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Heterogeneous Nitrogen Losses: Cost-Effectiveness Analysis of Changes in Management Across South Dakota

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HETEROGENEOUS NITROGEN LOSSES: COST-EFFECTIVENESS ANALYSIS OF CHANGES IN MANAGEMENT ACROSS SOUTH DAKOTA

BY

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This thesis is approved as a creditable and independent investigation by a candidate for the Master of Science in Economics degree and is acceptable for meeting the requirements for this degree. Acceptance of this thesis does not imply that the conclusions reached by the candidate are necessarily the conclusions of the major department.

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ABSTRACT

HETEROGENOUS NITROGEN LOSSES: COST-EFFECTIVENESS ANALYSIS OF CHANGES IN MANAGEMENT ACROSS SOUTH DAKOTA

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The loss of nitrogen fertilizer into the atmosphere and waterways is of increasing concern for citizens and policy makers. This is particularly relevant for hypoxia in rivers, lakes, and oceans, but also relevant for policy makers in reducing the increasing concentration of greenhouse gases (GHG) in the atmosphere. GHGs trap heat in the atmosphere and include: carbon dioxide, methane, nitrous oxide and fluorinated gases. Overall, the estimated contribution from the agricultural sector to GHG emissions was 9% in 2013 (EPA, 2013). Further, the addition of nitrogen to the soil through the use of synthetic fertilizers is a main contributor to nitrous oxide (N_20) emissions. Approximately 74% of U.S. N_2O emissions were from synthetic fertilizer applications according to the EPA (2013). However, these emissions are not spatially homogenous, nor homogenous across crop production systems. The objective of this study is to begin to spatially account for the heterogeneous nitrogen losses from nitrogen fertilizer applications on South Dakota farms.

This study conducts a cost-effectiveness analysis (CEA) to determine the best strategies, and areas, to reduce GHG emissions from nitrogen application in South Dakota. This form of analysis is done by spatially comparing the amount of emissions

reductions per acre across the state, assuming alternative mitigation strategies and adoption rates. Using the environmental factors (climate type, soil texture, soil organic carbon, soil drainage, soil pH and crop type), and management decisions (no till, conventional till, and reduced till, crop rotations, and application timing), we assess the areas and methods in South Dakota that can be targeted for considering management changes to gain the most cost effective continuous improvement in stemming nitrogen losses. The purpose is to minimize costs from changes in management, but provide the maximum reduction in nitrogen losses.

Spatial heterogeneity in GHG Emissions can vary considerably. For example, the coefficient of variation for N_2O emission measurements typically range between 100 to 300% (Thornton and Valente, 1996; Snyder, C.S. et al., 2009). A switch from conventional tillage to reduced tillage and to no-till is expected to mitigate GHG emissions across all areas. However, it is important to spatially examine the heterogeneous effect on emissions reduction from mitigation efforts, given factors that contribute to heterogeneous GHG flux. This is particularly relevant in light of efforts to develop standardized metrics for determining GHG rates, and reductions from baseline, that may be used by agri-businesses and retailers for sourcing agricultural inputs. The intent of such effort is to provide an efficient method to promote food products and verifiable, sustainable marketing claims to consumers (Field to Market 2012 V2). Consequently, universally accepted management mitigation metrics may result in heterogeneous impacts to reducing emissions and costs, depending on site-specific environmental and soil factors that cannot be altered.

Findings from this study will aid land grant extension personnel in targeting educational programs to areas where it is cost effective to enhance sustainable agriculture and mitigate GHG emissions from nitrogen fertilizer application. Results of the study will also inform stakeholders of the costs and trade-offs of changes in management decisions, such as timing of fertilizer application and fertilizer efficiency improvement methods (e.g. Brink et al., 2005).

Management techniques, yields, and fertilizer applications data used for this study have been retrieved from USDA-ARMS data. Soil characteristics were obtained from NRCS soil data (GSSURGO), and crop rotations and locations were derived from USDA-FSA certified acres and the National Land Cover Database (NLCD). Arc-GIS software was used to combine the multiple data sets, into spatially homogenous response units. The Environmental Policy Integrated Climate (EPIC) model was used to simulate the homogenous response units to calculate all emission values. Simetar was then used to derive certainty equivalence values for changes in management and nitrogen runoff, which helped determine most effective management practices and the costs from our management control.

Chapter 1

Problem Identification and Research Objectives

1.1 Introduction

In modern agriculture, the use of nitrogen fertilizers to boost crop production is common practice. Most crop producers apply nitrogen fertilizers at some stage of production to increase production and improve returns. The management practice used to apply fertilizer can result in significant externalities including: contaminating water bodies like rivers, lakes and oceans, contaminating ground water, and also polluting the atmosphere through the emission of nitrous oxide. The purpose of this study is to determine the cost effectiveness of various nitrogen application strategies to reduce nitrogen losses.

Nitrous oxide (N_2O), one of the main greenhouse gases, is emitted from both natural and human sources. Natural sources like oceans and soils under natural vegetation are responsible for 62 percent of N_2O in the atmosphere, whereas human activities such as agriculture and fossil fuel combustion contribute 38 percent of total emissions (Denman, K.L., et al, 2007). Of the various human activities which contribute to nitrous oxide emissions, agriculture is the largest source. According to the Environmental Protection Agency (EPA), agricultural soil management through the application of synthetic fertilizers accounted for about 74 percent of the total U.S. N_2O emissions in 2013.

In addition to the loss of nitrogen escaping into the atmosphere, another externality from fertilizer application is nitrogen loss to waterways and groundwater. It is estimated that N exported from agricultural ecosystems to waterways, as a percentage of fertilizer inputs, ranges from 10% to as high as 80% depending on the soil type (Howarth et al., 1996). This makes the timing and quantity of N application important management decisions for producing crops efficiently and with minimal externalities. Sharpley and Rekolainen (1996) state that the greater proportional losses of nitrogen into aquatic ecosystems may result from higher nitrogen application rates and less flexibility in the timing of applications, thus creating varying costs to altering fertilizer management across production regions and types.

The total estimated costs of externalities from nitrogen loss ranged between $81 to $441 billion/year or $108.61/kgN in the early 2000s (Sobota et al., 2015). This implies that the costs of mitigating nitrogen losses through effective management practices may be less than the benefits from improved quality of air and water while sustaining sufficient crop production.

1.2 Research Objectives

The research objectives of this project are:

- Model and compare the effects of various management choices, categorized as treatments, on yield and mitigation of GHG emissions.
- Perform stochastic dominance techniques to determine best nitrogen management practices.
- Conduct a Cost-Effectiveness Analysis (CEA) to determine the best strategies and areas to mitigate GHG emissions from nitrogen fertilizer application.

1.3 Significance of the Study

The agricultural sector has a significant role to play in the mitigation of GHGs and reducing nitrogen in waterways. The knowledge from this research is expected to help policy makers to make informed decisions regarding best nitrogen management practices. It is also aimed at helping ag producers make effective management decisions to increase productivity and improve environmental quality. (Claassen & Ribaudo, 2016).

Subsequent chapters of this study are organized as follows. Chapter two will focus on reviewing literature that highlights the importance of fertilizer management practices and how they impact the environment and climate change. Furthermore, it will center attention on empirical findings on the role of fertilizers in agriculture, management decisions and measures to mitigate GHG emissions. The chapter will also describe the EPIC model used to simulate the crops (corn, soybean and spring wheat). Chapter three will highlight the study area, types of data, mode of data collection and the data analysis conducted. Chapter four will discuss the results from the simulation and quantitative analysis using stochastic dominance to rank the various treatments. Chapter five will conclude by discussing a number of policy implications.

Chapter 2

Literature Review

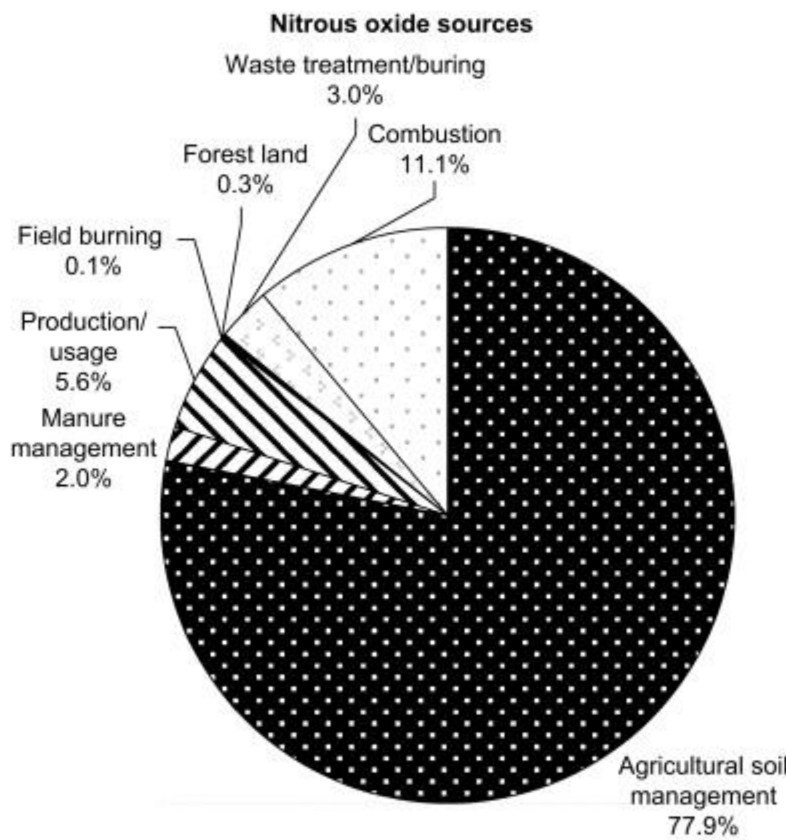
We summarize findings on the role that fertilizer management plays in greenhouse gas emissions and water contamination. We pay particular attention to changes in management decisions like tillage and nutrient application timing that affect nitrogen losses. This section further focuses on research which utilized the model used in simulating the input variables. The Environmental Policy Integrated Climate (EPIC) model, used in this study, is a daily time-step model which has an input section where the user can calibrate the weather, soil, field management and site data into the system. The model then simulates and outputs results which can be used to address challenges like GHG emissions, leaching, volatilization and nitrogen run-off from soil surfaces into water bodies.

2.1 Empirical findings on the role of fertilizers in Agriculture and GHG emissions

The emission of greenhouse gases from agriculture is generally generated from three sources: machinery used for cultivating the land, production and application of fertilizers and pesticides, and the soil organic carbon (SOC) that is decomposed following tillage and later evaporates into the atmosphere (West and Marland, 2002). The production and application of synthetic fertilizers to the soil contributed 74% of total U.S. nitrous oxide (N_2O) emissions in 2014 (EPA, 2015). The quantity of fertilizer applied varies among crop types, type of crop rotation and tillage practices.

Fertilizers have also played a substantial role in the tripling of world food production over the past five decades (Mosier & Syers, 2004). The projection of the world's population to increase by 70 percent by 2050 (FAO, 2009) implies that there will be more mouths to feed therefore fertilizers will continue to play an essential role in agriculture. In the U.S. for example, it is estimated that without the use of nitrogen fertilizers, corn yields would decline by 40 percent (Mikkelsen, 2014). Also, a long-term study in Missouri showed that 57 percent of grain yield was as attributable fertilizer and lime additions to the soil (Mikkelsen, 2014). Figure 2.1 shows the contribution of various agricultural practices to nitrous oxide emissions.

Figure 2.1. **Relative contribution of agricultural activities to N_2O emission in the United States**



Source: US EPA, 2007.

GHGs are mostly emitted from management of agricultural soils, cause variability in the long-term trends of weather conditions and are expected to increase the frequency and severity of extreme events such as floods, hailstorms and droughts (Schmidhuber & Tubiello, 2007). With a continuation of this trend, food stability and security will be threatened in the long run.

This has influenced the decision of some key players in the agricultural industry (ranging from producers, agribusinesses, food and retail companies and non-profit organizations) to form an alliance and work together to define, measure and develop a supply chain system for agricultural sustainability. This alliance defined specific outcomes outlined in Field to Market (2012) which included:

- Increasing agricultural productivity to meet future nutritional needs
- Improving the environment, including water, soil, and habitat
- Improving human health through access to safe, nutritious food; and
- Improving the social and economic well-being of agricultural communities

Field to Market's mission is to increase productivity to meet future demands while continuously improving sustainability. The report defined metrics for calculating emissions from fertilizer applications using the Intergovernmental Panel on Climate Change (IPCC) standardized values. The report also analyzed the trend of six crops (corn, cotton, potatoes, rice, soybeans and wheat) and environmental indicators (land use, soil erosion, irrigation water applied, energy use and greenhouse gas emissions). The analysis for GHG emissions was done per unit of production for six crops: corn (-36%), cotton (-22%), potatoes (-22%), rice (-38%), soybeans (-49%), and wheat (-2%). All these crops showed an improvement (decrease of greenhouse gas emissions over the period 1980 to 2011) but it was evident there are additional practices that can be implemented. The report explored broad scale crop-level progress relevant to key challenges and indicators for agricultural sustainability and provided methods by which to measure them. To conclude, the report acknowledged the progress of the alliance but also acceded to the need to incorporate more crops, expand the environmental indicators and explore or further analyze the impacts of increasing crop production.

2.2 Impact of Management Decisions and Measures to Mitigate GHG Emissions in Agriculture

The management decisions farmers take play a pivotal role in the mitigation of greenhouse gases. Paustian et al. (2006) states that farmers' decisions are motivated first and foremost by what they perceive to be most profitable and thus mitigation practices must be economically attractive to farmers. One of the numerous ways by which farmers can increase their profitability is through an increase in yield. Doraiswamy (2000) conducted a research using spring wheat in North Dakota to estimate crop condition and yield. The paper used a satellite remote sensing technology and information from NOAA –AVHRR[1] to provide spatial county-level data. This data were used as input parameters for calibration into the EPIC model. The model was then used to simulate crop growth and yield. Of the various models considered, it was comprehensively demonstrated that the EPIC model is well suited for studies in semi-arid areas in states like South Dakota and North Dakota due to the model's rigorous soil-water (soil moisture) budget component. After the simulation using the EPIC model, the summary statistics were also analyzed. The simulated model predicted spring wheat yields within one bushel per acre of the reported and the overestimation of yields was attributed to the effect of pests and diseases which were not considered during the parameter calibration.

[1] NOAA – AVHRR: National Oceanic and Atmospheric Administration - Advanced Very High Resolution Radiometer.

Philips et al. (1993) used the 1987 National Resource Inventory (NRI) to provide a random sample of one hundred cropland sites growing corn and soybean in Illinois. The authors focused on four alternative management scenarios; continuous corn and soybean/corn rotations under conventional tillage and no-till systems. The distinct management contrasts examined were continuous corn versus soybean/corn rotation, and conventional tillage versus no-till.

