Insights from stochastic programs on aligning farmer profit motive with environmental goals

by

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DEDICATION

I would like to dedicate this thesis to my parents, Melih Emirhüseyinoğlu and Suna Özbek, for their unconditional love and support at every stage of my education.

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ABSTRACT

Uncertainty and risk are inherent in agricultural production. Agricultural risks arise due to uncertain weather conditions, including temperature and precipitation, that affect farm yield or changing market conditions that affect crop prices. Each year, agricultural producers make several management decisions to maximize farming incomes. However, their profits are subject to weather and market conditions beyond their control. The immense agricultural industry in Midwest is a major contributor to the US economy and critical for the global food supply. However, nitrogen (N) and other nutrients needed in agricultural production to increase farm yield can cause serious environmental problems, including aquatic dead zones, depletion of the ozone layer, and increased greenhouse gas emissions. Farm management decisions, including higher-level decisions such as how to utilize agricultural lands to more specific lower-level decisions such as fertilizer management, may cause different economic and environmental consequences when combined with uncertainties.

For sustainable production, confronting agricultural uncertainty is not only a severe concern for agricultural producers but also preoccupies policymakers. Policymakers can have many broad objectives, including protecting agricultural producers financially for a steady production level, ensuring an adequate food supply, or sustaining natural resources. Designed policies and incentives commonly target agricultural producers to achieve financial and environmental goals. Hence, designing new policies and identifying necessary incentives require understanding producer decision-making behavior under uncertainty. This dissertation consists of three papers aimed at improving this understanding and helping policymakers design financial incentives that would better align the farmer profit motive with environmental goals. With that purpose, stochastic programs that explicitly include random variables in decision-making problems are built to address (i) what are the optimal decisions under uncertainty to maximize agricultural profit? (ii)

what are the environmental implications of those decisions, if there are any? (iii) what insights can be provided to policymakers?

Specifically, in Chapter 2, land use decisions on a watershed scale are considered under annual precipitation uncertainty. From the viewpoint of a policy maker concerned with regional costs and benefits, we develop variants of a multistage stochastic program to maximize profit while satisfying nutrient reduction constraints. Case study results indicate that, although significant financial incentives might be required for landowners to implement optimal strategies, substantial reductions in nutrient loss can be achieved. In Chapter 3, the research focus is shifted to the farm-level. Annual farming decisions, including fertilizer management (application rate and timing), planting, and FCI purchase, are investigated under uncertainty about the growing season weather (e.g., temperature, precipitation) and crop price. A two-stage stochastic mixed-integer program to find the annual farm management decisions that maximize the expected farm profit is built. The complicated interactions between fertilizer management and crop insurance decisions observed in the numerical study suggest that crop insurance programs can affect water quality by influencing the adoption of environmentally beneficial practices. Chapter 4 provides a much more comprehensive financial risk model considering all financial risk-mitigating instruments (RMIs) from the 2018 Farm Bill currently available for US agricultural producers. We build a two-stage stochastic program, including CVaR as a risk measure, to optimize utilization of the risk-mitigating instruments (RMIs) as well as the fertilizer application rate under a range of risk preferences. The interaction between N application rate and RMIs is investigated to help policymakers and researchers understand the financial and environmental impacts of those tools.

CHAPTER 1. GENERAL INTRODUCTION

The Midwest, often called the "Corn Belt", is one of the most extensive agricultural production areas in the world and consistently affects the global economy. According to a recent report (USDA, 2021), around one-third of total corn and soybean production in the world originates from the US, and the state of Iowa is the biggest supplier among the states. Currently, the value of Iowa's agricultural production and processing industries represents more than 10 percent of the total state GDP and it accounts for around 20% of the jobs (USDA, 2020).

This immense agricultural industry, however, also poses a serious ecological threat. Surface runoff and leaching of key nutrients, nitrogen (N) and phosphorus (P), needed in agricultural production causes nutrient loads in waterways and negatively impacts water quality by depleting the oxygen level in surface waters. This phenomenon is known as hypoxia. Nutrient loss within the Mississippi River basin moves downstream and creates the Gulf of Mexico dead zone, one of the largest in the world at nearly 9,000 square miles (EPA, 2017). Although estimates differ, several studies agree that Iowa contributes a considerable amount (20-40%) of the nutrients in the Gulf compared to the eleven other states along the Mississippi River (Goolsby et al., 2000; Jones et al., 2018; Turner and Rabalais, 2004). A major statewide study by Iowa State University et al. (2017) summarizes strategies to reduce N concentration and P load in surface waters and reveals that a 45% nutrient reduction statewide (41% and 29% load reduction from non-point sources in N and P respectively) is required to achieve environmental goals set by the Mississippi River/Gulf of Mexico Watershed Nutrient Task Force (2008).

Each year, farmers face several management decisions to maximize net income. Farm management is a complex process that is exposed to a wide range of risks and uncertainties. Elements such as weather, soil, and market conditions significantly impact agricultural profits and are subject to forces beyond the farmers' control. Complex interactions exist among farm management decisions and uncertainties, and those relationships affect both farm income and nutrient loss. In this dissertation, several agricultural decisions (e.g., land use, fertilizer management, and utilization of insurance programs) are investigated to maximize agricultural profits and the nutrient pollution implications of these optimal decisions are assessed. We incorporate uncertainty in the decision-making process by building stochastic programs to find optimal decisions under uncertainty. The goal is to provide valuable insights for policymakers (whether they are concerned with environmental goals or simply trying to protect farmers economically). In the next section, we introduce key terms and concepts which can be helpful to inform the reader.

