yield and acreage are already expanding northward. As climate change continues to warm the Northern Great Plains, corn yield and area planted will continue to increase in these states. Longer-term climate projections, along with seasonal weather forecasts will help farmers to understand how they can adapt to a climate that is changing systematically but is also highly variable.

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APPENDIX

Table A1. Descriptive statistics of Minnesota data.

Variable	Unit	Mean	Std Dev	Minimum	Maximum
Yield	Bu./acre	145.77	32.83	51.78	220.16
Land	Acres	294.68	116.41	78.75	545.54
Seed	$/acre	72.71	30.80	29.62	137.10
Fertilizer	$/acre	97.02	44.91	32.77	224.16
Pesticide	$/acre	33.02	7.00	17.80	55.59
Labor	$/acre	13.00	4.53	3.38	28.69
Machinery	$/acre	6.50	2.56	0.38	17.18
Rainfall	Inches	21.51	4.90	12.05	38.85
Temperature	°F	61.48	1.86	56.18	65.30
Min Temperature	°F	36.34	3.15	24.80	44.00
Max Temperature	°F	81.09	2.83	73.30	88.80

Table A2. Descriptive statistics of North Dakota data.

Variable	Unit	Mean	Std Dev	Minimum	Maximum
Yield	Bu./acre	113.61	26.01	13.96	184.34
Land	Acres	316.71	154.52	61.13	794.92
Seed	$/acre	60.94	25.63	19.84	110.61
Fertilizer	$/acre	75.18	38.46	24.00	172.22
Pesticide	$/acre	23.91	5.10	14.05	58.02
Labor	$/acre	19.28	6.89	2.76	37.02
Machinery	$/acre	4.41	2.65	0.11	19.05
Rainfall	Inches	14.97	3.75	6.92	24.34
Temperature	°F	59.55	1.49	54.58	62.85
Min Temperature	°F	32.13	3.09	22.70	38.10
Max Temperature	°F	82.72	3.86	74.20	93.30

Table A3. Descriptive statistics of South Dakota data.

Variable	Unit	Mean	Std Dev	Minimum	Maximum
Yield	Bu./acre	115.46	30.70	30.57	177.92
Land	Acres	259.81	87.07	131.28	576.33
Seed	$/acre	66.14	28.53	28.91	144.73
Fertilizer	$/acre	68.49	32.26	28.21	155.87
Pesticide	$/acre	28.40	9.83	12.44	60.28
Labor	$/acre	22.43	16.67	5.66	86.21
Machinery	$/acre	8.22	3.20	1.23	18.64
Rainfall	Inches	26.83	7.96	8.73	43.64
Temperature	°F	58.37	6.76	45.63	67.26
Min Temperature	°F	44.54	7.86	31.60	61.05
Max Temperature	°F	84.66	3.33	77.25	95.18

Table A4. Descriptive statistics of Nebraska data.

Variable	Unit	Mean	Std Dev	Minimum	Maximum
Yield	Bu./acre	119.42	36.50	19.03	187.04
Land	Acres	221.62	97.18	58.77	539.63
Seed	$/acre	53.92	21.60	19.24	96.73
Fertilizer	$/acre	67.66	32.87	21.40	159.48
Pesticide	$/acre	38.03	10.25	18.17	78.48
Labor	$/acre	20.52	15.92	5.55	96.77
Machinery	$/acre	6.75	4.48	0.00	22.84
Rainfall	Inches	21.02	4.83	8.43	34.05
Temperature	°F	66.22	1.48	61.50	70.05
Min Temperature	°F	39.93	2.71	33.90	46.30
Max Temperature	°F	87.99	3.33	80.70	96.20

Table A5. Descriptive statistics of Wisconsin data.

Variable	Unit	Mean	Std Dev	Minimum	Maximum
Yield	Bu./acre	152.10	21.11	105.55	202.00
Land	Acres	253.22	50.92	173.61	374.91
Seed	$/acre	72.64	28.89	34.94	128.00
Fertilizer	$/acre	99.77	41.82	46.48	199.58
Pesticide	$/acre	38.53	6.15	27.45	55.59
Labor	$/acre	14.67	4.18	7.77	27.10
Machinery	$/acre	6.76	2.17	1.36	12.57
Rainfall	Inches	23.51	4.50	17.03	35.74
Temperature	°F	62.11	1.19	59.03	64.39
Min Temperature	°F	38.05	2.50	33.30	44.55
Max Temperature	°F	81.14	2.64	75.75	89.05