The primary purpose of the study was to evaluate the effects of alternative crop rotations and tillage practices on soil erosion, soil carbon, and nutrient export through processes such as leaching using the EPIC model. This is very important because leaching causes nitrates to leak into ground water, which is a major public health concern. Also, the research focused on the effect of soil erosion which reduces the long term productivity of agricultural lands and transports plant nutrients, particularly nitrogen and phosphorus to surface waters. The analysis was generally aimed at controlling pollution and emission of harmful gases into the atmosphere. After using the EPIC model to perform a one-hundred-year simulation of each of the four management scenarios, mean annual values were calculated for the effect of the following variables of interest: crop yield, soil erosion, N losses in surface runoff, subsurface transport and percolation, organic N transport by sediment, soluble phosphorus (P) loss in runoff, and phosphorus runoff in sediment. Average yields and standard deviation from the hundred sites were closely matched to the reported yields. Mean corn and soybean yields ranged from 3.44 to 9.44 t/ha and 1.55 to 3.36 t/ha compared to expected yield ranges of 3.71 to 9.01 t/ha and 1.23 – 3.34 t/ha, respectively. This showed that the management operations and fertilizer applied appear to have been modeled correctly using EPIC. The study concluded that comparatively, no-till significantly reduced soil erosion rates which further led to reduced losses of Nitrogen (N) and Phosphorus (P) in the eroded soil. Also, soybean/corn rotations had lower soluble N losses in surface runoff than the corresponding conventional tillage or no-till practices under continuous corn. In conclusion, the predictions by the EPIC model for changes in soil erosion, N and P losses under different management practices were in line with site-specific field studies.

2.3 Description of the Environmental Policy Integrated Climate (EPIC) model

2.3.1 Introduction

The Environmental Policy Integrated Climate (EPIC) model is a daily time-step model which has the ability to simulate and produce results over long periods of time (1-4,000 years). It was initially referred to as the Erosion Productivity Impact Calculator. As the name implies, it was developed to help in the assessment of soil erosion impact on productivity and cropping conditions representing a broad spectrum of U.S. agricultural production areas (Williams et al, 1984; Gassman et al, 2004). It was first utilized in the 1985 Resource Conservation Act (RCA) analysis.

The EPIC model version 0810 is an open-source software which has a built-in Fortran programming language to enable development and application of model calibration (e.g. Tatsumi, 2016). EPIC requires the user to input weather, soil, field management and site data into the system. The model consists of nine major components, namely hydrology, weather, soil erosion, nutrient cycling, plant growth, pesticide control, tillage, economic budgets and plant environmental control (Williams, 1990). It also contains parameters to simulate about 100 crops and up to 12 plant species (Izaurralde et al., 2001). There are several options available to simulate components like hydrology, soil erosion, surface run-offs and peak run-offs (Wang et al, 2012; Wang et al, 2011c). EPIC also contains subroutines to simulate carbon dioxide (CO_2) fertilization effects on plant growth and water use (Stockle et al., 1992a, b). In simulating the surface runoff, the Curve Number (CN) method (USDA-NRCS, 2004; Mockus, 1972) was employed. This method has an option for daily adjustments to be made considering the depth of the soil. The peak run-off rates were simulated using the modified rational formula (Williams, 1995) and SCS TR55 peak rate estimate (USDA-NRCS, 1986). Izaurralde et al (2004) modified the EPIC model by adding enhanced carbon and nitrogen algorithms based on the Century model approach and equations (Parton et al., 1987,1994; Gassman et al., 2004). Also incorporated in the EPIC model is the tillage sub-model which mixes crop residues and nutrients within the plow depth. It is also responsible for simulating changes in bulk density, converting standing residue to flat residue, and determining ridge height and surface roughness (Izaurralde et al., 2001). EPIC has undergone various modifications since its inception in 1985. Williams et al (1989) modified the model to include more crops. They made use of the fact that since crop yield is a factor of soil productivity, the model must be capable of simulating crop yield realistically for soils with a wide range of erosion damage. The simulation included leaf interceptions of solar radiation, conversion to biomass, division of biomass into roots, above-ground mass and economic yield, water use, nutrient uptake and simulation of numerous crops. Table 2.1 lists modifications and enhancements to the model since its first use in 1985.

TABLE 2.1. Examples of modifications to EPIC components or input data since the second RCA study

Modified Component or Input Data	Source[a]
Improved and expanded crop growth submodel	Williams et al. (1989) Jones et al. (1991)
Enhanced root growth functions	Bouniols et al. (1991)
Improved nitrogen fixation routine for legume crops that calculates fixation as a function of soil water, soil N, and crop physiological stage	
Incorporation of pesticide routines from GLEAMS model	Sabbagh et al. (1991) Kiniry et al. (1992a) Stockle et al. (1992a)
Improved crop growth parameters for sunflower	
Incorporation of CO_2 and vapor pressure effects on radiation use efficiency, leaf resistance, and transpiration of crops	Kiniry et al. (1992b)
Incorporation of functions that allow two or more crops to be grown simultaneously	Potter and Williams (1994) Kiniry et al. (1995)
Improved soil temperature component	
Improved crop growth parameters for cereal, oilseed, and forage crops grown in the North American northern Great Plains region	
Improved and expanded weather generator component	Williams (1995)
Incorporation of NRCS TR-55 peak runoff rate component	Williams (1995)
Incorporation of MUSS, MUST, and MUSI water erosion routines	Williams (1995)
Incorporation of nitrification-volatilization component	Williams (1995)
Improved water table dynamics routine	Williams (1995)
Incorporation of RUSLE water erosion equation	Renard (1997)
Improved snowmelt runoff and erosion component	Purveen et al. (1997)
Improved EPIC wind erosion model (WESS)	Potter et al. (1998)
Incorporation of Baier-Robertson PET routine	Roloff et al. (1998)
Incorporation of Green and Ampt infiltration function (2000)	Williams, Arnold, and Srinivasan
Enhanced carbon cycling routine that is based on the Century model approach	Izaurralde et al. (2004)
Incorporation of a potassium (K) cycling routine (2004)	De Barros, Williams, and Gaiser

[a]Some sources do not explicitly document the modification but are the best description of the modification (Wang et al., 2012).

2.3.2 Justification of EPIC model

Numerous studies have been conducted using the EPIC model which usually centered on crop yield (Brown et al, 1997; Guerra et al, 2004; Roloff et al, 1998a; Wang et al, 2009), climate change impacts (Mearns et al, 2001; Easterling et al, 2003), nitrogen run-off and leaching (Chung et al,2002; Wu et al, 1997; Benson et al, 1992; Ribaudo et al, 2005), fertilizer use and application rates (Edwards et al, 1994; Watkins et al, 1998), soil organic carbon (SOC) analysis (Abrahamson et al, 2009; Causarano et al, 2007) and pesticide activities (Sabbagh et al, 1991; Shirley et al, 2001). Although EPIC has been tested and applied in the analysis of myriad scenarios across the United States and the world at large, Wang et al (2005) quantified the sensitivity and uncertainty aspects of the model's prediction. One of their main objectives of the study was to predict crop yield and soil organic carbon (SOC) using the generalized likelihood uncertainty estimation (GLUE). The sensitivity analysis was conducted using the extended Fourier amplitude sensitivity test (FAST) to identify the principal sources of uncertainty in the model. The 34-year research study on a continuous corn crop yield was performed at the Arlington Agricultural Research Station in Wisconsin. The long-term study (1958 – 1991) also aimed at assessing the effect of N fertilizers on corn. A randomized complete block design was used in the assessment. The block was divided into three plots based on the N fertilization rates at 0, 56, 112 kg N/ha from 1958 to 1962; at 0, 92, 184 kg N/ha from 1963 to 1972 and at 0, 140, 280 kg N/ha from 1973 to 1983 (Table 2.2) (Vanotti et al, 1997; Wang et al, 2005). In 1984, each of the non-control plots were further divided into subplots. The rates of fertilization then reduced to 0, 84 and 168 kg N/ha to assess the effects of lime on corn yield, shown in Table 2.2.

Table 2.2: N fertilization treatments (Wang et al, 2005).

Year	Fertilizer	N Fertilization Rate (kg N ha^{-1})				
		Treatment 1[a]	Treatment 3	Treatment 7	Treatment 5	Treatment 9
1958-1962	Ammonium nitrate	0	56		112	
1963-1972	Anhydrous ammonia	0	92		184	
1973-1983	Anhydrous ammonia	0	140		280	
1984-1991	Urea	0	0	84	0	168
[a]Control plot						

Nitrogen fertilizer was applied to the plots ten days prior to planting. The study ensured the same tillage, planting and harvesting dates for all five treatments. Corn was normally planted between the first and fourth weeks of May each year and harvested in the fourth week of October. Wang et al, (2005) used the USDA-SCS runoff curve number method (Mockus, 1972) to estimate run-off and the Penman-Montieth method (Montieth, 1995) and estimate any potential evapotranspiration. Table 2.3 is a summary of the management activities for the period of study.

Table 2.3: Summary of management activities (Wang et al., 2005).

Date	Management Activity
9 April – 14 April	Tillage
About 10 days before corn planting	Fertilizer application
22 April – 29 April	Tillage
24 April 31 May	Corn planting, and starter fertilizer application
2 October – 25 October	Corn harvest

In performance of the uncertainty analysis, six yield related parameters (biomass-energy ratio, harvest index, potential heat units, water stress-harvest index, SCS curve number index coefficient and difference of soil water content at field capacity and wilting point) and three soil organic carbon (SOC) related parameters (fraction of organic carbon in microbial biomass pool, fraction of humus in passive pool and microbial decay rate coefficient) were considered. After establishing the parameters to be used for the analysis, the generalized likelihood uncertainty estimates (GLUE) was implemented and EPIC was used to run all 1,500 parameter sets. In the GLUE approach, responses from the model are compared with observations and each parameter set is weighted via the likelihood measures. The likelihood estimation was then performed by calculating the model output's cumulative distribution together with prediction quantiles based on the likelihood weights (Beven and Binley, 1992; Wang et al, 2005). The uncertainty analysis was done based on the estimates of the likelihood weights. The variances, probability distributions, cumulative density functions and 90% confidence intervals were used to characterize prediction uncertainty. A variance-based sensitivity analysis was also done based on the generated samples. The sampling strategy implemented in the GLUE approach was also applied to compute variance-based sensitivity indices. This necessitated the use of the Fourier amplitude sensitivity test (FAST) sample (Saltelli et al., 1999).

Another study where the EPIC model was utilized was conducted by Ribaudo et al. (2005) to measure the amount of nitrogen run-off into the Gulf of Mexico from the Mississippi Basin. The objective of the paper was to develop an action plan to help reduce nitrogen run-off from both point and nonpoint sources. The research used the U.S. Agriculture Sector Mathematical Programming (USMP) regional model which has the EPIC model incorporated into it. The EPIC model was used to calculate leaching and estimates of soil erosion and nutrient losses to run-off. The paper concluded that the action plan of reducing nitrogen run-off will come at a tradeoff of increasing agricultural prices which would further affect agricultural production outside the Basin.

Wang et al. (2005) were also concerned about the accuracy of the prediction of crop yield and SOC dynamics of the EPIC model. To evaluate the model performance in simulating SOC dynamics, the initial SOC content in the top 20cm of the soil was measured in 1958. The SOC was measured again in 1984 and 1990. Between 1958 and 1984, the model captured the effect of fertilizer inputs on SOC by showing significant increase in SOC. Using the GLUE approach, an output probability distribution function and confidence limits were obtained from the 1,500-simulated parameter sets. The results revealed that the observed average corn yield fell within 90% confidence for all five treatments (Wang et al., 2005). This showed that statistically the use of the EPIC model in the prediction of corn yield and SOC are reliable and accurate. The sensitivity test also performed using the likelihood weights showed more interaction influence, that is, good results are not driven by a particular parameter but by a set of interactive parameters.

This informed the decision to employ the EPIC model in the simulation of the data set used in this research.

Chapter 3

Research Design

3.1 Introduction

This section discusses the study area, climate data, fertilizer and the data analysis using EPIC model to simulate data over a period of thirty (30) years. The data obtained from the USDA – ARMS dataset was simulated into the EPIC model to provide timely information on crop growth and potential yields which can be used in strategic planning to meet agricultural needs. Further details of the variables used in this research are discussed below.

3.2 Study area

This research focuses on crops grown in the state of South Dakota. Corn, soybeans and spring wheat are the predominant crops grown in South Dakota, comprising 68.4% of the total crop acreage planted (USDA – NASS, 2012). Corn is the most dominant crop accounting for 35.1%, followed by soybeans which makes up 27.1% of total cropland planted. The types of soil found and used to grow crops in the state are generally loam, sandy loam with dark to black soil surfaces and limy sub-soils (USDA Soil Survey Report, 2004). Other crops cultivated in South Dakota include sunflower, sorghum, beans, field pea, barley and oats. Pasture and hay are also produced on a large scale.