1.1. Background and Motivation

In the US Midwest, significant progress toward reducing soil erosion has been made over the past couple of decades, mainly thanks to lasting conservation programs and raising awareness through public outreach (Iowa State University et al., 2017). Even if the current progress is not enough and there are still valid concerns about reducing sediment and phosphorus loading to streams, N leaching is a more urgent concern and tends to be the limiting factor on achieving nutrient reduction targets when compared to P runoff (see Chapter 2). According to Billen et al. (2013), approximately half of the N fertilizer is lost to the ecosystem. The excess chemical N input causes serious environmental problems, including aquatic dead zones, depletion of the ozone layer, and increased greenhouse gas emissions (Erisman et al., 2013). Recent studies show that the modern agriculture strategies adopted to maximize yield pressurize the planetary boundary on the biogeochemical flows of N and threaten future food security (Gerten et al., 2020). Therefore, in this dissertation, we primarily focus on N application and its loss through leaching.

1.1.1 Nitrogen Cycle

N is an essential nutrient for all living organisms as N atoms are found in all proteins and DNA. Moreover, plants need N to produce the chlorophyll used in photosynthesis. The N deficiency causes plants to be less green, stunts plant growth, and reduces crop yield (Sawyer, 2015). In nature, N exists in many different forms, including inorganic (e.g., ammonia, nitrate) and organic (e.g., amino and nucleic acids). Around 78% of the earth's atmosphere consists of N gas in the form of N_2. Despite this abundance, N is a limiting nutrient in agriculture because plants cannot utilize atmospheric N directly in this gas form (Delwiche, 1970). The conversion of atmospheric nitrogen into a utilizable chemical form (e.g., ammonia) for living organisms is known as N fixation. The leguminous plants hosting nitrogen-fixing bacteria (e.g., Azotobacter, Clostridium, Anabaena) commonly carry out this process (Bernhard, 2010). Because of this relationship, legumes often increase the N content of the soil. Natural events such as lightning and fires also cause a smaller amount of N to be fixed. With the Green Revolution and increasing food demand, synthetic fertilizer usage and production exponentially increased in the last century (Fowler et al., 2013). According to Stein and Klotz (2016), industrial N fixation (the Haber-Bosch process) feeds more than 40% of the human population, and as a result, the synthetic N fixation rate already exceeded natural biological fixation and pushed the N cycle beyond sustainability (Cherkasov et al., 2015). The excessive use of N fertilizers is one reason for N pollution in groundwater and surface waters.

The process of absorbing nitrates and ammonium into organic nitrogen is known as N assimilation or uptake. Organisms that cannot fix N have to assimilate nitrate and ammonium to satisfy their needs. Plants absorb N from the soil using their roots and eventually convert them into amino acids, nucleic acids, and chlorophyll. After the organisms decompose (die), the organic N returns to the soil. This reverse process involving the conversion of organic N back to inorganic N (ammonium) is called mineralization. Once N gets back into the form of ammonium in the soil, it becomes available for plants again (Masclaux-Daubresse et al., 2010; Stein and Klotz, 2016).

Not all ammonium (${NH_4}^+$) and ammonia (NH_3) in the soil are assimilated by the plants. Some portion is further transformed into nitrate (${NO_3}^-$) through the process called nitrification. This two-step transformation (where the first step involves the oxidation of ammonia to nitrite and the second step involves the oxidation of nitrite to nitrate) is mostly done by soil-living dwelling bacteria and requires oxygen, in other words, aerobic conditions (e.g., in the surface layers of soil) (Bernhard, 2010). Note that ammonium is positively charged and therefore stick to negatively charged soil organic matter. Nitrate, on the other hand, is negatively charged and cannot be detained by soil particles. Because of low retention and high solubility by soil, Nitrate-N can move below the root zone and enter groundwater or surface water through tile drainage systems, causing nitrate pollution (Pepper et al., 2011). Therefore, nitrification has negative impacts both environmentally and economically, as it increases N loss through leaching. Farmers use nitrification inhibitors to slow down the biological transformation of ammonium to nitrate. However, the exact impact of inhibitors is dependent on the amount of ammonium and the water content of the soil at a given time (Iowa State University et al., 2017).

Denitrification is the final stage of the nitrogen cycle and occurs under anaerobic conditions. It transforms nitrate into nitrogen gas and releases it back to the atmosphere (Bernhard, 2010). In agriculture, denitrification also means the loss of N from the soil and may be costly for farmers in the short term. Environmentally, however, it stops potential N leaching, and therefore it plays a beneficial role. Some of the edge-of-field nutrient reduction practices aim to remove nitrate from agricultural fields taking advantage of denitrification transformation. For instance, bioreactors provide the additional carbon and energy substrates (commonly wood materials) to support denitrification (Lopez-Ponnada et al., 2017). Similarly, buffers are responsible for reducing N leaching by increasing denitrification and slowing down the outflow (Burt et al., 1999; Iowa State University et al., 2017).

Kyveryga et al. (2004) explore the impact of soil temperature and pH on nitrification rates. Low temperature slows down nitrification. High N content in the soil and higher precipitation are positively correlated with the soil acidity. Consequently, a higher soil pH results in higher nitrification rates. Therefore, the study concludes that the economic and environmental benefits of delaying N fertilizer application from fall to spring are greater in higher-pH soils. That also means, ideally, a most accurate optimization study maximizing farm productivity or minimizing

N loss through leaching requires timely information of weather features (e.g., rainfall, temperature), soil data, and how N management decisions interrelate with those inputs.

1.1.2 Fertilizer Management and 4R

Agricultural productivity has to increase dramatically to feed continuously increasing population. Therefore, improvement in productivity and efficiency is required to maximize nutrient use, optimize harvestable yield, provide crops with the necessary nutrients, and minimize nutrient losses from the field (Fróna et al., 2019). 4R nutrient stewardship provides a framework to increase farmer profitability, enhance environmental protection and improve sustainability. As the name implies, there are four main elements associated with the stewardship including (i) right rate, (ii) right time, (iii) right source, and (iv) right location (Johnston and Bruulsema, 2014; The Nature Conservancy, 2021).