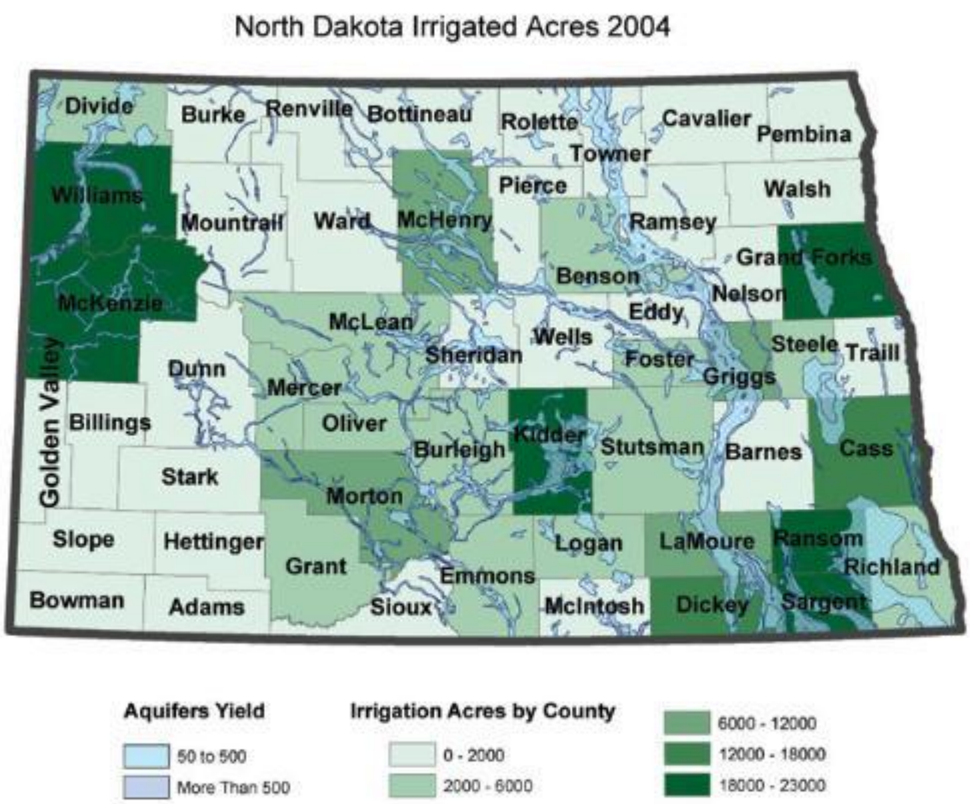


Figure A1. North Dakota irrigated acres in 2004.
Source: North Dakota Department of Commerce.

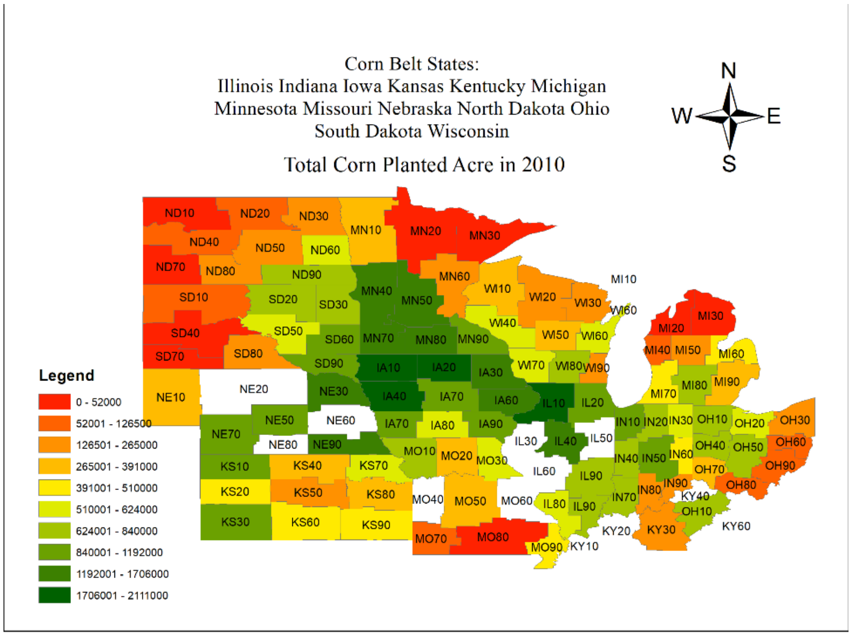


Figure A2. Planted corn acreage in Agricultural Statistics District within states in 2010. Ones with white color represents no data.