3.3 Climate Data

One of the parameter data supplied by the EPIC model relates to weather. The choice of weather can either be calibrated by the user or generated from long-term averages into weather stations representing a particular area. EPIC is a dynamic model which allows the user to specify two weather files: the weather and wind weather files. If the regular weather and wind station identification parameters are not specified, EPIC will use the latitude and longitude data simulated into the model and choose the closest weather and wind stations. For this study, the monthly climate data used are the mean and standard deviation of maximum air temperature (^{o}C), mean and standard deviation of minimum air temperature (^{o}C), mean (mm), standard deviation (mm), and skewness of precipitation, the probability of wet day after dry day and the probability of wet day after wet day, number of days of rain per month, maximum half hour rainfall (mm), mean solar radiation (MJ/m^2 or Langley), mean relative humidity (fraction) and mean wind speed (m/s). The eight weather stations for South Dakota: North Central (NC), North East (NE), North West (NW), Central (C), East Central (EC), South East (SE), South Central (SC), and South West (SW) are represented in Figure 3.1:

Figure 3.1: South Dakota weather stations

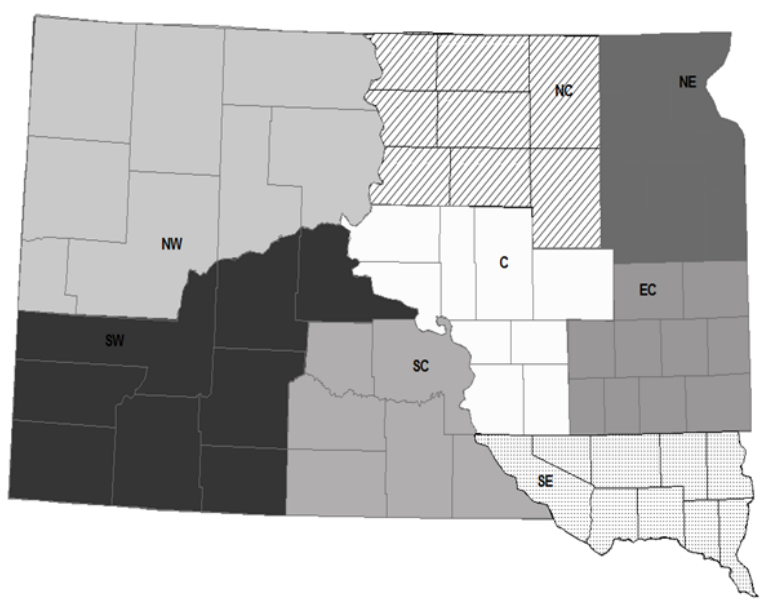
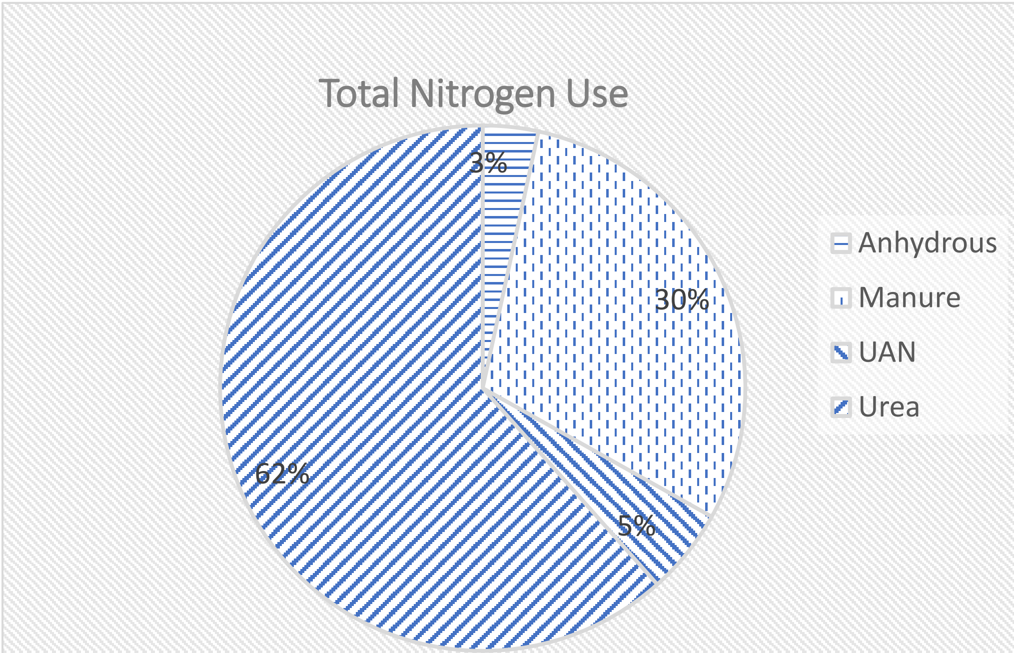


Figure 3.2 Total nitrogen use (tons)



To account for the timing of fertilizer application which will help in setting up the control experiment, the timing of all four categories of fertilizers was analyzed to ascertain which fertilizer was used most at a particular time period. The time periods were fall before seeding, spring before seeding, at seeding, and after seeding. A pictorial view is shown in the bar chart (Figure 3.3).

Figure 3.3 Nitrogen Use and Timing.

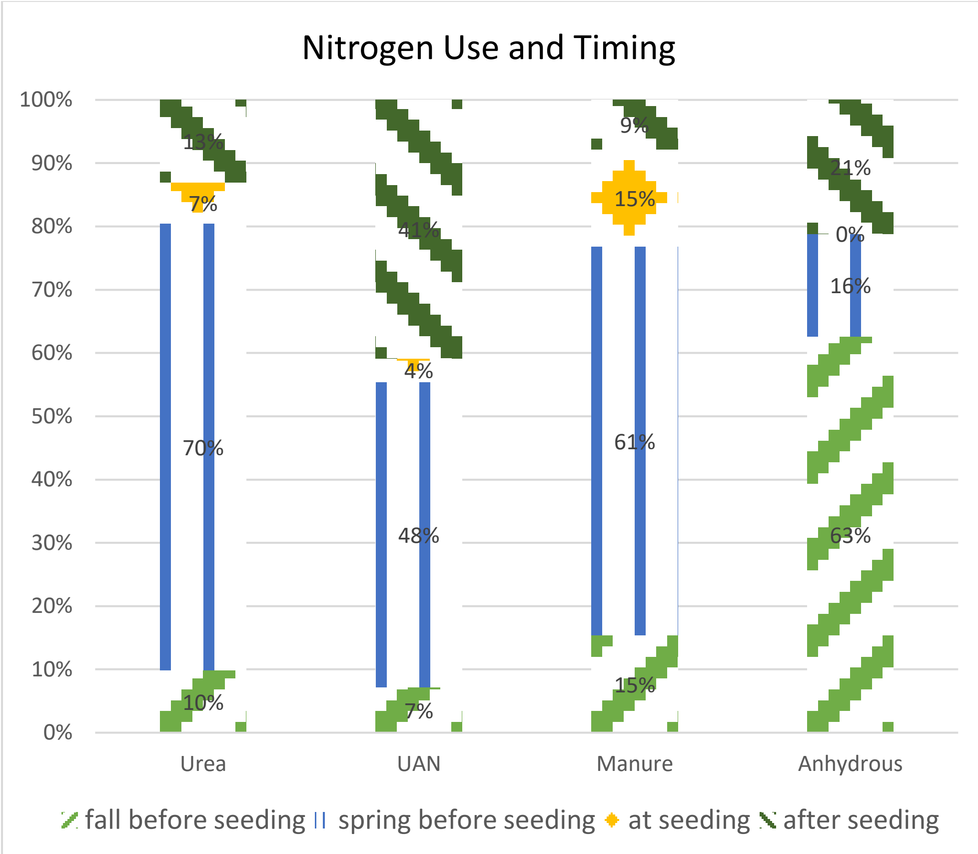


Figure 3.3 shows that urea is mostly used by farmers both before and a few weeks after planting. It contributes approximately 67% of the fertilizers used before seeding and 61% of those used after planting (USDA – NASS, 2010). At seeding, other types of fertilizers (largely manure and other nitrogen-based fertilizers) are used.

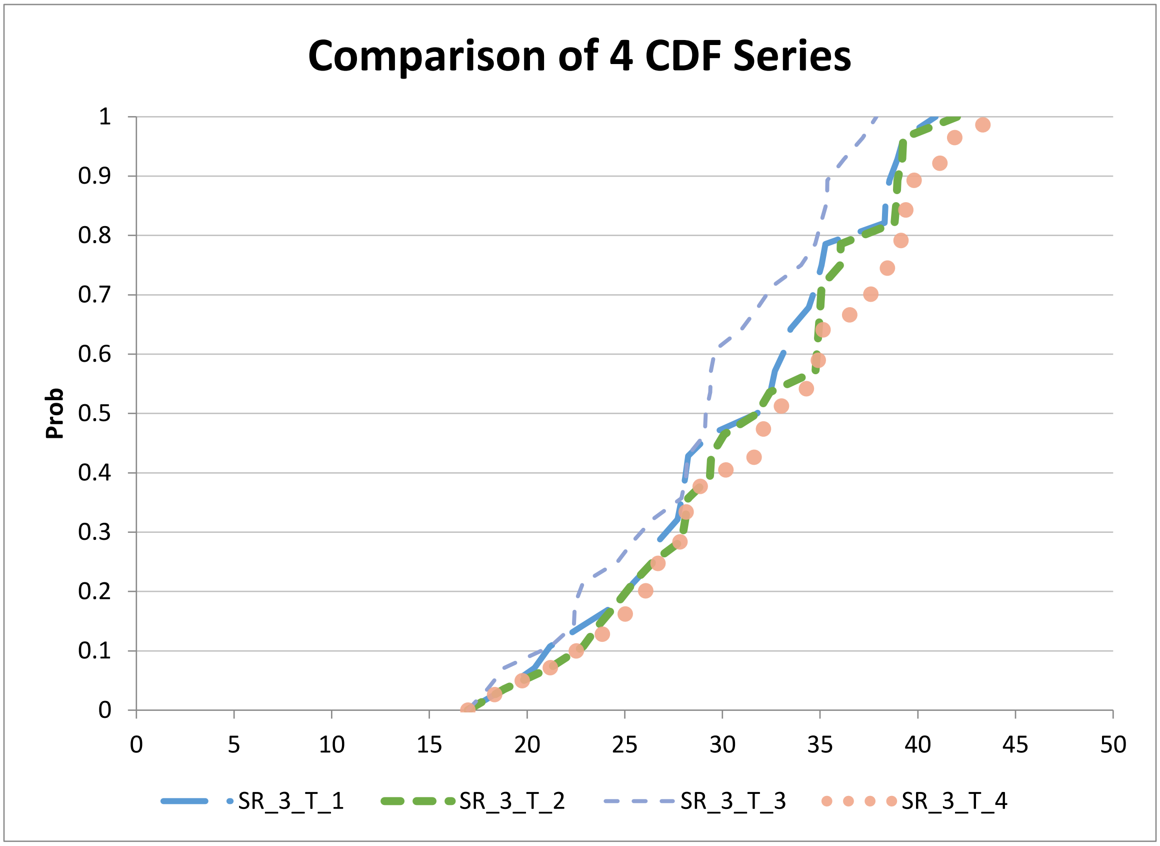
3.5 Empirical Methodology

The analysis of the data was done using Simetar after using the EPIC model to simulate the yield values and nitrogen losses over a thirty-year period. Simetar is an econometric and simulation software used to perform risk analysis of policy changes on agribusiness and is capable of presenting graphical analysis in the form of cumulative density functions. The major functions of Simetar include random variable simulation, statistical analysis and test, graphical analysis, ranking risky alternatives, econometric modelling and forecasting.

Before Simetar was used for the analysis, the five dominant management strategies were identified and categorized into treatments. The first was the control treatment, which is representative of the dominant method of nitrogen application for farms in South Dakota. The control treatment (T_1), which consists of 75% of nitrogen, was placed on the field a few weeks before and at planting. The rest (25%) was applied six weeks after planting. The first treatment (T_2) was set up with 55% of the fertilizer being placed on the field before and at planting. The other forty-five percent (45%) was placed on the field a few weeks after just like the control. The second treatment (T_3) comprised 25% of the fertilizer being applied a few weeks before and at planting, whereas the majority (75%) was applied six weeks after planting. The third treatment (T_4) maintained the mode of fertilizer application from the control but changed the tillage from conventional to no-till. Finally, treatment four (T_5), auto-fertilization, was simulated in the EPIC model to provide crops with just the right quantity of fertilizer needed to grow and bear fruits. After deciding on the various treatments to implement, we further ranked the slopes of the farms into five distinct slopes (slope rank one to slope rank five).

After the simulation with EPIC model, the results of the variables of interest (annual output, crop growth, crop yield, and soil carbon) were merged together using SAS. Simetar was then employed to calculate the first and second order stochastic dominance, the certainty equivalence and the Stochastic Efficiency with Respect to a Function (SERF) with lower and upper RAC (Risk Aversion Coefficient) values between 0 and 1 of each of the management decisions.

A random variable X has a first-order stochastic dominance over another variable Y if for any outcome ‘p’, X gives at least as high a probability of receiving p as does Y. A random variable X has a second-order stochastic dominance over Y if X is more predictable, that is, less risky, and has a mean of at least Y. In the context of this research, stochastic dominance was used to identify risk efficient strategies between the various treatments. Figure 3.4 shows the cumulative distribution functions (CDFs) of treatments of simulated yield values for Beadle county under slope rank three.



From the CDFs, treatment three has a first and second order stochastic dominance over treatments one, two and four because its smallest probability is always equal to or greater than the probabilities of the other treatments.

The risk aversion coefficient categorizes the risk levels of producers/farmers. Liu et al (2017) classified risk aversion levels used for stochastic dominance with respect to a function as slightly risk averse (0 – 1.0), moderately risk averse (1.0 – 3.0), and strongly risk averse (3.0 – 4.0). After assuming that producers/farmers were slightly risk averse, the certainty equivalence values were computed using the Poisson distribution, $\frac{\lambda^k}{k!e^{\lambda}}$, where λ is mean yield and *k* is the number of years of the simulation. These certainty equivalence values were used to derive the dollar amount of the incentive needed for producers to be indifferent between treatments.

Chapter 4

Empirical Results

The main objective of this study is to model and compare the effects of various management choices on yield and N_2O emissions. The second objective is to construct a stochastic dominance function to determine the best management practices and perform a cost-effective analysis to discover efficient ways of mitigating N_2O emissions. To make the most effective management decisions regarding yield, returns and N_2O emissions, all 66 counties in SD were ordered and paired in terms of slope ranks and treatments. After using the EPIC model to simulate the yield over a thirty-year period, the yield values were ranked in order of preference (from most preferred to least preferred) within each of the counties. To assess which treatment is most effective, the analysis considered the best ranked treatment on average within each slope rank. This was done in two parts (one without assuming a cost function and another one with a cost function for each treatment). As expected, treatment five (T_5, auto-fertilization treatment) was the most dominant treatment among the slope ranks without considering a cost function. However, this (T_5) is not realistically achievable because it is impossible for producers to know the perfect amount of fertilizer that the crops need at every point in time till they bear fruits. This made it feasible to choose the next best option. Stochastic dominance was used to order the treatments to choose the best. This is defined as the process of ranking decisions based on the probabilities of two or more random variables.

Considering slope ranks one to four, and implementing the stochastic dominance theory, treatment three (T_3) was the preferred treatment. This treatment puts 25% of the fertilizer few weeks before and at planting and the rest (75%) a few weeks after planting.

Slope ranks one and four had similar preferences. They preferred treatment three, followed by treatments two, treatment four, and then the control treatment (treatment one) respectively. Slope ranks two and three also preferred treatment three over the rest. Treatment two is the next best option after treatment three just like the cases of slope ranks one and four. However, slope ranks two and three preferred the control treatment over treatment four. Counties with land categorized as slope rank five chose treatment three as their most preferred choice over treatment five which dominated all other ranks. Treatment two was the third most preferred, followed by the control treatment then treatment four, as the least preferred.

Table 4.1 Average Treatment Preferences within slope ranks with respect to yields

Slope Rank	**Most preferred treatment**	**2nd most preferred**	**3rd most preferred**	**4th most preferred**	**Least preferred treatment**
1	T_5	T_3	T_2	T_4	T_1
2	T_5	T_3	T_2	T_1	T_4
3	T_5	T_3	T_2	T_1	T_4
4	T_5	T_3	T_2	T_4	T_1
5	T_3	T_5	T_2	T_1	T_4

To analyze the effect of management choices on GHG emissions, a similar simulation was conducted for total nitrogen loss considering the various treatments. As expected, the auto-fertilization treatment (T_4) stood out as the best treatment across all five slope ranks because it puts the right amount of fertilizer needed by the crop at any point in time thereby minimizing the emission of GHGs. The next best alternative was treatment two. It was also preferred to the other treatments in all the slope ranks except slope rank two where treatment one was preferred to that. The control treatment was the second least preferred treatment in all the slope ranks and the least preferred treatment was treatment three (Table 4.2). To assess the effect of leaching on total nitrogen loss, the study analyzed the GHG emissions without the leaching component. This was done to determine the effect of leaching on total nitrogen loss from fertilizer application. The result showed that leaching did not affect the amount of total nitrogen loss significantly. The order of preferences remained the same throughout the slope ranks as in Table 4.2.