Right rate focuses on matching the nutrient amount to satisfy crop needs. This is not an easy task as there are many factors to consider, including yield goals, variations due to weather conditions, soil characteristics, and the impact of other management decisions such as crop rotations, cover crops, etc. Too much fertilizer increases nutrient losses to the environment. Therefore, finding a balance between the environmental conditions and the farmers' economic situation considering crop needs is a huge task. Right time aims to ensure nutrient availability in the soil for crop growth and development. Ideally, producers need to match the required nutrient uptake during the uptake timings to achieve maximum yield potential. The idea here is to increase the nutrient use efficiency by synchronizing nutrient availability in the soil with the crop demand. Important management decisions, including fertilizer application timing (e.g., split fertilizer applications, two or more fertilizer applications during the growing season rather than providing all N as a single application prior to or at planting) or use of inhibitors and technological tools, are a few examples of ways to increase crop uptake efficiency. Therefore, the rate of nutrient uptake during the uptake timings and the risk of nutrient loss to the environment are valuable pieces of information while making those decisions (Johnston and Bruulsema, 2014; The Nature Conservancy, 2021).

Right source means the use of the right fertilizer source to match the specific crop needs considering the crop type, soil properties, and cost. Right place aims to keep nutrients where the crops can use them by considering key criteria such as the placement of seeds and nutrient mobility in order to increase nutrient delivery efficiency by limiting the nutrient losses from fields (Mikkelsen et al., 2009; Johnston and Bruulsema, 2014; The Nature Conservancy, 2021). However, Johnston and Bruulsema (2014) underline that most smallholder farmers use fertilizer broadcasting rather than precision placements.

Since the fertilizer application decisions can cause different economic, social, and environmental outcomes, researchers explore those impacts using several indicators, including profitability, water quality, and eutrophication (Bruulsema et al., 2011; Johnston and Bruulsema, 2014; Burke et al., 2017; Fixen, 2020). In recent years, sustainability-related concerns significantly increased. As a result, the initial 4R stewardship is expanded through the integration of fertilizer management practices with conservation practices (e.g., cover crop, no-till, buffers). This expansion is also called 4R Plus, in which the term “Plus” represents the other conservation practices (Fixen, 2020; The Nature Conservancy, 2021).

1.1.3 Farmer Behavior Concerning Profit and Conservation Practices

Numerous studies include surveys and data collection to investigate the behavior of Midwestern farmers when making decisions (Feola et al., 2015; Mase et al., 2017; Yoshida et al., 2018). Prokopy et al. (2019) provide a comprehensive review investigating all studies between 1982 and 2017 and summarize how farmer behavior and other external factors affect the adoption of conservation practices. In this study, for simplicity, we assume all farmers are in business for annual profit. In Chapters 3 and 4, we consider uncertainty and crop insurance, and in Chapter 4, we further include the risk averse nature of farmers. According to Prokopy et al. (2019), since farmers trying to avoid risk are commonly self-oriented (in the business for profit), their risk aversion negatively affects the adoption of nutrient reduction practices. The study also underlines that the impact of crop insurance and government policies is hard to evaluate since the impact is dependent on unique circumstances and the specific practice.

For instance, since crop insurance represents a risk-management strategy, insurance policies purchased by farmers may reduce the N application rate. On the other hand, since other conservation practices such as split N application are perceived as a risk-reducing strategy by some producers, this perception may cause them to feel that those conservation practices are redundant when combined with crop insurance policies.

1.1.4 Uncertainty and Risk

Uncertainty and risk are typical features of agricultural production. While we define uncertainty as imperfect knowledge, risk is the exposure to uncertain unfavorable economic outcomes. Commonly, risk incorporates both objective and subjective components; e.g., an objective loss function and subjective risk perception (Rockafellar, 2007; Hansson, 2010; Menapace et al., 2013). Therefore, risk measures involve subjectivity (Bertsimas et al., 2004; Sun et al., 2018). Agricultural risks arise due to uncertain elements such as weather conditions, including temperature and precipitation that affect farm yield, or imperfect and changing market conditions that affect crop prices. All farming decisions, such as deciding how to benefit from land, choosing what plant to grow, or more complex fertilizer and planting management, may cause different economic and environmental consequences when combined with uncertainties. Since farmers cannot know the economic outcome of their decisions with certainty in advance, the weather and market uncertainty are serious concerns. Numerous articles provide management strategies and advice to agricultural producers in order to ease those concerns and alleviate the farming risks (Hay, 2007; Harwood, 1999; Akhtar et al., 2019; Ullah et al., 2016). Historically, the US Farm Bill provides financial assistance to farmers through several income support programs. With the 2014 Farm Bill, farmer concerns about uncertainty and the resulting risk were also acknowledged in the legislation, and direct income support payments were converted to insurance subsidies. Today, in the US, federal crop insurance (FCI) and income support policies (ISP) are the primary ongoing financial risk mitigating instruments (RMIs).