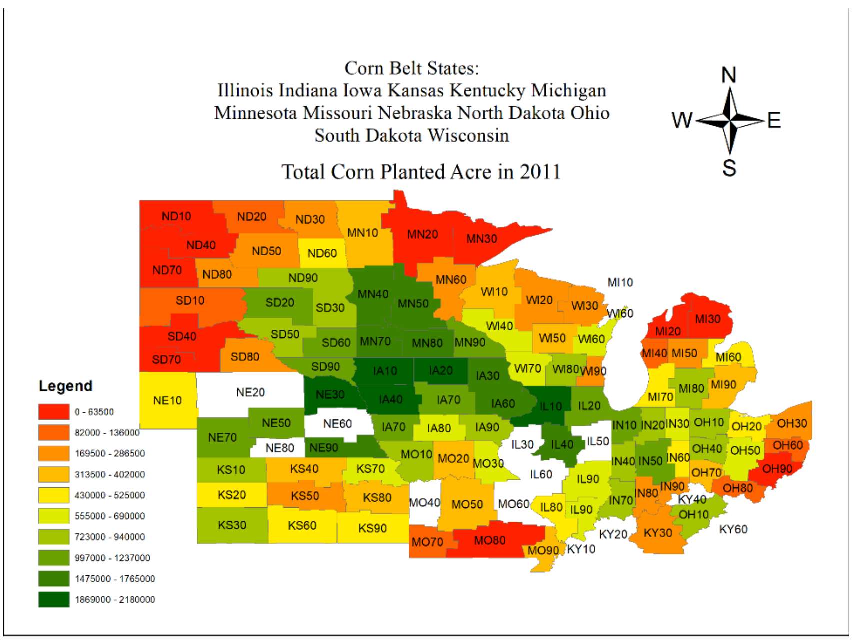


Figure A3. Planted corn acreage in Agricultural Statistics District within states in 2011. Ones with white color represents no data.

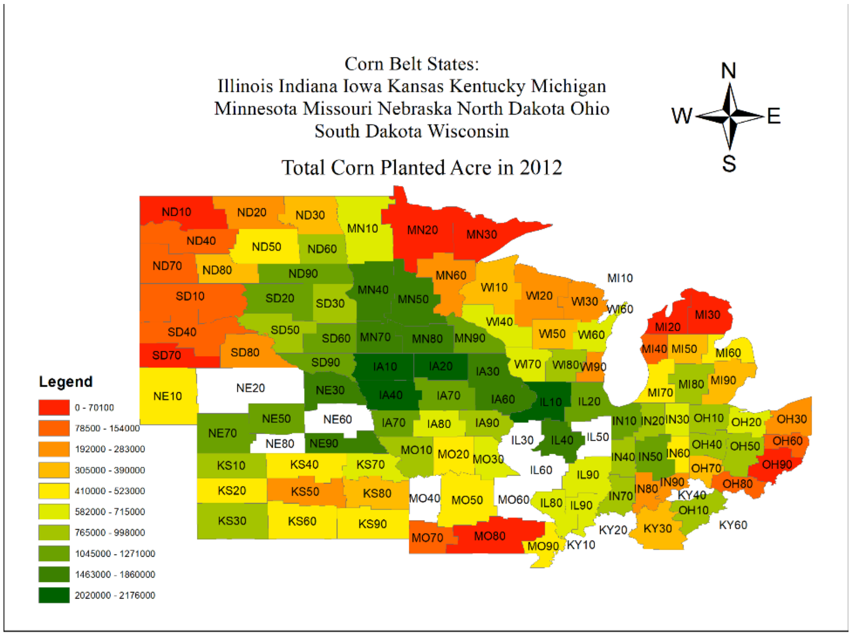


Figure A4. Planted corn acreage in Agricultural Statistics District within states in 2012. Ones with white color represents no data.

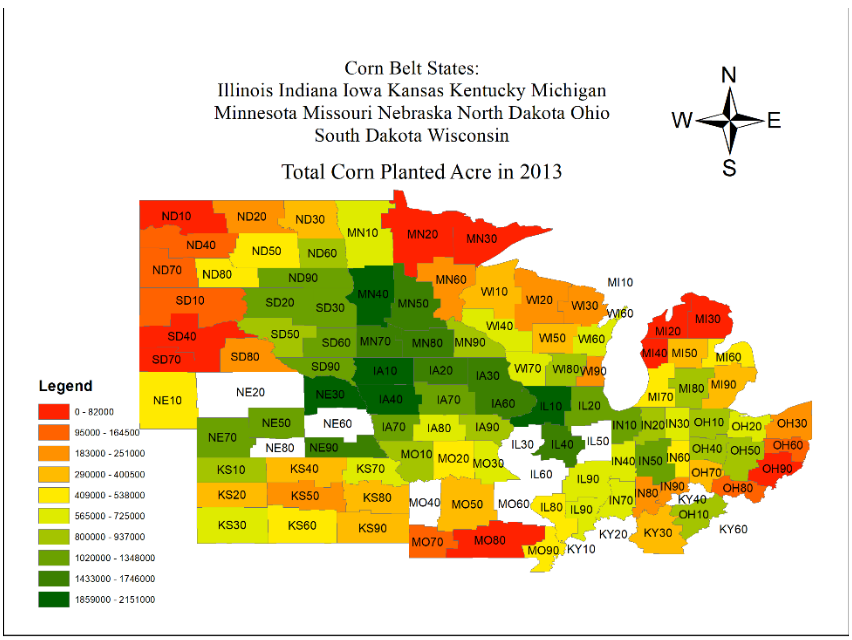


Figure A5. Planted corn acreage in Agricultural Statistics District within states in 2013. Ones with white color represents no data.