Table 4.2: Average Treatment Preferences Within Slope Ranks With Respect to GHG Emissions.

Slope Rank	**Most preferred treatment**	**2nd most preferred**	**3rd most preferred**	**4th most preferred**	**Least preferred treatment**
1	T_5	T_3	T_2	T_1	T_4
2	T_5	T_3	T_2	T_1	T_4
3	T_5	T_2	T_3	T_1	T_4
4	T_5	T_3	T_2	T_1	T_4
5	T_5	T_3	T_2	T_1	T_4

The next objective was to perform a cost-effectiveness analysis which was done by retrieving the certainty equivalent values after constructing a first and second order stochastic dominance function. Certainty equivalence is the guaranteed amount of money that an individual would view as equally desirable as a risky asset. In other words, it is the money or return that an individual is willing to accept rather than taking a chance on a higher, but uncertain return. Using Simetar, the certainty equivalent under negative exponential utility values were computed for all the slope-treatment combinations. To analyze the economic costs and effects of the various treatments, the control treatment was compared to the other treatments to estimate how much a farmer/producer would have to be compensated in order to move from the control treatment to a particular treatment (assuming no cost function). Treatment two generally does not need any compensation irrespective of the slope rank but it was almost always second best to treatment three in terms of yield and GHG emission ranking. However, considering treatment three's certainty equivalent values, some counties had to be compensated in order to consider adopting it. In Davison, Fall River, and Hutchison counties for example, farm lands with slope rank zero needed to be compensated ($12 per hectare) in order to be indifferent between the control treatment and treatment three. Aurora and Todd counties were the only two counties with farmlands under slope rank two which needed compensation to be indifferent between treatment three and the control treatment. Under slope rank four, Davison, Todd and Tripp counties had to be compensated with Tripp county needing as much as $22.64 per hectare to be indifferent. The largest number of counties to be compensated under treatment three was found in slope rank five. Coincidentally, treatment three was the most preferred treatment, even ahead of treatment five. To some extent, this explains why farmers/producers are sticking with the control treatment although treatment three produces the highest yield. In as many as eleven counties (Brule, Buffalo, Custer, Davison, Fall River, Faulk, Lyman, Marshall, Minnehaha, Tripp and Turner) producers have to be compensated to make them indifferent between the control and treatment three. Also, the compensation to be paid can go as high as $36.50 per hectare. Adopting treatment four will be a very expensive option due to the fact that most of the counties would have to be compensated comparatively higher than both treatments three and the control. For farmers/producers to be indifferent between treatment four and the control, the lowest compensation to be paid them is $58.5 per hectare which is $12 more than payments to be made to farmers to make them indifferent considering treatment three. The payments can go as high as $75 /ha which makes treatment four very expensive to adopt. It also rates third best or least preferred among the treatments thus making it infeasible. With respect to treatment five, it will cost an average of $3 less compared to the amount to be paid when adopting treatment three with regards to farmlands in slope rank one. However, farmlands in slope rank two will need an average of $4 /ha more than the compensation paid to adopt treatment three. In terms of slope ranks three and four, treatments three and five basically will have to pay the same compensation for farmers to be indifferent to changing from the control treatment. Treatment five will cost $10 more on average compared to treatment three if farmers are to adopt the control treatment.

Table 4.3 Maximum compensation ($) necessary for farmers/producers to be indifferent to treatments.

Slope rank	Treatment 2	Treatment 3	Treatment 4	Treatment 5
1	0.00	12.18	62.43	9.61
2	0.00	10.53	74.69	14.93
3	0.00	19.79	69.13	18.74
4	0.00	22.64	58.53	22.63
5	0.01	36.48	73.06	46.76

Assuming a cost function for each management practice, a heat map was used to analyze areas within South Dakota which needed some incentive to make them indifferent between the control and the other treatments. The assumption of cost of each treatment was $20 per hectare to change from the control to treatment two, $50 per hectare to change from the control to treatment three, $10 per hectare to adopt treatment 5. Figure 4.1a – Figure 4.1d show the heat map for the incentive needed ($/ha) to change management practices. The darker the shade gets, the lower the amount to be paid to get producers to be indifferent between treatments.

Figure 4.1a

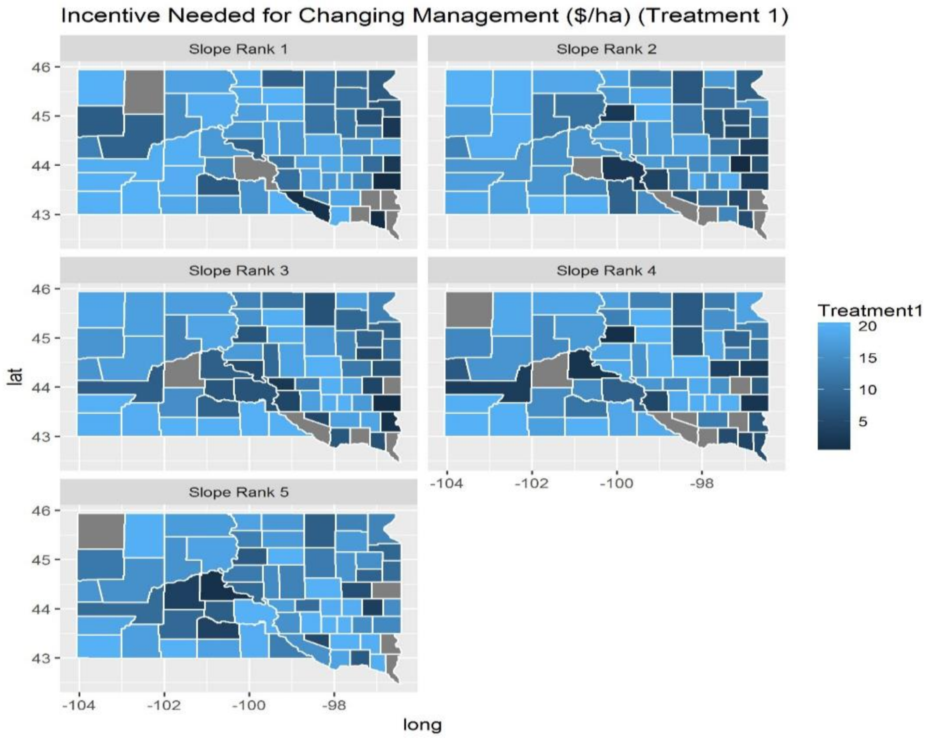


Figure 4.1b

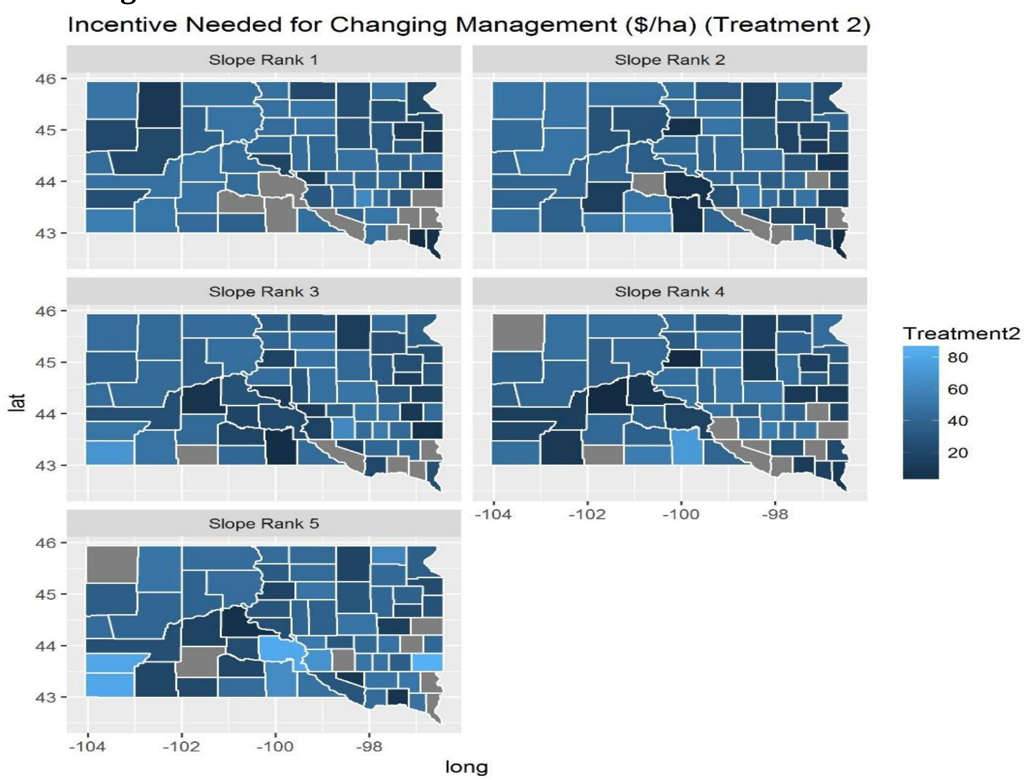


Figure 4.1c

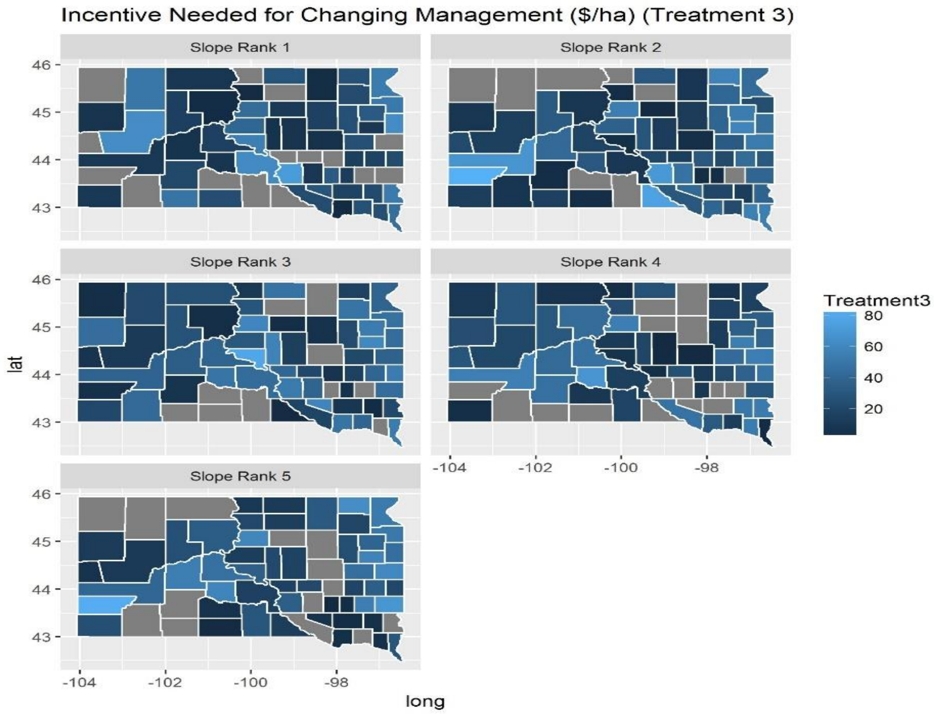
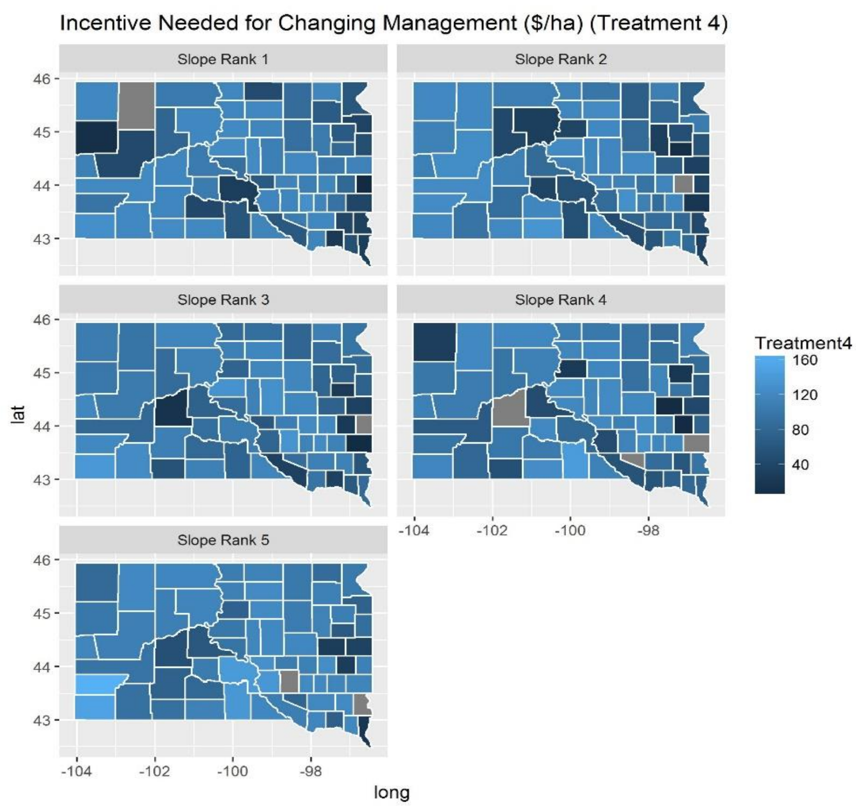


Figure 4.1d



The heat map was also used to highlight the counties to target for nitrogen loss reduction. Figure 4.2a – Figure 4.2d show the heat maps for South Dakota. The grey areas represent areas where a change to that treatment led to an increase in nitrogen loss.