Crop yield and the market-driven fluctuating crop price (unknown to farmers at the time of decision-making) are the major uncertainties affecting farm revenue for agricultural producers. Note that farm yield depends on random weather elements (e.g., precipitation, temperature) and the interaction of those elements with farming decisions. A farming decision is riskier if the probability of bad outcomes of that decision is greater. For example, crop rotations are expected to reduce the probability of low yield outcomes, and therefore, the risk associated with fertilizer application decisions. Crop insurance potentially mitigates the risk, because even if it does not affect the yield outcome, it reduces the probability of low profit. The yield protection (YP) and the revenue protection (RP) plans are the two most popular FCI alternatives in the US. YP protects against yield uncertainty, while RP offers protection for yield and crop price uncertainty combined. Since crop yield is the output of many interrelated components involving random weather features and farming decisions, yield insurance protects against systemic risk. The yield loss may arise from many different causes, and it is the result of the combination of many factors. Fertilizer management (N application and timing) is one such critical factor. Pannell (2017) demonstrates that the expected loss in profits from underapplication of N is bigger than that from overapplication. Therefore, applying N fertilizer in excess of crop needs is considered a rational response by self-oriented risk-averse farmers trying to minimize the crop risk and maximize profitability (Rajsic and Weersink, 2008; Greiner et al., 2009; Prokopy et al., 2019; Thorburn et al., 2020). Thorburn et al. (2020) investigates whether insurance could be an effective instrument to mitigate the risk of yield loss from reduced N applications. For that purpose the study examines a new type of parametric insurance, where the risk of N application rate is segregated from all other agricultural components. Further discussion about the interaction between N application and RMIs is provided in Chapter 4.

The RMIs are the primary economic tools available to farmers designed to mitigate the farming risks directly. According to Farm Bureau statistics, in 2018, 87% of all corn acreage was insured by crop insurance in US. In Iowa, this figure was 93%. Therefore, for any farmer concerned with maximizing the farm profit, insurance-related decisions should be part of the decision-making process. For that reason, several behavioral and economic studies investigating farmer's decisions consider insurance programs an essential factor affecting farmers' decisions (e.g., decisions related to maximizing production efficiency or adoption of nutrient reduction practices). Hence, insurance programs are a natural component of any investigation involving farmers. A major contribution of this dissertation is the consideration of interrelated crop insurance and fertilizer management decisions under uncertainty. To best of our knowledge, this dissertation contains the first mathematical programming studies investigating the crop insurance decisions of a Midwestern farmer. Accordingly, novel mathematical programming formulations are provided.

1.1.5 Decision-making under Uncertainty

Uncertainty is already acknowledged as one of the major limitations in agricultural decision-making (Aimin, 2010; Polasky et al., 2011; Takle et al., 2014; Hamsa and Bellundagi, 2017; Waldman et al., 2020). Stochastic programs are mathematical programming models for optimization problems that involve uncertainty. In the real-world, decision-making models commonly include uncertain parameters that can be modeled as random variables. Stochastic programs explicitly include the uncertainty in parameter values by exploiting the fact that the probability distributions of uncertain parameters can be estimated. Before making important decisions, decision-makers cannot know the particular realization of random variables in advance. Stochastic programs help decision-makers by modeling the decisions as nonanticipative of future outcomes.

In the literature, optimization models have frequently been applied to agriculture, and many of them involve stochastic programming (Singh, 2012; Li et al., 2017b; Dowson et al., 2019; Spiegel et al., 2020; Li and Hu, 2020). The content of those applications is very broad and involves different products, objectives, and assumptions. In US Midwest agriculture, decision management strategies addressing uncertainties mainly rely on historical analysis (e.g., field experiments or process-based simulation) or forecasting approaches. A popular optimization approach is to couple agro-simulation tools (commonly APSIM for farm-level analysis and SWAT for watershed-scale investigation) with metaheuristics (i.e., genetic algorithm, tabu search). Hence, it is impossible to know how close they get to the true optimum with no measurement of optimality gap. Furthermore, rather than considering uncertainty explicitly, those strategies directly incorporate historical values of uncertain parameters to simulate a specific outcome of the uncertain parameters. At best, uncertainty is included in the form of historical expectation of the investigated time horizon. Mathematical programming and specifically stochastic programming models concerning US Midwest agriculture are limited and case-specific.

1.2. Problem Statement

Policymakers can have many broad objectives, including protecting agricultural producers financially for a steady production level, ensuring an adequate food supply, or sustaining natural resources. In any case, most policies and incentives specifically target agricultural producers to achieve financial and environmental goals. The first step in designing new policies and identifying necessary incentives is understanding producer decision-making behavior under uncertainty. Based on that understanding, it may be possible to evaluate the effectiveness of existing policies, such as the necessary incentive rates to achieve the social goals or the financial and environmental consequences of existing Farm Bill programs.

Each year, agricultural producers face several management decisions to maximize farm profit. The scope of those decisions may be broad, from higher-level decisions such as how to utilize agricultural lands to more specific lower-level decisions such as fertilizer management. We define farm profit as the difference between farm revenue and farming costs, where farm revenue is the product of farm yield and crop price. Both revenue components, farm yield, and the market-driven crop price are subject to significant uncertainty and unknown to farmers at the time of decision making. Specifically, farm yield is the output of many interrelated components involving random weather features (e.g., precipitation, temperature) and farming decisions.

Farmers observe their crop yield only after farming decisions are made and the realization of uncertainties are observed. Because farming costs are more directly controllable we do not consider cost uncertainty. Farm management is a very complex process since decision-makers cannot anticipate their decisions' profit outcome. For sustainable production, confronting agricultural uncertainty is not only a serious concern for farmers but also preoccupies policymakers with environmental concerns.

In this dissertation, uncertainty is the primary concern addressed in agricultural decision-making. For economic and environmental sustainability, it is important to understand how uncertainty affects farmer decisions and resulting environmental consequences. This dissertation aims to improve this understanding and help policymakers design financial incentives that would better align the farmer profit motive with environmental goals. For that purpose, we adopt stochastic programming as a modeling approach because it allows us explicitly include random variables in decision-making problems and eliminate the limitations from previous studies by helping us identify the true optimum under uncertainty.