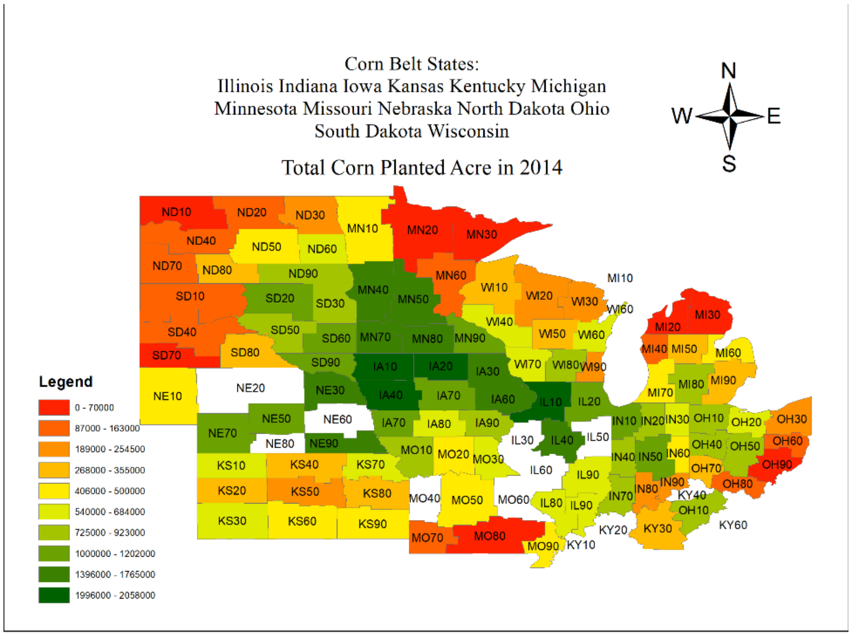


Figure A6. Planted corn acreage in Agricultural Statistics District within states in 2014. Ones with white color represents no data.

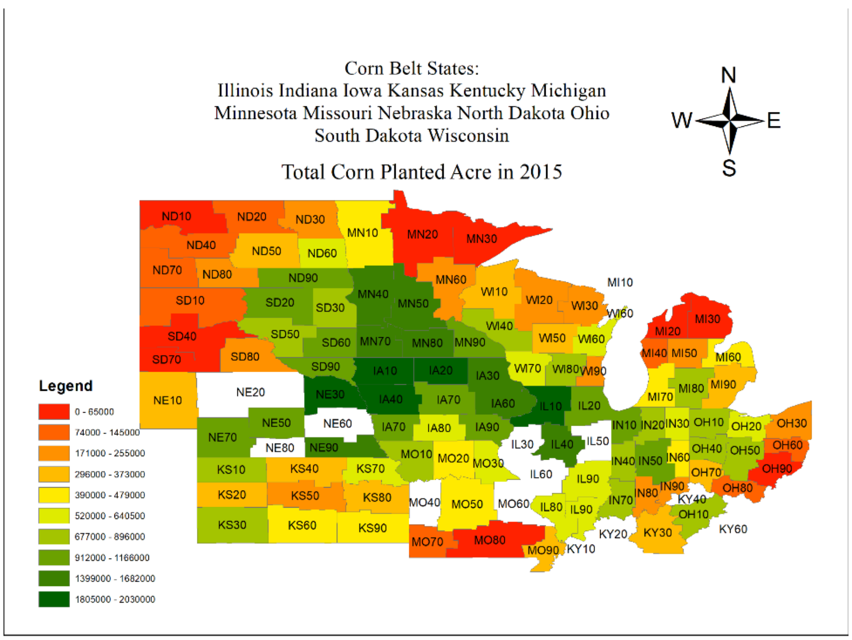


Figure A7. Planted corn acreage in Agricultural Statistics District within states in 2015. Ones with white color represents no data.