Figure 4.2a

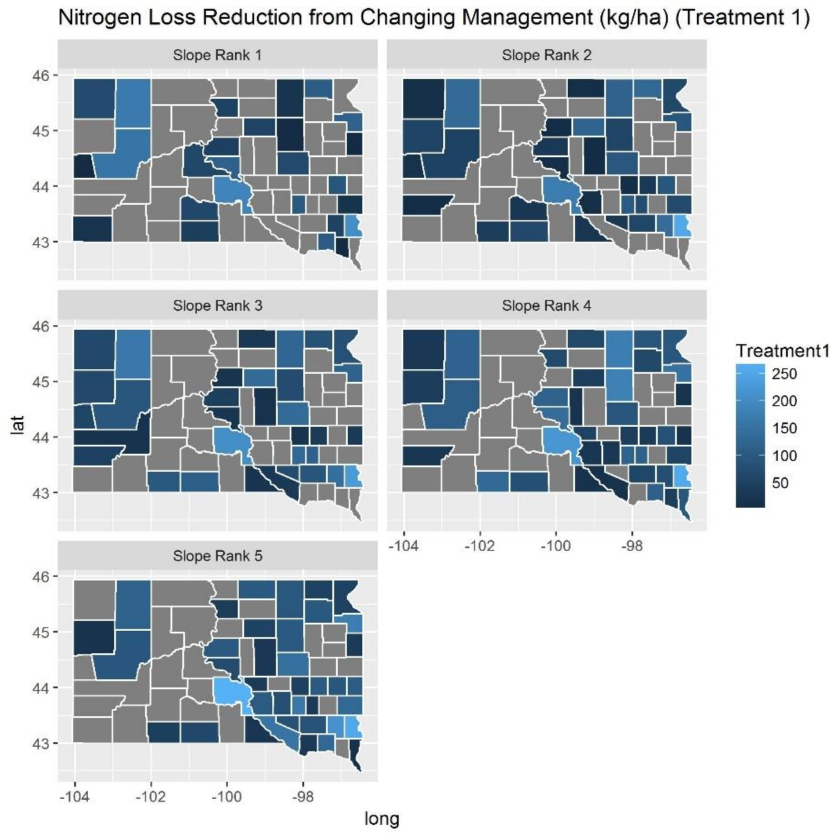


Figure 4.2b

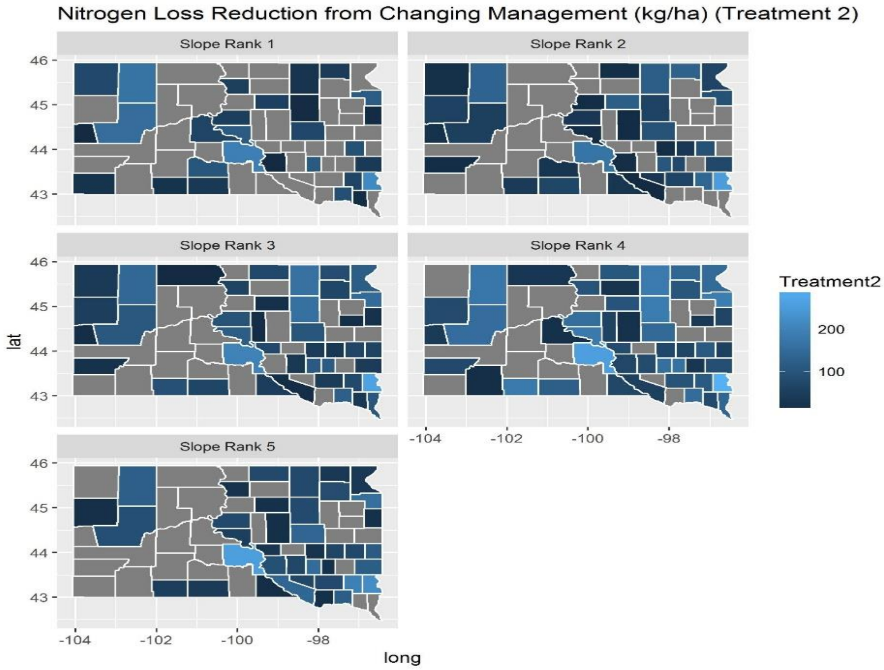


Figure 4.2c

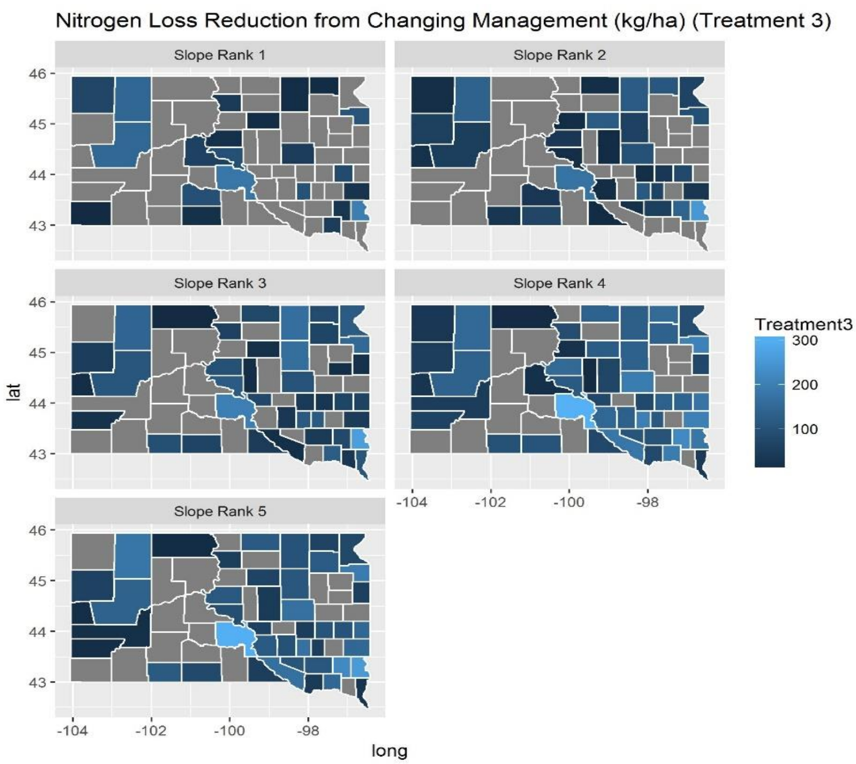
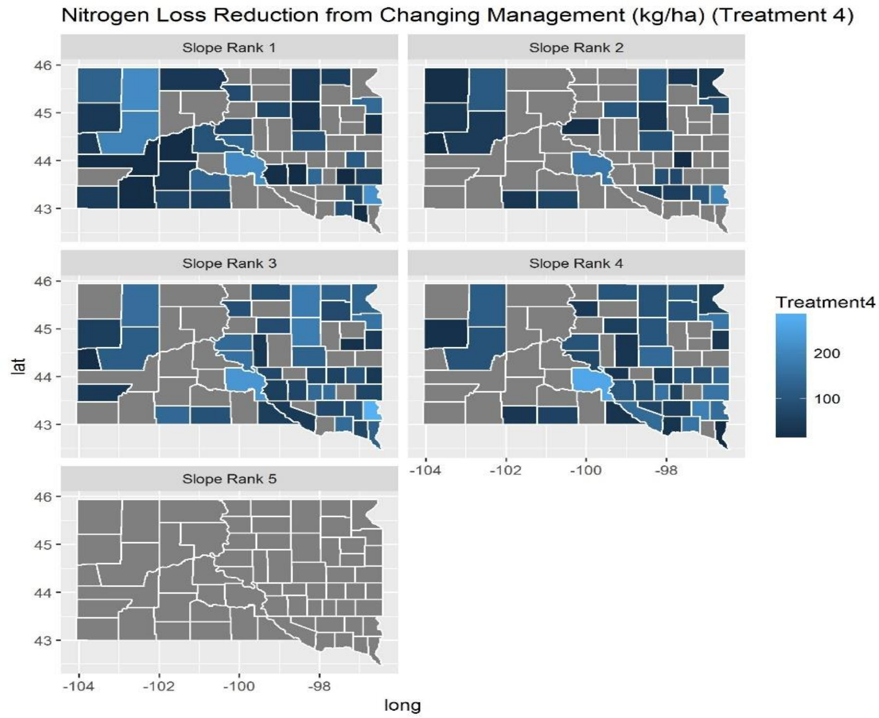


Figure 4.2d



Another analysis which used the heat maps was one which considered the social benefits of reducing nitrogen losses. Social cost of N_2O (kg/ha) loss has a global warming potential (GWP) of 265 – 298. Using a conversion of 1 kg/ha N_2O = .265 tons of carbon equivalent, this implies that society would theoretically be willing to pay $10.60 per hectare for 1 kg/ha of N_2O reduction assuming a $40 per ton social benefit. Figure 4.3a - Figure 4.3d show the nitrogen reduction per dollar of incentive needed to be paid to farmers/producers to change management. The darker areas highlighted counties where there is a higher social cost than benefit from adopting that particular treatment.

Figure 4.3a

Figure 4.3b

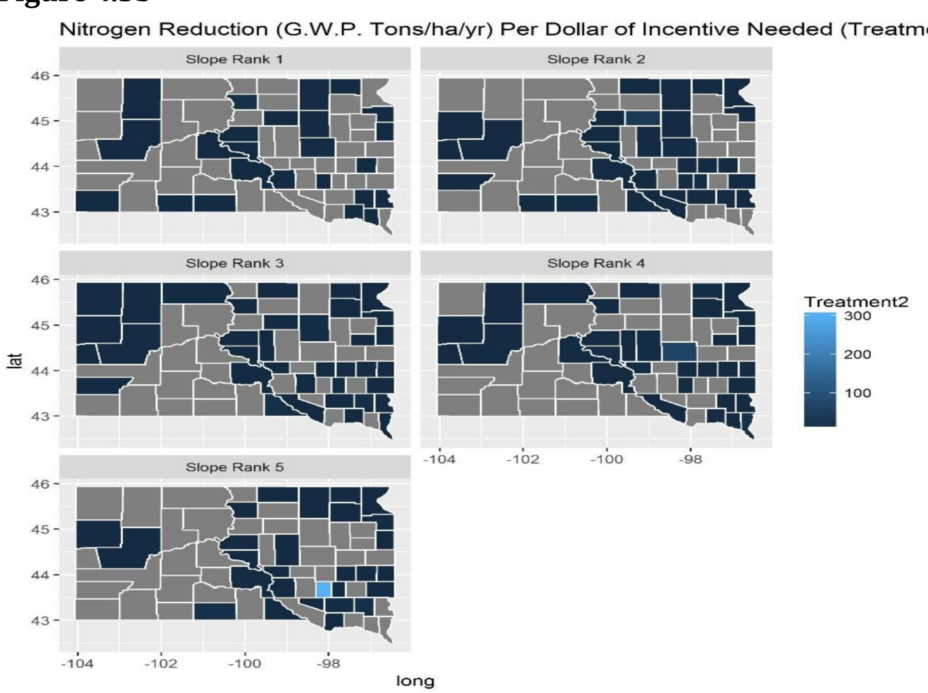


Figure 4.3c

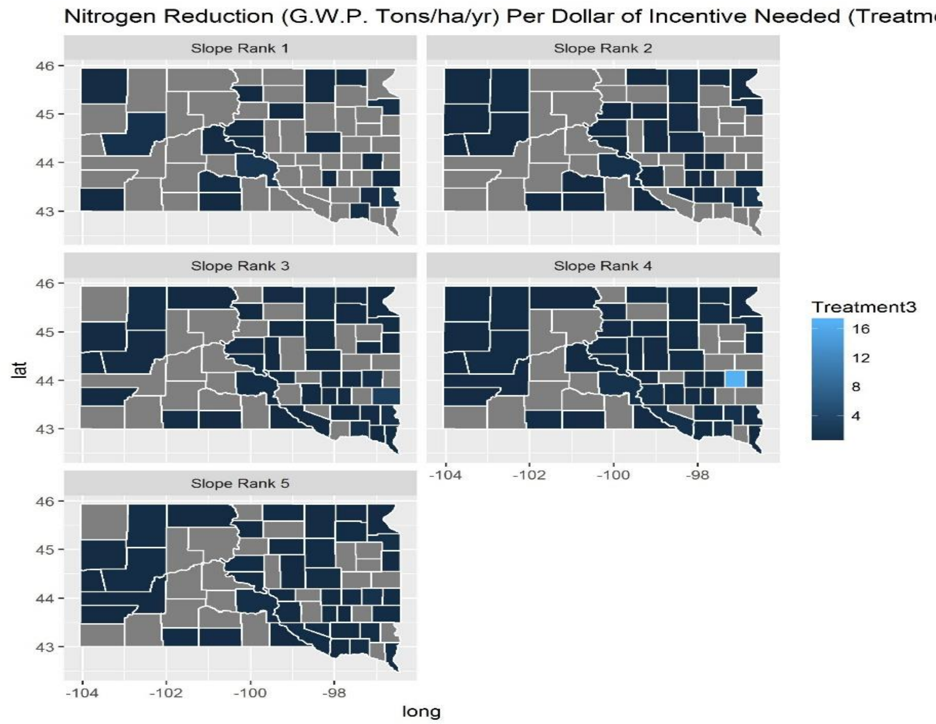
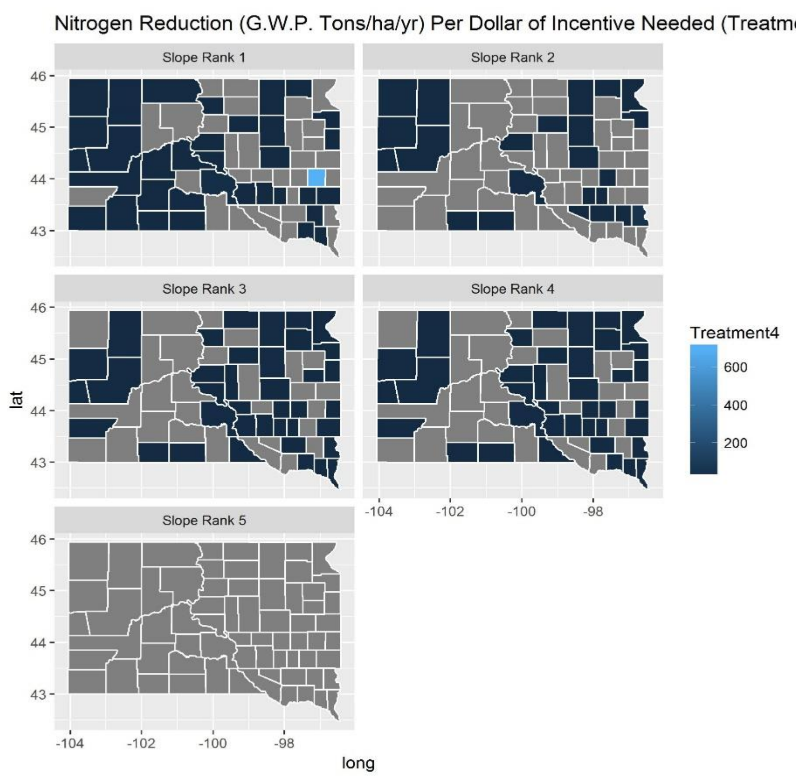


Figure 4.3d



Chapter 5

Conclusion

The impact of agricultural management practices are important environmental issues which need to be researched and addressed accordingly. This study focused on the particular management practice of fertilizer application in terms of quantity and timing. The research also considered cost-effective ways to mitigate the emission of GHGs from nitrogen fertilizer application. Findings are expected to help both policy makers and producers make enlightened decisions regarding nitrogen management practices.

One of the major constraints of this research is that the data considered is at the county level so some site-specific impacts may be lost in the analysis. Additionally, the stochastic dominance analysis assumed that producers were slightly risk averse. This means that further studies assuming moderately risk averse producers can be explored in the future to reveal other dynamics of preference. Also, since prices of crops and the cost of production changes over time, a sensitivity analysis will be another way of highlighting the impact of various management practices.