1.3. Summary of Work

In this dissertation, we investigate several agricultural decisions to maximize agricultural profits. Specifically, in Chapter 2, land use decisions on a watershed scale are considered under annual precipitation uncertainty. In Chapter 3, the research focus is shifted to the farm-level, and annual farming decisions, including fertilizer management (application rate and timing), planting, and FCI purchase, are investigated under growing season weather (e.g., temperature, precipitation) and crop price uncertainty. The research focus is more targeted in Chapter 4 compared to Chapter 3. Specifically, Chapter 4 provides a much more comprehensive financial risk model considering all financial risk-mitigating instruments (RMIs) from the 2018 Farm Bill currently available for US agricultural producers. The interaction between N application rate and RMIs is investigated to help policymakers and researchers understand financial and environmental impacts of those tools. Overall, stochastic programs are built to address (i) what are the optimal decisions under uncertainty to maximize agricultural profit? (ii) what are the environmental implications of those decisions, if there are any? (iii) what insights can be attained for policymakers?

1.3.1 Chapter 2 Summary

In Chapter 2, land use decisions on a watershed level are investigated from the viewpoint of a policymaker under annual precipitation uncertainty. This policymaker has two goals: first, to maximize agricultural profit and second, to meet the nutrient reduction targets. The whole watershed area is considered as a single entity by prioritizing the total prosperity instead of individual benefits for farmers. This viewpoint aligns with Iowa State University et al. (2017) where it is assumed that all Iowans need to work together to achieve the nutrient reduction goals.

Specifically, we build a multi-stage stochastic mixed-integer program for land use decisions to maximize the agricultural profits of a watershed while meeting target reductions in nitrate-N and P levels. The general structure of the problem can be considered as a variant of a stochastic assignment problem where we assign one of the land use alternatives to each location to maximize profit with nutrient reduction constraints.

The mathematical expressions to calculate the crop yield, total P delivery to streams, and the total nitrate-N contribution are based on those used in open-source web platform called People in Ecosystems Watershed Integration (PEWI). PEWI is an interactive decision-making tool that helps its users to analyze land use alternatives and their ecological consequences (Chennault et al., 2016). The tool allows its users to conduct “what-if” analyses by presenting quantitative performance measures of proposed land use combinations. Our model assumes that nutrient loss from a location is proportional to its area and total loss in the watershed is the sum of individual locations. Therefore, we ignore the upstream-downstream relationship when calculating nutrient loss by isolating each cell. Incorporating such dependency requires a more data-intensive modeling approach and would result in a highly nonlinear model.

While other land-use optimization studies rely on a combination of metaheuristic search techniques with agricultural simulation tools to solve their multi-objective models (Memmah et al., 2015), we demonstrate the ability of a commercial mixed-integer solver to obtain solutions in a reasonable amount of time.

We analyze and compare two constraint relaxation strategies for their effects on the expected profit. First, the results of simply relaxing the nutrient reduction targets reveal complicated interactions between the constraints and uncertain precipitation levels. Second, a chance-constrained formulation allows the decision-maker to specify a probability with which nutrient reduction targets are met in each year, granting the solver freedom to choose which low-probability outcomes will be ignored. The chance-constrained formulation outperforms the solution to the deterministic expected value formulation by providing a more profitable way to achieve the same nutrient reduction amounts and incorporate flexibility for policymakers in meeting reduction targets. To ensure the cooperation of landowners under optimal strategies, necessary financial incentives are identified. Numerical results show that, although the financial burden to ensure such cooperation is significant, optimal strategies generate a substantial reduction in nutrient loss.

1.3.2 Chapter 3 Summary

In Chapter 3, we shift the research focus to the farm-level and investigate annual farming decisions, including fertilizer management (application rate and timing), planting, and crop insurance purchase. Instead of exploring the problem from a policymaker's perspective and hypothesize the cooperation of farmers for a bigger cause, we approach the problem from a farmer's viewpoint. For simplicity purposes, we assume that the farmer in question is self-oriented and trying to maximize the annual profit from crop production. Accordingly, we construct a decision making model with a single objective. As a result, rather than prioritizing the environmental goals, this chapter primarily aims to select the best set of decisions to maximize the farm profit under uncertainty. Therefore, this chapter aims not just to inform farmers but also to provide valuable insights to policymakers so they can take preventive actions if needed (e.g., implement a fertilizer-based incentive to reduce N application, modify the insurance programs or suggest new alternatives).

Haigh et al. (2015) investigate the U.S. corn farmer's decision calendar and provide a detailed mapping of farming decisions. The study also expresses how and what weather features affect the yield, N loss, and other decisions. In Chapter 3, we construct a very similar farmer timeline (see Section 3.4.1.4). Grounding our decision model on this timeline, we propose a novel two-stage stochastic program for optimal annual farm management. Specifically, we structure a two-stage stochastic program by splitting the farmer's timeline into two periods, (i) from fall until spring, and (ii) from spring until harvest time in fall. It is important to underline that we do not consider fall precipitation uncertainty. Uncertain elements considered in this chapter are growing season temperature, precipitation, workday availability to perform investigated farming decisions, and crop price.

Optimization in operations research has frequently been applied to agriculture (Singh, 2012; Li et al., 2017a; Yan and Li, 2018). Those applications broadly include resource management, cropping pattern optimization, groundwater and irrigation management, and increasing production efficiency. Although some decisions studied fall under farm management, each study's content and methods vary widely due to the investigation of different products, objectives, and assumptions Among them, several consider fertilizer management (Bloemhof-Ruwaard and Hendrix, 1996; Peña-Haro et al., 2011; Hyytiäinen et al., 2011; Moghaddam and DePuy, 2011). To the best of our knowledge, the existing optimization literature does not investigate a US Midwest farmer's annual management decisions for growing a grain product under real-world uncertainties to the extent discussed in this paper. The connection between uncertainties and decisions involving fertilizer management, planting, and crop insurance have not been formulated as a mathematical program. Furthermore, the major novelty of the stochastic program presented in this chapter is the incorporation of crop insurance. In the literature, we only managed to find a single optimization model considering crop insurance decisions (Liu et al., 2008), and the study investigates a peanut farm in Florida.