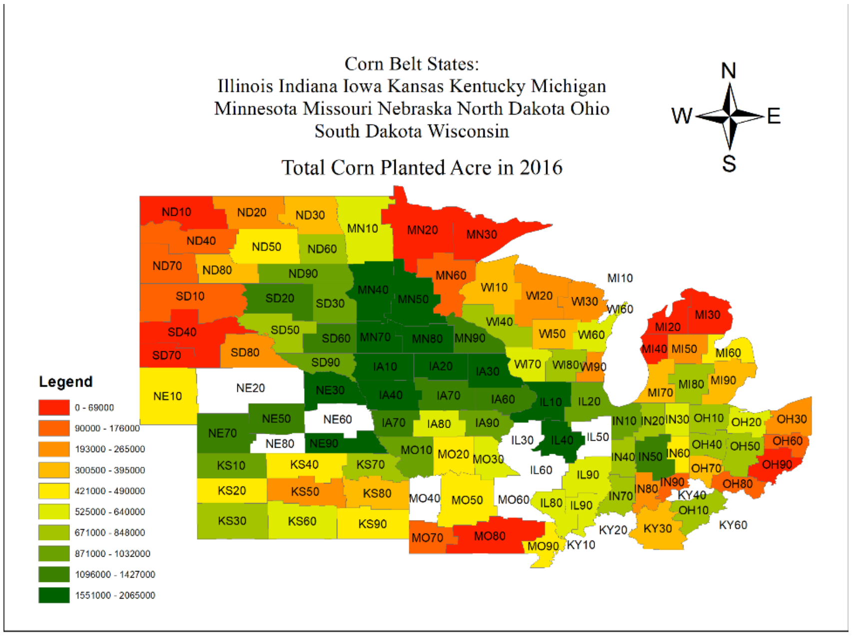


Figure A8. Planted corn acreage in by Agricultural Statistics District within states in 2016. Ones with white color represents no data.

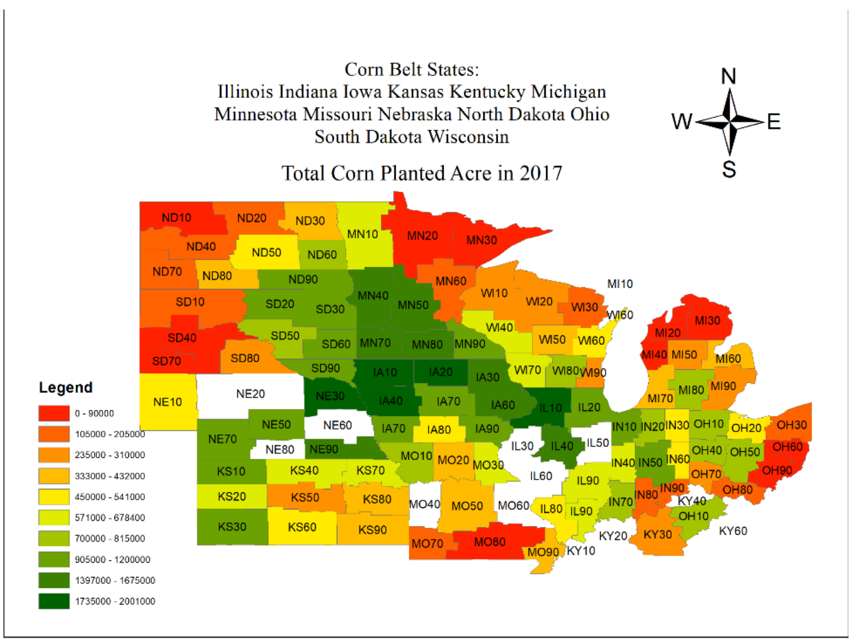


Figure A9. Planted corn acreage in by Agricultural Statistics District within states in 2017. Ones with white color represents no data.

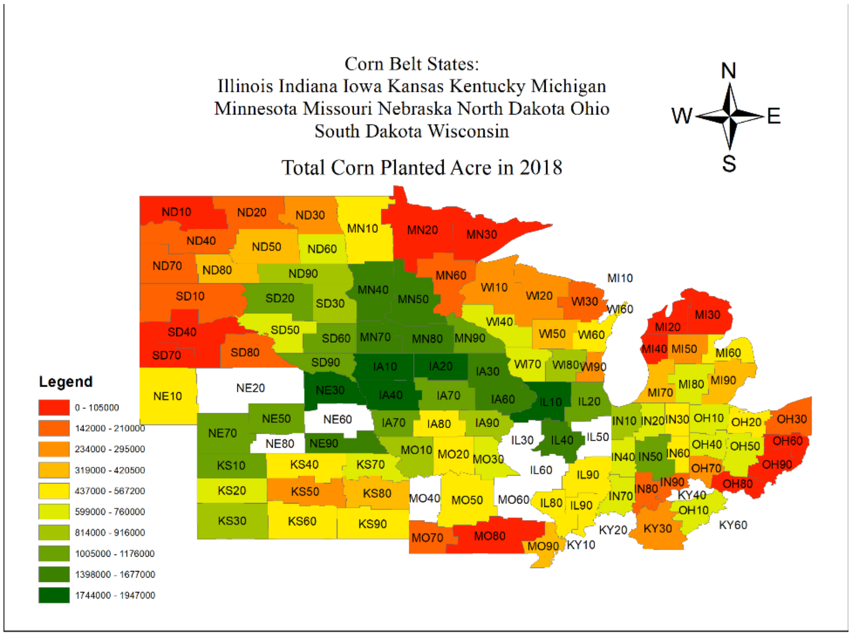
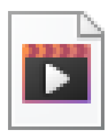


Figure A10. Planted corn acreage in Agricultural Statistics District within states in 2018. Ones with white color represents no data.