Despite the limitations, this research provides significant insight concerning areas in South Dakota to focus emission reduction efforts. It also helps explain the importance of incentivizing and compensating producers in the mitigation of greenhouse gases and the reduction of nitrogen run-off into waterways.

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Appendix

Table A.1: Summary Statistics for Slope Ranks in South Dakota.

	SR_1	SR_2	SR_3	SR_4	SR_5
N	107840	107920	107920	107880	107840
MIN	7E-05	0.010575	0.016113	0.023006	0.035324
MAX	0.010565	0.016112	0.023005	0.035317	0.630119
MEAN	0.00734	0.013418	0.019356	0.028406	0.053812
STD	0.002273	0.00161	0.001963	0.003497	0.028737

NB: SR_1 = Slope rank 1; SR_2 = Slope rank 2; SR_3 = Slope rank 3; SR_4 = Slope rank 4; SR_5 = Slope rank 5.

Table A.2: Summary Statistics for Slope Ranks in South Dakota by County.

County	Statistics	SR_1	SR_2	SR_3	SR_4	SR_5
Aurora	N	2320	1600	960	640	160
	MIN	0.001627	0.01058	0.016362	0.027491	0.037969
	MAX	0.010514	0.01564	0.021956	0.034945	0.049404
	MEAN	0.007429	0.013455	0.018973	0.029892	0.043686
	STD	0.002362	0.001696	0.002142	0.002357	0.005735
Beadle	N	3280	1440	880	320	560
	MIN	0.002714	0.010785	0.017144	0.024168	0.035356
	MAX	0.010201	0.016034	0.022751	0.032606	0.051682
	MEAN	0.007733	0.013113	0.019682	0.029041	0.043569
	STD	0.001879	0.001627	0.001896	0.003542	0.005559
Bennett	N	880	1600	1120	1440	400
	MIN	0.005796	0.012571	0.016997	0.02304	0.036721
	MAX	0.010508	0.016081	0.021715	0.035063	0.043172
	MEAN	0.008004	0.014639	0.018711	0.028294	0.039063
	STD	0.001622	0.000995	0.001347	0.003712	0.002259
Bon Homme	N	1120	1760	2080	2400	2480
	MIN	0.002165	0.010817	0.016468	0.023006	0.035905
	MAX	0.010383	0.016018	0.021312	0.035265	0.139134
	MEAN	0.007617	0.013745	0.018984	0.028779	0.069053
	STD	0.00238	0.00168	0.001415	0.003857	0.030002
Brookings	N	880	2000	2720	3040	2880
	MIN	0.003632	0.010945	0.016339	0.023585	0.036818
	MAX	0.010473	0.016109	0.022941	0.031458	0.075958
	MEAN	0.007195	0.013999	0.019028	0.027059	0.049977
	STD	0.001988	0.001522	0.001875	0.002235	0.010329
Brown	N	4480	2000	1360	800	880
	MIN	0.001883	0.010648	0.01615	0.023425	0.039216
	MAX	0.010464	0.01604	0.022973	0.03515	0.069813
	MEAN	0.007869	0.013394	0.019021	0.027854	0.053228
	STD	0.001894	0.001748	0.00205	0.003759	0.010993
Brule	N	560	960	880	1040	960
	MIN	0.004392	0.010745	0.016957	0.023123	0.036101
	MAX	0.010377	0.015516	0.022574	0.034323	0.081592
	MEAN	0.007441	0.013091	0.019655	0.030187	0.050566
	STD	0.00195	0.001563	0.001695	0.003212	0.015765

NB: SR_1 = Slope rank 1; SR_2 = Slope rank 2; SR_3 = Slope rank 3; SR_4 = Slope rank 4; SR_5 = Slope rank 5.

Table A.2: Summary Statistics for Slope Ranks in South Dakota by County Cont'd.

County	Statistics	SR_1	SR_2	SR_3	SR_4	SR_5
Buffalo	N	1120	1520	1120	1040	880
	MIN	0.004313	0.010789	0.016486	0.023638	0.037906
	MAX	0.010281	0.015385	0.021738	0.032729	0.05968
	MEAN	0.008057	0.013096	0.01891	0.028262	0.045604
	STD	0.001871	0.001707	0.001803	0.002857	0.008382
Butte	N	480	1440	1200	1840	2400
	MIN	0.007391	0.011277	0.016484	0.023786	0.036175
	MAX	0.010317	0.015952	0.02219	0.035088	0.630119
	MEAN	0.008972	0.013736	0.019545	0.030245	0.084372
	STD	0.000886	0.001361	0.001993	0.003105	0.125683
Campbell	N	400	720	960	1040	1200
	MIN	0.004715	0.01115	0.016537	0.023202	0.035863
	MAX	0.009193	0.01574	0.022924	0.032931	0.079375
	MEAN	0.00746	0.013144	0.019742	0.028024	0.053682
	STD	0.001509	0.00157	0.002173	0.003322	0.013687
Charles Mix	N	2560	2000	1520	880	1600
	MIN	0.002045	0.010929	0.017184	0.023896	0.036169
	MAX	0.010285	0.01606	0.021577	0.034454	0.227117
	MEAN	0.007113	0.013299	0.019306	0.02892	0.071253
	STD	0.002444	0.001701	0.001438	0.00373	0.048942
Clark	N	3760	4080	3200	3120	2240
	MIN	0.002069	0.010696	0.016251	0.023014	0.036363
	MAX	0.010275	0.01591	0.022907	0.035178	0.070356
	MEAN	0.008035	0.01314	0.019469	0.027255	0.0471
	STD	0.001826	0.00155	0.001978	0.003494	0.009356
Clay	N	6080	1760	1360	1360	1840
	MIN	0.000298	0.010711	0.016272	0.023034	0.035385
	MAX	0.010475	0.016011	0.022949	0.034603	0.098708
	MEAN	0.006201	0.013077	0.019507	0.027171	0.056526
	STD	0.002585	0.00165	0.002242	0.003651	0.017337
Codington	N	720	2160	2320	1440	1520
	MIN	0.006553	0.010635	0.016517	0.023437	0.036545
	MAX	0.010352	0.015981	0.023005	0.033609	0.089965
	MEAN	0.008421	0.013318	0.019538	0.027927	0.050067
	STD	0.001179	0.001495	0.001871	0.002583	0.012887

NB: SR_1 = Slope rank 1; SR_2 = Slope rank 2; SR_3 = Slope rank 3; SR_4 = Slope rank 4; SR_5 = Slope rank 5.

Table A.2: Summary Statistics for Slope Ranks in South Dakota by County Cont'd.

County	Statistics	SR_1	SR_2	SR_3	SR_4	SR_5
Corson	N	160	1520	2400	2960	2320
	MIN	0.008738	0.010627	0.016121	0.023039	0.035981
	MAX	0.009157	0.015916	0.022965	0.035297	0.093134
	MEAN	0.008947	0.013492	0.019088	0.027544	0.050202
	STD	0.00021	0.001441	0.001933	0.003349	0.014693
Custer	N	800	480	960	800	560
	MIN	0.000872	0.010814	0.017705	0.025171	0.036448
	MAX	0.010507	0.015683	0.022706	0.034029	0.086139
	MEAN	0.007511	0.013784	0.019917	0.028652	0.054068
	STD	0.002641	0.001904	0.001626	0.003009	0.014943
Davison	N	3280	1440	1120	1040	400
	MIN	0.002474	0.010718	0.016977	0.023448	0.041603
	MAX	0.010513	0.015207	0.022367	0.032816	0.067861
	MEAN	0.007587	0.013071	0.019775	0.028724	0.048983
	STD	0.002084	0.001304	0.00172	0.003044	0.009739
Day	N	1600	2240	3520	2800	2960
	MIN	0.000928	0.010991	0.016201	0.023183	0.035385
	MAX	0.010202	0.015888	0.022966	0.035113	0.097106
	MEAN	0.007191	0.012992	0.019743	0.027629	0.049363
	STD	0.002432	0.001423	0.002295	0.003407	0.013613
Deuel	N	1200	2560	2560	2720	2960
	MIN	0.000667	0.011439	0.016181	0.023278	0.03576
	MAX	0.009406	0.01606	0.022817	0.034236	0.115165
	MEAN	0.006602	0.013812	0.019484	0.02782	0.052836
	STD	0.002487	0.001625	0.002119	0.003463	0.015081
Dewey	N	320	1280	2960	3040	1760
	MIN	0.002397	0.0108	0.016154	0.023899	0.035513
	MAX	0.010333	0.015661	0.022937	0.035238	0.097833
	MEAN	0.007426	0.014031	0.019376	0.028975	0.057165
	STD	0.003237	0.001237	0.002158	0.003202	0.018628
Douglas	N	1680	1360	960	400	480
	MIN	0.003606	0.010708	0.016874	0.023071	0.036742
	MAX	0.01047	0.015944	0.022847	0.030419	0.085228
	MEAN	0.007779	0.012804	0.019109	0.0249	0.050676
	STD	0.002062	0.001826	0.00212	0.002775	0.017203

NB: SR_1 = Slope rank 1; SR_2 = Slope rank 2; SR_3 = Slope rank 3; SR_4 = Slope rank 4; SR_5 = Slope rank 5.

Table A.2: Summary Statistics for Slope Ranks in South Dakota by County Cont'd.

County	Statistics	SR_1	SR_2	SR_3	SR_4	SR_5
Edmunds	N	400	640	400	240	240
	MIN	0.000283	0.013039	0.017103	0.023659	0.037095
	MAX	0.008645	0.015466	0.022258	0.026435	0.103257
	MEAN	0.005778	0.014299	0.019255	0.025048	0.05946
	STD	0.002893	0.000961	0.001693	0.001136	0.031036
Fall River	N	320	400	640	800	720
	MIN	0.002262	0.011867	0.016291	0.023225	0.036366
	MAX	0.010365	0.015206	0.02044	0.03511	0.060822
	MEAN	0.006922	0.013351	0.018213	0.028202	0.046549
	STD	0.003019	0.001078	0.001374	0.004179	0.008869
Faulk	N	2240	2240	1280	960	800
	MIN	0.003172	0.01098	0.016232	0.024539	0.035763
	MAX	0.010402	0.016079	0.022629	0.035294	0.050393
	MEAN	0.008002	0.01364	0.01942	0.028257	0.040904
	STD	0.002064	0.00152	0.00177	0.003251	0.004897
Grant	N	3040	2560	2160	1840	3760
	MIN	0.001357	0.01098	0.016121	0.023352	0.03568
	MAX	0.01042	0.0159	0.022987	0.034752	0.110567
	MEAN	0.007542	0.013217	0.019169	0.03033	0.053862
	STD	0.002348	0.001459	0.002121	0.003523	0.017053
Gregory	N	400	400	1120	1600	2240
	MIN	0.006892	0.011902	0.016351	0.023167	0.03596
	MAX	0.009885	0.015985	0.021471	0.034068	0.077953
	MEAN	0.008415	0.013648	0.018789	0.028884	0.052711
	STD	0.001025	0.001334	0.001621	0.003206	0.011231
Haakon	N	480	1280	1760	1920	1920
	MIN	0.001345	0.011336	0.016164	0.024624	0.036034
	MAX	0.010531	0.014495	0.022708	0.032739	0.101576
	MEAN	0.007774	0.012928	0.019063	0.028437	0.052661
	STD	0.003114	0.001028	0.002014	0.002551	0.016151
Hamlin	N	1040	2160	2560	2480	1520
	MIN	0.004442	0.011567	0.016153	0.023142	0.037137
	MAX	0.010523	0.016069	0.022957	0.035317	0.096615
	MEAN	0.007632	0.014109	0.019584	0.028678	0.048569
	STD	0.002174	0.001561	0.002128	0.004128	0.014723

NB: SR_1 = Slope rank 1; SR_2 = Slope rank 2; SR_3 = Slope rank 3; SR_4 = Slope rank 4; SR_5 = Slope rank 5.

Table A.2: Summary Statistics for Slope Ranks in South Dakota by County Cont'd.

County	Statistics	SR_1	SR_2	SR_3	SR_4	SR_5
Hand	N	4160	4080	1680	1520	1360
	MIN	0.004507	0.010658	0.016201	0.023105	0.035763
	MAX	0.010565	0.015919	0.022475	0.034698	0.077433
	MEAN	0.007466	0.013285	0.019426	0.029457	0.05079
	STD	0.001667	0.001523	0.001846	0.003427	0.01315
Hanson	N	1200	1200	1200	640	320
	MIN	0.004799	0.011305	0.016401	0.02327	0.037232
	MAX	0.009707	0.015508	0.022516	0.030992	0.07097
	MEAN	0.007957	0.012969	0.018151	0.028358	0.050437
	STD	0.001643	0.001348	0.001604	0.002341	0.013917
Harding	N	240	480	2160	2360	2160
	MIN	0.005842	0.013587	0.016132	0.023874	0.035324
	MAX	0.009075	0.015224	0.02276	0.035239	0.146134
	MEAN	0.007952	0.014577	0.019409	0.029442	0.055105
	STD	0.001496	0.000655	0.001907	0.003635	0.028452
Hughes	N	2880	1600	1120	1520	1680
	MIN	0.001737	0.010588	0.01637	0.024977	0.036133
	MAX	0.010317	0.015816	0.022829	0.034258	0.072307
	MEAN	0.006993	0.013177	0.02007	0.029204	0.048058
	STD	0.002481	0.001669	0.00174	0.002704	0.010454
Hutchinson	N	1760	1440	1440	1600	560
	MIN	0.004107	0.010651	0.016417	0.02451	0.035494
	MAX	0.010352	0.015764	0.022164	0.03488	0.074477
	MEAN	0.008242	0.012795	0.0185	0.030451	0.049577
	STD	0.001706	0.00138	0.001875	0.003308	0.015326
Hyde	N	2320	1760	1120	1200	1200
	MIN	0.000744	0.011289	0.016429	0.023028	0.037055
	MAX	0.010469	0.016032	0.022695	0.033773	0.063123
	MEAN	0.007655	0.013531	0.020183	0.026807	0.046015
	STD	0.002431	0.001423	0.001776	0.00312	0.008328
Jackson	N	800	1040	2240	3920	2400
	MIN	0.005596	0.010736	0.016231	0.023185	0.035925
	MAX	0.009643	0.01611	0.022839	0.035069	0.066432
	MEAN	0.007733	0.013756	0.01976	0.029592	0.043965
	STD	0.001411	0.001915	0.002068	0.003314	0.007544

NB: SR_1 = Slope rank 1; SR_2 = Slope rank 2; SR_3 = Slope rank 3; SR_4 = Slope rank 4; SR_5 = Slope rank 5.

Table A.2: Summary Statistics for Slope Ranks in South Dakota by County Cont'd.