Agricultural economists also provide detailed analysis about insurance programs (Plastina and Hart, 2018; Boehlje and Langemeier, 2016; Schnitkey and Zulauf, 2016; Barnaby and Russell, 2016). As already underlined, the future farm yield and crop price, which are unknown elements to farmers at the time of policy purchase decision, are the factors determining insurance indemnity. However, these studies use either historical information of a selected period or point estimates of uncertain elements to back up their analysis. Unfortunately, this significantly limits the implications obtained from previous research as those studies fail to reflect yield and price uncertainty. Recall that the insurance programs are tools created to mitigate risk. Leaving uncertainty out from the context will not make evaluating risk possible. Thus, previous research does not provide an entirely accurate investigation of insurance programs. In Chapters 3 and 4, we confront this limitation.

Confronting yield and revenue uncertainty is not only a serious concern for agricultural producers, but it also preoccupies the policymakers and social planners with environmental concerns. Unlike farmers trying to maximize their short-term profitability, policymakers' primary objective is to improve water quality by incentivizing nutrient reduction practices (e.g., EQIP, CSP, cost-share programs) (McMinimy et al., 2019; Liu et al., 2020; Medina et al., 2021). However, identifying the types and amount of payment required for the adoption of such practices is not an easy task (Claassen et al., 2014). Since farm-level practices are subject to uncertainty, the resulting risk affects the farmers' perceived cost of adopting nutrient management practices (Bosch and Pease, 2000). Several studies identify farm risk as one reason for farmers' neglect of environmental practices (Minnesota Pollution Control Agency, 2014; Greiner et al., 2009; Prokopy et al., 2019). Farmers who do not adopt nutrient reduction practices argue that incentives do not cover the additional costs and effort required to follow the practices. For example, instead of following the optimal nitrate application rate maximizing farm yield, some farmers prefer to use more than that amount believing it will reduce the yield risk. Environmentalists commonly refer to experimental tests to validate the additional economic benefits of adopted nutrient reduction practices. However, the majority of those experiments are performed under specific weather and soil conditions, while the rest capture the inherent uncertainties in the form of expectation only. Regardless, those studies fall short of representing underlying risks from the farmer's perspective. As an example, Iowa State University et al. (2017) aggregates several experiments on nutrient reduction practices from the literature and summarizes the impact of N reduction practices on corn yield using two criteria: (i) change in yield expectation and (ii) standard deviation of the yield change. At first glance, it seems like the uncertainty concept is represented using standard deviation. However, this is actually a very incomplete description of uncertainty since the probability distribution is not specified. As a result, it is challenging to provide theoretical backing to any implications that can be derived from the study.

In Chapter 3, we try to answer: (i) What are the optimal fertilizer management, planting, and insurance decisions maximizing expected profit of a Midwestern corn producer under uncertainty (considering farmers' timeline and interactions between uncertainty and decisions)? (ii) What are the potential water quality implications of the results? Our results aligns with Iowa State University et al. (2017) and indicate that it is impossible to achieve nutrient reduction targets simply considering fertilizer management practices.

According to Setiyono et al. (2011); Kyveryga et al. (2004, 2014), rainfall and temperature are the primary elements causing the uncertainty in N management in Midwest. In fact, both Setiyono et al. (2011) and Sawyer (2015) are trying to find optimal N application rates maximizing the farm profitability, yet both studies admit that unpredictable growing season weather is the major limitation. Kyveryga et al. (2004) summarizes several resulting risk factors of weather elements: environmental losses of N to water and air, economic losses due to over and under applications of N, and the difficulty of estimating available N supply in the soil. Since all those risk factors are dependent on unobserved weather conditions, quantifying the impact of management decisions is a very challenging task. According to the same study, participatory learning, analyzing feedback information from many farms over time, is a standard method used by researchers to assess those risk factors and estimate the yield response of N fertilizer. In Chapters 3 and 4 of this study, we take advantage of such studies. However, this assumption also brings out several limitations.

The impact of fertilizer management decisions considered and their interactions with weather uncertainties are aggregated from several empirical studies and used as an input for the optimization models. However, it is highly challenging to observe all those conditions simultaneously and investigate complicated interactions. Therefore, the experiments whose results we use as an input for our model are carefully designed to isolate the impact of one variable, such as fertilizer application rate, on yield. Therefore, we are unable to incorporate the simultaneous interactions of agricultural components and instead assume that our data is mutually independent. For example the impact of precipitation uncertainty on yield and fertilizer application rate on yield is collected from separate studies. As a result, our case study fails to incorporate systematic interaction of those two segregated inputs. An alternative and potentially a better approach to handle this problem would be to estimate the yield and N loss using crop simulation tools. However, it is also essential to underline that such simulation tools are not entirely accurate and especially limited in estimating N loss (Archontoulis et al., 2014; Soufizadeh et al., 2018; Shahhosseini et al., 2019).

The farm management decisions and weather features together determine the crop yield. Because farmers make fertilizer management decisions without full information on random weather events, the crop yield is the major uncertain element in Chapters 3 and 4. In Chapter 3, total growing season precipitation and average temperature are considered as the random variables affecting the crop yield directly. Therefore, our mathematical model uses the yield expectations of growing season weather (generated based on empirical tests at different locations) as an input. However, it is important to note that the growing season aggregation of random variables comes up with certain limitations. For instance, excessive rainfall at a specific time (e.g., precipitation on a specific day or week) may adversely affect productivity (dependent on also many other factors such as planting time and temperature, which determines the growth stage of the plant and growing degree days) but may not be reflected accurately because of data aggregation. To alleviate this limitation, in Chapter 4, a more comprehensive representation of random variables is incorporated.