Planted Corn
Acres.mp4

Figure A11. Animated clip of corn acreage changes from 2010 to 2018.

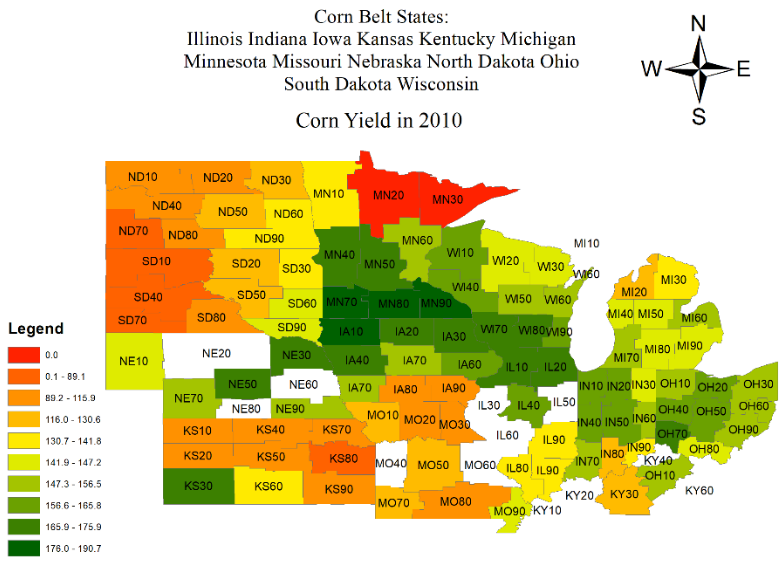


Figure A12. Average corn yield in Agricultural Statistics District within states in 2010. Ones with white color represents no data.

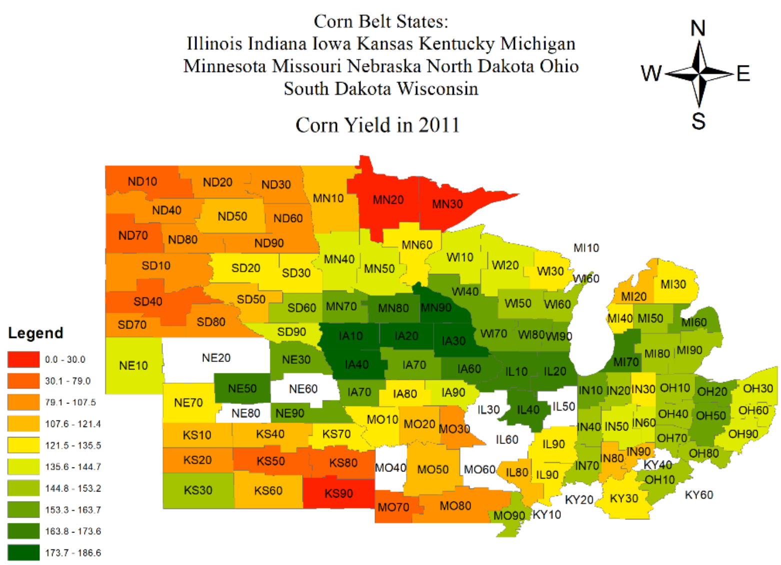


Figure A13. Average corn yield in Agricultural Statistics District within states in 2011. Ones with white color represents no data.

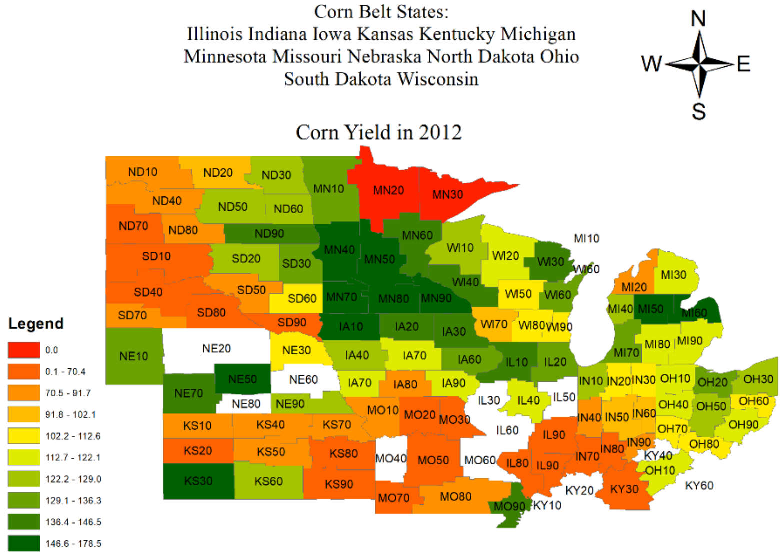


Figure A14. Average corn yield in Agricultural Statistics District within states in 2012. Ones with white color represents no data.