County	Statistics	SR_1	SR_2	SR_3	SR_4	SR_5
Jerauld	N	2320	2800	2400	1520	1120
	MIN	0.000969	0.010586	0.016223	0.023249	0.035516
	MAX	0.010464	0.015881	0.022663	0.03474	0.056239
	MEAN	0.007731	0.013011	0.019544	0.028162	0.043759
	STD	0.002581	0.001558	0.002075	0.003755	0.005215
Jones	N	720	720	720	480	1680
	MIN	0.001844	0.011417	0.016752	0.023832	0.035465
	MAX	0.009626	0.016037	0.022228	0.031454	0.069205
	MEAN	0.005627	0.013097	0.019384	0.027481	0.044352
	STD	0.002118	0.001438	0.001868	0.002658	0.007685
Kingsbury	N	1360	2160	2160	1040	1280
	MIN	0.005486	0.011501	0.017049	0.023134	0.035587
	MAX	0.010551	0.01591	0.022339	0.033352	0.059893
	MEAN	0.00864	0.013892	0.01959	0.026419	0.043476
	STD	0.001351	0.001317	0.001511	0.003215	0.00651
Lake	N	400	2480	2960	2000	2240
	MIN	0.00539	0.010873	0.016168	0.023088	0.035791
	MAX	0.009715	0.015989	0.022897	0.033562	0.076226
	MEAN	0.008382	0.014351	0.018973	0.027026	0.049733
	STD	0.001619	0.001184	0.002058	0.00268	0.012422
Lawrence	N	240	800	1040	1280	2640
	MIN	0.008836	0.010844	0.016224	0.023682	0.03594
	MAX	0.010083	0.015973	0.022798	0.033434	0.348668
	MEAN	0.009598	0.013686	0.019621	0.028441	0.076083
	STD	0.000547	0.001909	0.002065	0.003148	0.055197
Lincoln	N	1040	1680	960	960	800
	MIN	0.000965	0.01081	0.016493	0.023786	0.040771
	MAX	0.010189	0.015237	0.021692	0.034764	0.14765
	MEAN	0.006812	0.013132	0.01857	0.029012	0.074394
	STD	0.002703	0.001493	0.001666	0.004142	0.032483
Lyman	N	720	880	480	1440	800
	MIN	0.00463	0.011138	0.016941	0.023042	0.038242
	MAX	0.010476	0.016108	0.022108	0.033645	0.08572
	MEAN	0.007798	0.014308	0.019444	0.027979	0.049044
	STD	0.001771	0.001476	0.00193	0.003075	0.01357

NB: SR_1 = Slope rank 1; SR_2 = Slope rank 2; SR_3 = Slope rank 3; SR_4 = Slope rank 4; SR_5 = Slope rank 5.

Table A.2: Summary Statistics for Slope Ranks in South Dakota by County Cont'd.

County	Statistics	SR_1	SR_2	SR_3	SR_4	SR_5
Marshall	N	1360	2000	1920	1920	1200
	MIN	0.00403	0.010683	0.016434	0.023029	0.03593
	MAX	0.010333	0.015504	0.022598	0.034189	0.102018
	MEAN	0.00769	0.012757	0.019098	0.026858	0.054646
	STD	0.001573	0.001641	0.001814	0.003001	0.019857
McCook	N	960	560	800	560	400
	MIN	0.006049	0.011135	0.017453	0.023916	0.041374
	MAX	0.010011	0.014981	0.021663	0.035233	0.071131
	MEAN	0.008173	0.013431	0.019647	0.028533	0.050689
	STD	0.001286	0.001399	0.001531	0.003501	0.010616
McPherson	N	1680	800	960	1520	3360
	MIN	0.001357	0.010693	0.016274	0.023216	0.035649
	MAX	0.009974	0.015629	0.022834	0.033136	0.129115
	MEAN	0.007712	0.013587	0.019922	0.027	0.056561
	STD	0.001887	0.001698	0.002217	0.003322	0.018783
Meade	N	480	960	1200	3360	3760
	MIN	0.00529	0.010677	0.016456	0.023538	0.035341
	MAX	0.010151	0.015786	0.022652	0.035015	0.119956
	MEAN	0.008569	0.014366	0.020075	0.029445	0.056013
	STD	0.001815	0.001317	0.001937	0.00352	0.022465
Mellette	N	1680	880	1760	2960	2000
	MIN	0.001822	0.010645	0.016283	0.023169	0.037421
	MAX	0.009678	0.015785	0.022737	0.035285	0.059061
	MEAN	0.006779	0.013054	0.019443	0.028439	0.045524
	STD	0.002143	0.001586	0.002239	0.003251	0.006434
Miner	N	2400	2320	2640	1120	800
	MIN	0.001147	0.010825	0.016711	0.023468	0.035417
	MAX	0.010245	0.015739	0.02269	0.034938	0.064016
	MEAN	0.006957	0.013261	0.019329	0.028282	0.048487
	STD	0.002342	0.001576	0.001695	0.003508	0.009609
Minnehaha	N	480	1600	1440	2800	2480
	MIN	0.00523	0.010838	0.016217	0.023084	0.035381
	MAX	0.009174	0.016095	0.021896	0.034808	0.11121
	MEAN	0.007096	0.013887	0.018619	0.028318	0.061383
	STD	0.001287	0.001914	0.001555	0.003612	0.01854

NB: SR_1 = Slope rank 1; SR_2 = Slope rank 2; SR_3 = Slope rank 3; SR_4 = Slope rank 4; SR_5 = Slope rank 5.

Table A.2: Summary Statistics for Slope Ranks in South Dakota by County Cont'd.

County	Statistics	SR_1	SR_2	SR_3	SR_4	SR_5
Moody	N	1600	2880	2400	3200	1920
	MIN	0.001328	0.010665	0.016654	0.023085	0.035776
	MAX	0.010292	0.016036	0.022842	0.034667	0.092209
	MEAN	0.006583	0.013784	0.019058	0.028097	0.051201
	STD	0.002234	0.001783	0.001878	0.003225	0.014312
Pennington	N	1600	1760	1200	2000	2560
	MIN	0.000969	0.010723	0.016171	0.023667	0.035487
	MAX	0.010519	0.015973	0.022978	0.035242	0.144914
	MEAN	0.00749	0.01274	0.01969	0.02899	0.063004
	STD	0.003031	0.00151	0.002308	0.003803	0.024376
Perkins	N	160	320	1920	2560	2720
	MIN	0.00783	0.011819	0.017374	0.023664	0.035425
	MAX	0.00896	0.015868	0.022831	0.034658	0.09316
	MEAN	0.008395	0.014165	0.019867	0.0291	0.052112
	STD	0.000566	0.00155	0.001814	0.003504	0.012992
Potter	N	1680	2480	1680	1360	1280
	MIN	0.003473	0.010578	0.016436	0.023062	0.036919
	MAX	0.010451	0.015831	0.022782	0.035038	0.089102
	MEAN	0.008045	0.013065	0.019607	0.029099	0.047121
	STD	0.002048	0.001549	0.001968	0.003874	0.013108
Roberts	N	2800	2240	1840	1520	2800
	MIN	0.000617	0.010576	0.016316	0.023166	0.036381
	MAX	0.010547	0.015958	0.022829	0.034196	0.129853
	MEAN	0.007292	0.013135	0.01922	0.027772	0.056517
	STD	0.002228	0.001741	0.001772	0.00328	0.018751
Sanborn	N	3840	2560	2080	880	960
	MIN	7E-05	0.010575	0.016466	0.024165	0.036953
	MAX	0.010494	0.015924	0.0229	0.033863	0.072138
	MEAN	0.007215	0.013269	0.019205	0.028739	0.047619
	STD	0.002115	0.001571	0.001811	0.00283	0.011081
Shannon	N	720	1120	1360	1280	800
	MIN	0.000141	0.012742	0.016263	0.023251	0.036412
	MAX	0.009903	0.0159	0.022982	0.035219	0.075438
	MEAN	0.005057	0.014465	0.019666	0.027837	0.043416
	STD	0.003176	0.000986	0.002022	0.004363	0.011067

NB: SR_1 = Slope rank 1; SR_2 = Slope rank 2; SR_3 = Slope rank 3; SR_4 = Slope rank 4; SR_5 = Slope rank 5.

Table A.2: Summary Statistics for Slope Ranks in South Dakota by County Cont'd.

County	Statistics	SR_1	SR_2	SR_3	SR_4	SR_5
Spink	N	6880	3600	2640	960	1840
	MIN	0.00234	0.010671	0.01616	0.023473	0.036061
	MAX	0.01054	0.015964	0.02277	0.035225	0.073717
	MEAN	0.00698	0.013248	0.019457	0.028415	0.046803
	STD	0.002245	0.001661	0.002001	0.00422	0.008623
Stanley	N	320	320	1280	960	1840
	MIN	0.008581	0.012575	0.016143	0.02402	0.035889
	MAX	0.00957	0.013425	0.022879	0.034581	0.083871
	MEAN	0.009149	0.012994	0.019709	0.028589	0.046209
	STD	0.000389	0.000305	0.002195	0.002478	0.011018
Sully	N	1840	1040	640	1040	1120
	MIN	0.003166	0.010803	0.01669	0.02319	0.036274
	MAX	0.010253	0.016045	0.021605	0.03523	0.062257
	MEAN	0.007402	0.013366	0.019213	0.027588	0.046218
	STD	0.001914	0.001998	0.001801	0.003236	0.008569
Todd	N	640	2400	2000	2080	1440
	MIN	0.003826	0.01098	0.01645	0.023137	0.036202
	MAX	0.010429	0.016112	0.022803	0.034987	0.081244
	MEAN	0.006899	0.013789	0.019604	0.028542	0.047926
	STD	0.001785	0.00174	0.002014	0.004155	0.013078
Tripp	N	800	2080	2160	2400	3520
	MIN	0.003199	0.01069	0.016295	0.023014	0.035468
	MAX	0.009019	0.016085	0.021792	0.034416	0.071483
	MEAN	0.006965	0.013308	0.018927	0.02856	0.045438
	STD	0.00189	0.001717	0.001646	0.003385	0.007654
Turner	N	1840	2720	2320	1360	1280
	MIN	0.003777	0.010607	0.016113	0.023098	0.038438
	MAX	0.010017	0.016081	0.022508	0.035166	0.127237
	MEAN	0.00762	0.012965	0.01962	0.028471	0.058769
	STD	0.001936	0.001487	0.002005	0.003641	0.022046
Union	N	4000	1440	800	720	1600
	MIN	0.000371	0.011576	0.016159	0.023474	0.036395
	MAX	0.010346	0.015757	0.022409	0.034853	0.155142
	MEAN	0.006313	0.013754	0.019294	0.028793	0.061607
	STD	0.002696	0.001155	0.00177	0.003831	0.029231

NB: SR_1 = Slope rank 1; SR_2 = Slope rank 2; SR_3 = Slope rank 3; SR_4 = Slope rank 4; SR_5 = Slope rank 5.

Table A.2: Summary Statistics for Slope Ranks in South Dakota by County Cont'd.

County	Statistics	SR_1	SR_2	SR_3	SR_4	SR_5
Walworth	N	1200	1040	1120	1120	1360
	MIN	0.003248	0.010584	0.016625	0.023157	0.036413
	MAX	0.010464	0.015733	0.020881	0.034744	0.095971
	MEAN	0.007088	0.012533	0.019106	0.030147	0.051618
	STD	0.002005	0.001509	0.001192	0.003778	0.014151
Yankton	N	2640	1680	1680	1600	1760
	MIN	0.002272	0.010968	0.016122	0.023793	0.037811
	MAX	0.010212	0.016016	0.022535	0.034267	0.277725
	MEAN	0.006242	0.013307	0.019091	0.027859	0.073729
	STD	0.002294	0.001476	0.001862	0.003308	0.052547
Ziebach	N	480	400	2320	3120	2160
	MIN	0.003746	0.010639	0.016177	0.023331	0.035813
	MAX	0.009195	0.01564	0.022977	0.034701	0.114917
	MEAN	0.007311	0.012769	0.01965	0.027875	0.051289
	STD	0.001932	0.001747	0.002318	0.002931	0.01778

NB: SR_1 = Slope rank 1; SR_2 = Slope rank 2; SR_3 = Slope rank 3; SR_4 = Slope rank 4; SR_5 = Slope rank 5.

Table A.3: Summary of Yield (Returns) Values Based on Management Strategies.

Name	Mean	Std Dev	Coef Var	Skewness	Minimum
SR_0_T_0	21.75	6.03	27.74	-0.38	5.36
SR_0_T_1	21.81	6.03	27.64	-0.36	5.50
SR_0_T_2	21.89	6.01	27.43	-0.33	5.78
SR_0_T_3	22.21	5.96	26.81	-0.41	6.09
SR_0_T_4	21.91	5.89	26.86	-0.33	6.13
SR_1_T_0	29.21	6.33	21.68	-0.27	16.94
SR_1_T_1	29.68	6.33	21.34	-0.30	16.94
SR_1_T_2	30.36	6.39	21.06	-0.36	16.94
SR_1_T_3	28.01	5.76	20.55	-0.32	16.94
SR_1_T_4	31.67	7.08	22.34	-0.34	16.94
SR_2_T_0	29.05	5.82	20.03	-0.40	16.96
SR_2_T_1	29.43	5.88	19.99	-0.43	16.96
SR_2_T_2	30.02	6.02	20.06	-0.47	16.96
SR_2_T_3	28.28	5.34	18.89	-0.46	16.94
SR_2_T_4	31.47	6.81	21.63	-0.41	16.96
SR_3_T_0	29.93	6.64	22.17	-0.27	16.96
SR_3_T_1	30.42	6.64	21.81	-0.30	16.96
SR_3_T_2	31.07	6.71	21.60	-0.36	16.96
SR_3_T_3	28.66	5.95	20.76	-0.33	16.96
SR_3_T_4	32.09	7.33	22.83	-0.33	16.96
SR_4_T_0	28.81	5.71	19.83	-0.48	16.95
SR_4_T_1	29.43	5.75	19.54	-0.48	16.95
SR_4_T_2	30.36	6.01	19.79	-0.51	16.95
SR_4_T_3	27.38	5.07	18.51	-0.50	16.95
SR_4_T_4	31.22	6.66	21.35	-0.42	16.95

Legend: SR_1_T_1 = Slope rank 1 treatment 1; SR_1_T_2 = Slope rank 1 treatment 2; SR_1_T_3 = Slope rank 1 treatment 3; SR_1_T_4 = Slope rank 1 treatment 4,………., SR_4_T_3 = Slope rank 4 treatment 3; SR_5_T_5 = Slope rank 5 treatment 5.

Table A.4: Summary of Total Nitrogen Loss Values Based on Management Strategies.