1.3.3 Chapter 4 Summary

Historically, the US government has provided financial assistance to farmers through several financial programs defined in the Farm Bill. These programs are revised periodically to react to what happened in agricultural markets in prior years. As a result, their shape has evolved over time. In the 2014 Farm Bill, farmer concerns about uncertainty and the resulting risk were explicitly acknowledged in the legislation, and direct income support payments were converted to contingent payments taking the form of crop insurance subsidies. Today, in the US, federal crop insurance (FCI) and contingent income support programs (ISP) are the primary financial risk-mitigating instruments (RMIs) available to agricultural producers. In Chapter 3, we demonstrate that the federal crop insurance (FCI) programs have the potential to alter farm management decisions. The case study results reveal the complicated and contradictory interactions that display the need for more extensive investigations of insurance programs and their impact on environmental practices. In Chapter 4, we build a more comprehensive financial risk model considering all RMIs available to US farmers. Rather than focusing on several farm management decisions, we further intensify the research focus on the interaction between N rate and RMIs. Accordingly, we expand the discussion about the role of insurance programs in agricultural production by providing a thorough analysis of both financial and environmental aspects.

Major improvements in Chapter 4 include:

- We include more detail on FCI and additionally consider ISP with its supplemental coverage option (SCO) to build a more comprehensive model that can help policymakers and researchers understand financial and environmental impacts of those tools.

- The risk attitude of the producers is incorporated into the model. Specifically, a novel two-stage stochastic program, including CVaR as a risk measure, to find optimal RMI choices and N application rates under a range of risk preferences is constructed.

- The dependencies among uncertain weather variables and market prices are considered.

- County-level discrete yield and market price scenarios where the yield is dependent on random weather variables are generated. Newly generated yield scenarios in Chapter 4 are demonstrated to be more reliable than scenarios generated in Chapter 3 (Emirhüseyinoğlu et al., 2022).

The RMIs induce both economic and environmental impacts. First, those programs are designed to provide financial security for agricultural producers. Second, those programs have the potential to alter farm management decisions. Therefore, they may cause unanticipated environmental consequences. The aim in this chapter is to help policymakers and researchers understand financial and environmental impacts of those financial tools. Accordingly, in this chapter, key contributions include:

- Since the 2014 Farm Bill, agricultural economists investigate the effectiveness of newly designed ISP and compare them with old direct support payments. Until now, they have failed to demonstrate the advantages of ISP. In this chapter, we show that ISP is financially more beneficial than the old direct support payments for most producers in terms of CVaR of profit.

- The 2014 Farm Bill and USDA define RMIs as a "safety net" for agricultural producers. The accuracy of this statement was another debate subject among agricultural economists. We demonstrate that optimal use of RMIs eliminates most of the risk resulting from yield and price uncertainties.

- Previous empirical studies indicate that risk aversion is negatively correlated with the adoption of environmentally beneficial practices (Prokopy et al., 2019). The optimal N application rate when RMIs are excluded from the model follows this pattern. However, our numerical results show that the inclusion of RMIs reverses this effect and the optimal N rate is slightly lower for more risk-averse producers.

- Optimal use of RMIs significantly lowers the magnitude of the incentives needed to reduce fertilizer use.

1.4. References

Aimin, H. (2010). Uncertainty, risk aversion and risk management in agriculture. *Agriculture and Agricultural Science Procedia*, 1:152–156.

Akhtar, S., LI, G.-c., Nazir, A., Razzaq, A., Ullah, R., Faisal, M., Naseer, M. A. U. R., and Raza, M. H. (2019). Maize production under risk: The simultaneous adoption of off-farm income diversification and agricultural credit to manage risk. *Journal of Integrative Agriculture*, 18(2):460–470.

Archontoulis, S. V., Miguez, F. E., and Moore, K. J. (2014). Evaluating APSIM maize, soil water, soil nitrogen, manure, and soil temperature modules in the Midwestern United States. *Agronomy Journal*, 106(3):1025–1040.

Barnaby, G. and Russell, L. A. (2016). Crop insurance will be at the center of the 2019 Farm Bill Debate. *Choices*, 31(316-2016-7834).

Bernhard, A. (2010). The nitrogen cycle: processes, players, and human impact. *Nature Education Knowledge*, 3(10):25.

Bertsimas, D., Lauprete, G. J., and Samarov, A. (2004). Shortfall as a risk measure: properties, optimization and applications. *Journal of Economic Dynamics and Control*, 28(7):1353–1381.

Billen, G., Garnier, J., and Lassaletta, L. (2013). The nitrogen cascade from agricultural soils to the sea: modelling nitrogen transfers at regional watershed and global scales. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 368(1621):20130123.

Bloemhof-Ruwaard, J. M. and Hendrix, E. M. (1996). Generalized bilinear programming: An application in farm management. *European Journal of Operational Research*, 90(1):102–114.

Boehlje, M. and Langemeier, M. (2016). The farm safety net: The good and not so good. *farmdoc daily*, 6.

Bosch, D. J. and Pease, J. W. (2000). Economic risk and water quality protection in agriculture. *Review of Agricultural Economics*, 22(2):438–463.

Bruulsema, T., Witt, C., García, F., Li, S., Rao, T. N., Chen, F., and Ivanova, S. (2011). A global framework for fertilizer BMPs. *Icon*.

Burke, W. J., Jayne, T. S., and Black, J. R. (2017). Factors explaining the low and variable profitability of fertilizer application to maize in Zambia. *Agricultural Economics*, 48(1):115–126.