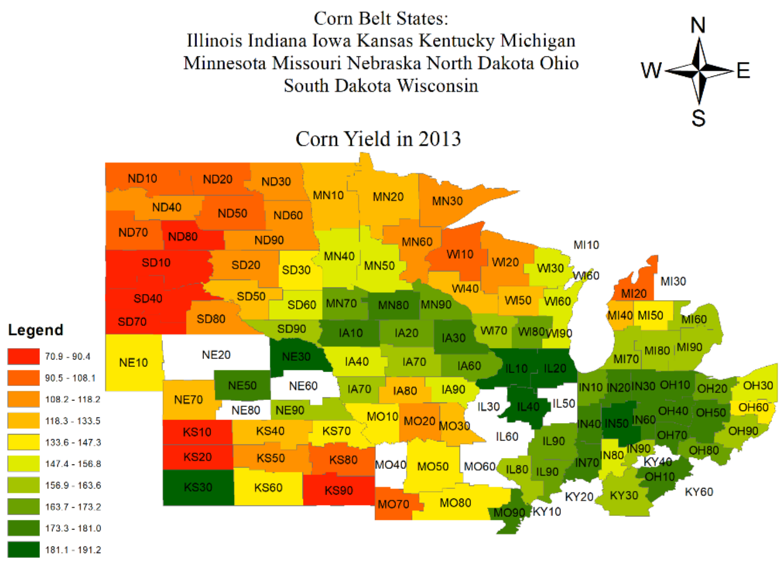


Figure A15. Average corn yield in Agricultural Statistics District within states in 2013. Ones with white color represents no data.

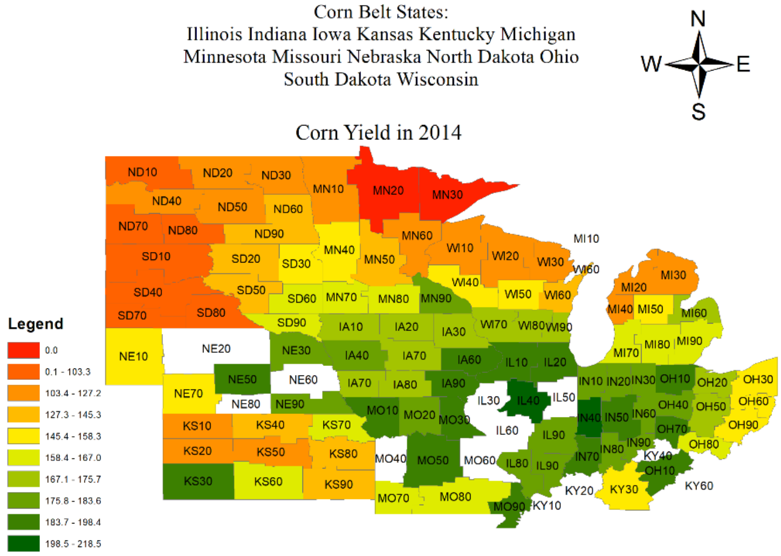


Figure A16. Average corn yield in Agricultural Statistics District within states in 2014. Ones with white color represents no data.

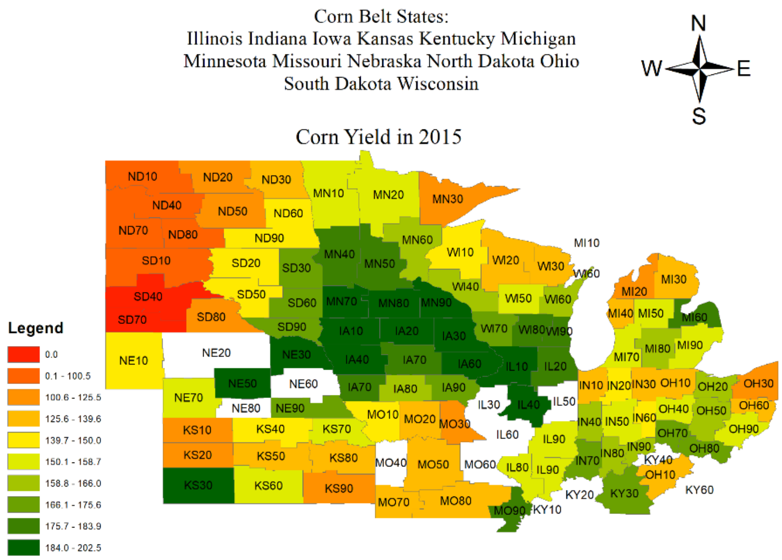


Figure A17. Average corn yield in Agricultural Statistics District within states in 2015. Ones with white color represents no data.