Name	Mean	Std Dev	Coef Var	Skewness	Minimum
SR_0_T_0	71.10	12.09	17.00	0.08	46.35
SR_0_T_1	70.33	12.31	17.51	0.05	45.54
SR_0_T_2	69.41	12.97	18.69	-0.05	44.50
SR_0_T_3	74.68	13.17	17.63	0.24	52.20
SR_0_T_4	58.79	10.88	18.50	0.42	38.39
SR_1_T_0	390.56	135.46	34.68	0.84	204.42
SR_1_T_1	389.04	136.22	35.01	0.84	199.74
SR_1_T_2	387.43	137.37	35.46	0.84	198.15
SR_1_T_3	406.35	141.92	34.93	0.93	219.13
SR_1_T_4	366.13	131.66	35.96	0.85	182.95
SR_2_T_0	433.18	139.37	32.17	0.71	227.71
SR_2_T_1	431.96	139.75	32.35	0.71	225.03
SR_2_T_2	430.48	140.42	32.62	0.70	222.65
SR_2_T_3	455.37	147.75	32.45	0.66	236.54
SR_2_T_4	411.42	138.12	33.57	0.67	203.13
SR_3_T_0	416.49	151.74	36.43	0.82	206.09
SR_3_T_1	414.84	152.58	36.78	0.82	202.70
SR_3_T_2	413.41	153.67	37.17	0.83	202.10
SR_3_T_3	432.86	159.22	36.78	0.92	225.59
SR_3_T_4	393.45	147.68	37.54	0.83	187.53
SR_4_T_0	307.06	105.68	34.42	0.68	144.23
SR_4_T_1	305.21	106.12	34.77	0.67	145.26
SR_4_T_2	303.06	106.78	35.23	0.66	145.37
SR_4_T_3	324.61	111.41	34.32	0.72	165.13
SR_4_T_4	289.50	101.41	35.03	0.68	139.65

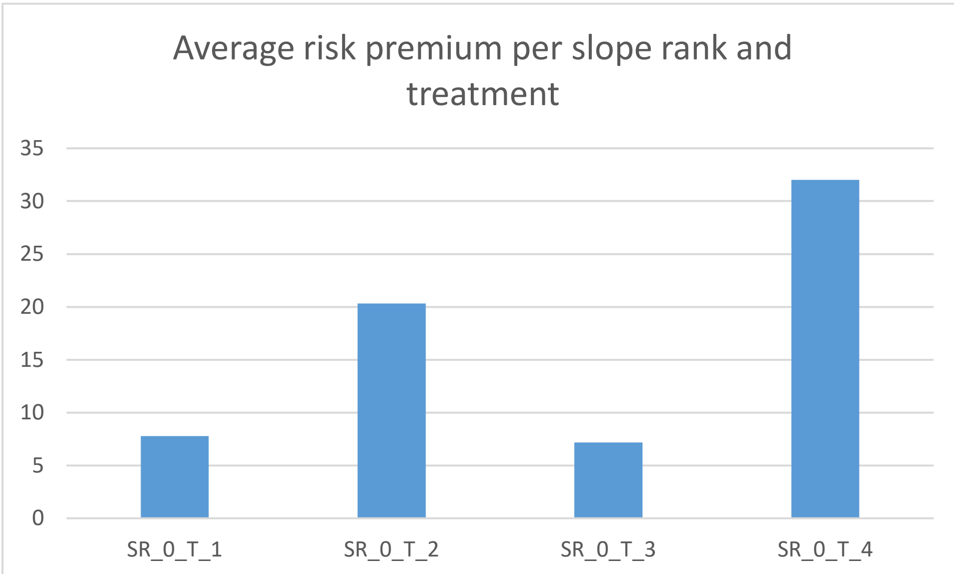
Legend: SR_1_T_1 = Slope rank 1 treatment 1; SR_1_T_2 = Slope rank 1 treatment 2; SR_1_T_3 = Slope rank 1 treatment 3; SR_1_T_4 = Slope rank 1 treatment 4,………., SR_4_T_3 = Slope rank 4 treatment 3; SR_5_T_5 = Slope rank 5 treatment 5.

Table A.5: Summary of Total Nitrogen Loss (Without Leaching) Values Based on Management Strategies.

Name	Mean	Std Dev	Coef Var	Skewness	Minimum
SR_0_T_0	58.84	11.53	19.60	0.29	38.55
SR_0_T_1	58.59	11.61	19.81	0.30	37.76
SR_0_T_2	58.16	11.63	19.99	0.32	36.92
SR_0_T_3	59.26	12.06	20.35	0.36	37.58
SR_0_T_4	54.64	10.86	19.88	0.40	35.74
SR_1_T_0	382.23	135.23	35.38	0.86	198.74
SR_1_T_1	380.71	135.98	35.72	0.86	194.09
SR_1_T_2	379.07	137.12	36.17	0.86	192.58
SR_1_T_3	400.18	141.82	35.44	0.94	214.71
SR_1_T_4	360.46	130.88	36.31	0.86	179.83
SR_2_T_0	427.11	141.62	33.16	0.68	219.52
SR_2_T_1	425.83	142.01	33.35	0.68	216.84
SR_2_T_2	424.28	142.70	33.63	0.68	214.46
SR_2_T_3	453.10	148.15	32.70	0.65	234.49
SR_2_T_4	409.18	138.57	33.86	0.66	200.58
SR_3_T_0	411.77	150.99	36.67	0.83	203.32
SR_3_T_1	410.11	151.82	37.02	0.83	199.92
SR_3_T_2	408.67	152.91	37.42	0.83	199.29
SR_3_T_3	428.74	158.04	36.86	0.92	223.62
SR_3_T_4	390.47	146.72	37.57	0.83	186.13
SR_4_T_0	305.60	105.39	34.49	0.68	143.53
SR_4_T_1	303.74	105.83	34.84	0.67	144.56
SR_4_T_2	301.60	106.49	35.31	0.66	144.66
SR_4_T_3	323.17	111.05	34.36	0.72	164.47
SR_4_T_4	288.69	101.14	35.03	0.68	139.35

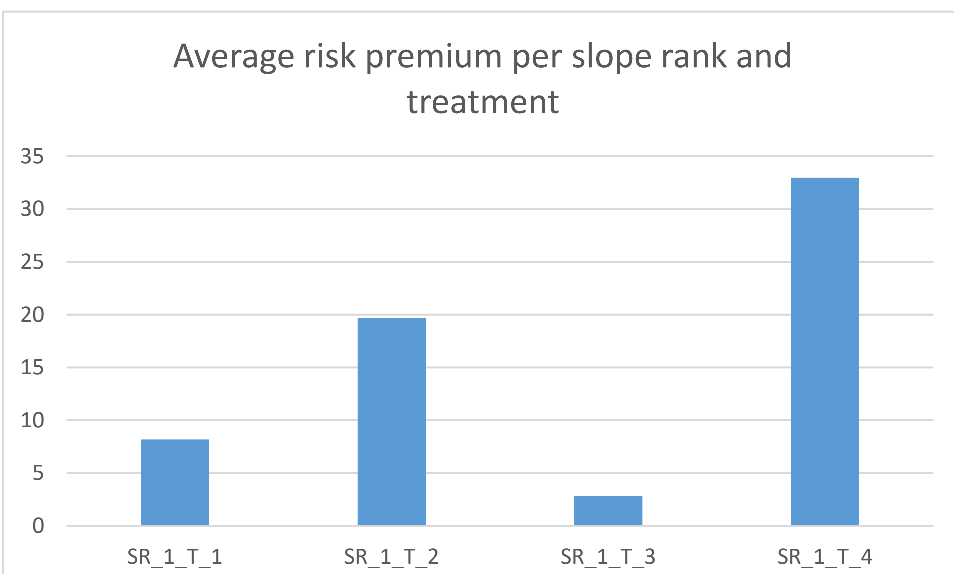
Legend: SR_1_T_1 = Slope rank 1 treatment 1; SR_1_T_2 = Slope rank 1 treatment 2; SR_1_T_3 = Slope rank 1 treatment 3; SR_1_T_4 = Slope rank 1 treatment 4,………., SR_4_T_3 = Slope rank 4 treatment 3; SR_5_T_5 = Slope rank 5 treatment 5.

Figure A.1: Risk Premiums to be Paid to Farmers/Producers to Adopt a Management Strategy.



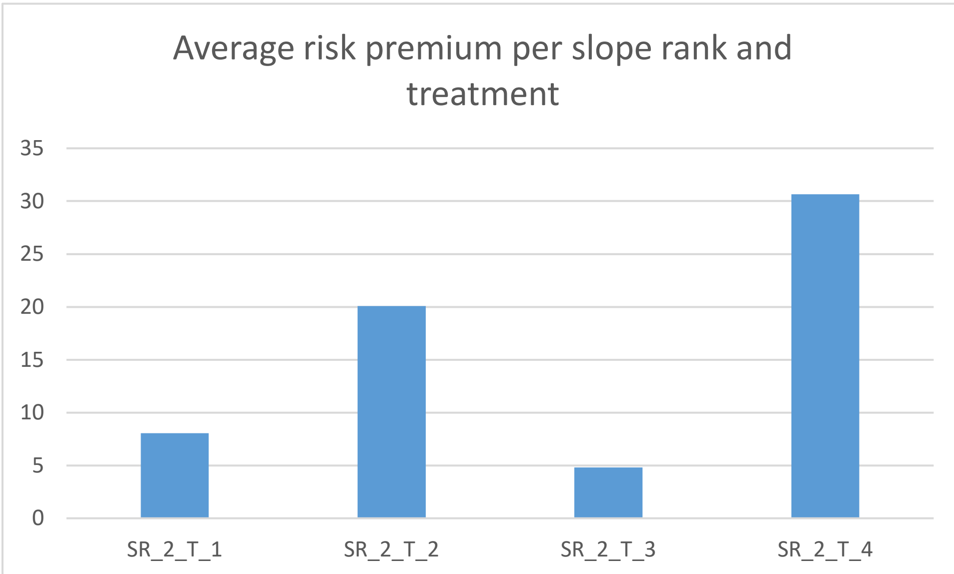
Legend: SR_0_T_1 = Slope rank 0 Treatment 1; SR_0_T_2 = Slope rank 0 Treatment 2; SR_0_T_3 = Slope rank 0 Treatment 3; SR_0_T_4 = Slope rank 0 Treatment 4

Figure A.2: Risk Premiums to be Paid to Farmers/Producers to Adopt a Manage Strategy.



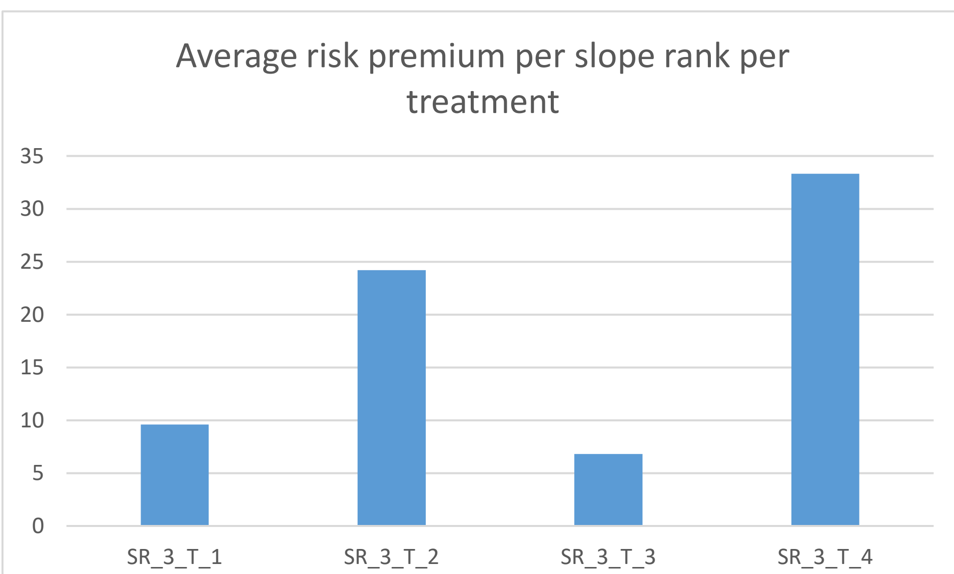
Legend: SR_1_T_1 = Slope rank 1 Treatment 1; SR_1_T_2 = Slope rank 1 Treatment 2; SR_1_T_3 = Slope rank 1 Treatment 3; SR_1_T_4 = Slope rank 1 Treatment 4

Figure A.3: Risk Premiums to be Paid to Farmers/Producers to Adopt a Manage Strategy.



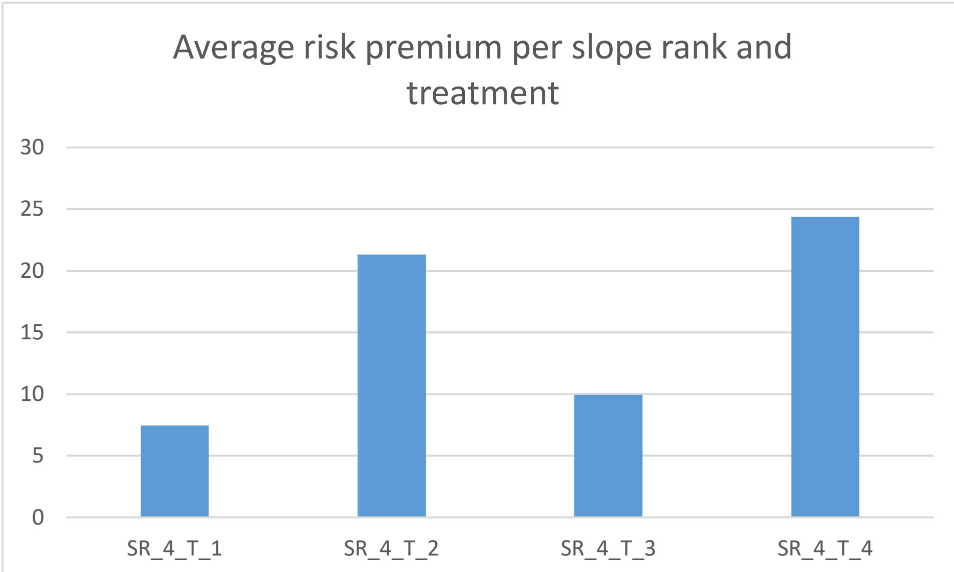
Legend: SR_2_T_1 = Slope rank 2 Treatment 1; SR_2_T_2 = Slope rank 2 Treatment 2; SR_2_T_3 = Slope rank 2 Treatment 3; SR_2_T_4 = Slope rank 2 Treatment 4

Figure A.4: Risk Premiums to be Paid to Farmers/Producers to Adopt a Manage Strategy.



Legend: SR_3_T_1 = Slope rank 3 Treatment 1; SR_3_T_2 = Slope rank 3 Treatment 2; SR_3_T_3 = Slope rank 3 Treatment 3; SR_3_T_4 = Slope rank 3 Treatment 4

Figure A.5: Risk Premiums to be Paid to Farmers/Producers to Adopt a Manage Strategy.



Legend: SR_4_T_1 = Slope rank 4 Treatment 1; SR_4_T_2 = Slope rank 4 Treatment 2; SR_4_T_3 = Slope rank 4 Treatment 3; SR_4_T_4 = Slope rank 4 Treatment 4