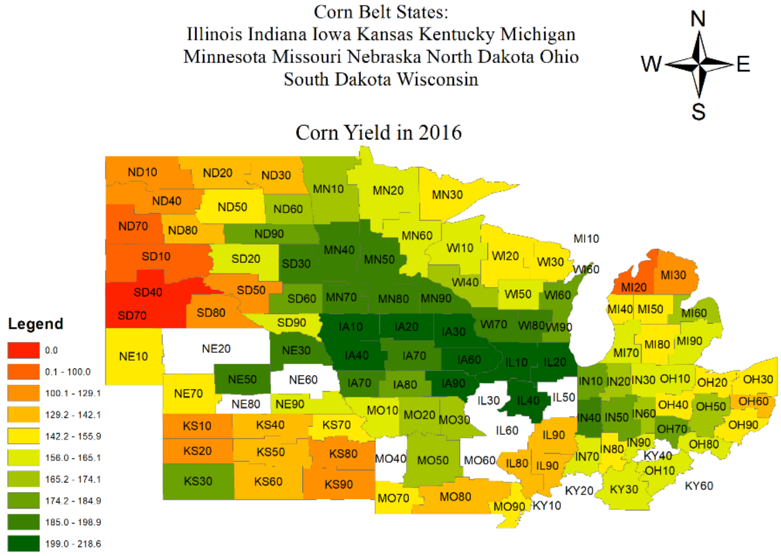


Figure A18. Average corn yield in Agricultural Statistics District within states in 2016. Ones with white color represents no data.

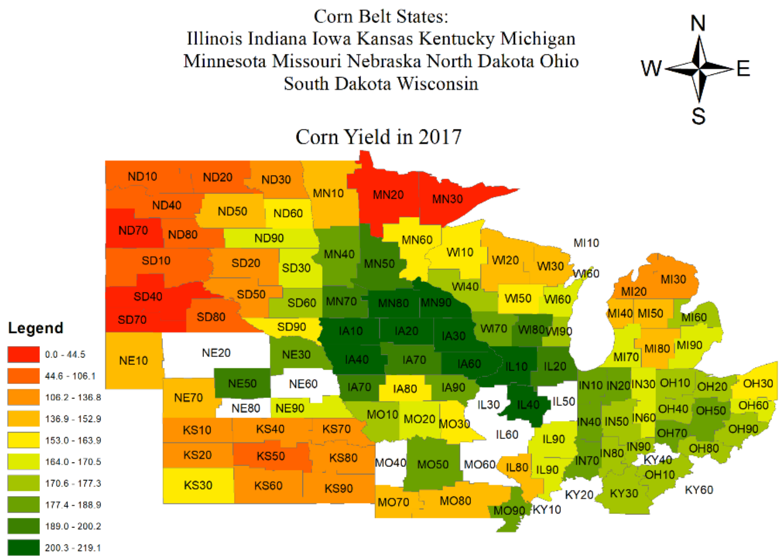


Figure A19. Average corn yield in Agricultural Statistics District within states in 2017. Ones with white color represents no data.

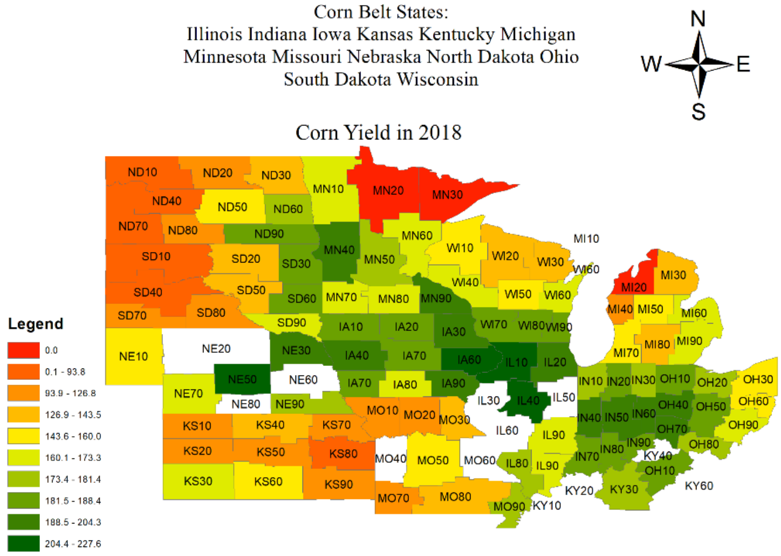


Figure A20. Average corn yield in Agricultural Statistics District within states in 2018. Ones with white color represents no data.

Average Corn Yield.mp4

Figure A21. Animated clip of average corn yield changes from 2010 to 2018.