Burt, T., Matchett, L., Goulding, K., Webster, C., and Haycock, N. (1999). Denitrification in riparian buffer zones: the role of floodplain hydrology. *Hydrological Processes*, 13(10):1451–1463.

Chennault, C. M., Schulte, L. A., and Tyndall, J. C. (2016). People in ecosystems/watershed integration: A web-based learning tool for evaluating ecosystem service tradeoffs from watersheds. *J. Soil Water Conserv.*, 71(2):31A–36A.

Cherkasov, N., Ibhadon, A., and Fitzpatrick, P. (2015). A review of the existing and alternative methods for greener nitrogen fixation. *Chemical Engineering and Processing: Process Intensification*, 90:24–33.

Claassen, R., Horowitz, J., Duquette, E., and Ueda, K. (2014). *Additionality in U.S. Agricultural Conservation and Regulatory Offset Programs*. ERR-170, U.S. Department of Agriculture, Economic Research Service.

Delwiche, C. C. (1970). The nitrogen cycle. *Scientific American*, 223(3):136–147.

Dowson, O., Philpott, A., Mason, A., and Downward, A. (2019). A multi-stage stochastic optimization model of a pastoral dairy farm. *European Journal of Operational Research*, 274(3):1077–1089.

Emirhüseyinoğlu, G., Ryan, S. M., Hu, G., and Shahhosseini, M. (2022). Scenario generation for decision-making using machine learning prediction models: A case study for crop yield in midwest. Technical report, Iowa State University.

EPA (2017). Northern Gulf of Mexico hypoxic zone. https://www.epa.gov/ms-htf/northern-gulf-mexico-hypoxic-zone. Mississippi River/Gulf of Mexico Hypoxia Task Force.

Erisman, J. W., Galloway, J. N., Seitzinger, S., Bleeker, A., Dise, N. B., Petrescu, A. R., Leach, A. M., and de Vries, W. (2013). Consequences of human modification of the global nitrogen cycle. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 368(1621):20130116.

Feola, G., Lerner, A. M., Jain, M., Montefrio, M. J. F., and Nicholas, K. A. (2015). Researching farmer behaviour in climate change adaptation and sustainable agriculture: Lessons learned from five case studies. *Journal of Rural Studies*, 39:74–84.

Fixen, P. E. (2020). A brief account of the genesis of 4R nutrient stewardship. *Agronomy Journal*, 112(5):4511–4518.

Fowler, D., Coyle, M., Skiba, U., Sutton, M. A., Cape, J. N., Reis, S., Sheppard, L. J., Jenkins, A., Grizzetti, B., Galloway, J. N., et al. (2013). The global nitrogen cycle in the twenty-first century. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 368(1621):20130164.

Fróna, D., Szenderák, J., and Harangi-Rákos, M. (2019). The challenge of feeding the world. *Sustainability*, 11(20):5816.

Gerten, D., Heck, V., Jägermeyr, J., Bodirsky, B. L., Fetzer, I., Jalava, M., Kummu, M., Lucht, W., Rockström, J., Schaphoff, S., et al. (2020). Feeding ten billion people is possible within four terrestrial planetary boundaries. *Nature Sustainability*, 3(3):200–208.

Goolsby, D. A., Battaglin, W. A., Aulenbach, B. T., and Hooper, R. P. (2000). Nitrogen flux and sources in the Mississippi River Basin. *Science of the Total Environment*, 248(2-3):75–86.

Greiner, R., Patterson, L., and Miller, O. (2009). Motivations, risk perceptions and adoption of conservation practices by farmers. *Agricultural Systems*, 99(2-3):86–104.

Haigh, T., Takle, E., Andresen, J., Widhalm, M., Carlton, J. S., and Angel, J. (2015). Mapping the decision points and climate information use of agricultural producers across the US Corn Belt. *Climate Risk Management*, 7:20–30.

Hamsa, K. and Bellundagi, V. (2017). Review on decision-making under risk and uncertainty in agriculture. *Economic Affairs*, 62(3):447–453.

Hansson, S. O. (2010). Risk: objective or subjective, facts or values. *Journal of Risk Research*, 13(2):231–238.

Harwood, J. L. (1999). *Managing risk in farming: concepts, research, and analysis*. Number 774. US Department of Agriculture, ERS.

Hay, J. (2007). Extreme weather and climate events, and farming risks. In *Managing Weather and Climate Risks in Agriculture*, pages 1–19. Springer.

Hyytiäinen, K., Niemi, J. K., Koikkalainen, K., Palosuo, T., and Salo, T. (2011). Adaptive optimization of crop production and nitrogen leaching abatement under yield uncertainty. *Agricultural Systems*, 104(8):634–644.

Iowa State University, Iowa Department of Agriculture and Land Stewardship, and Iowa Department of Natural Resources (2017). Iowa nutrient reduction strategy: A science and technology-based framework to assess and reduce nutrients to Iowa waters and the Gulf of

Mexico. http://www.nutrientstrategy.iastate.edu/sites/default/files/documents/2017%20INRS%20Complete_Revised%202017_12_11.pdf.

Johnston, A. and Bruulsema, T. (2014). 4R nutrient stewardship for improved nutrient use efficiency. *Procedia Engineering*, 83:365–370.

Jones, C. S., Nielsen, J. K., Schilling, K. E., and Weber, L. J. (2018). Iowa stream nitrate and the Gulf of Mexico. *PLOS One*, 13(4):1–17.

Kyveryga, P., Reeg, P., Mueller, T., and Anderson, C. (2014). Incorporating risk into 4R nutrient management decisions.

Kyveryga, P. M., Blackmer, A. M., Ellsworth, J. W., and Isla, R. (2004). Soil ph effects on nitrification of fall-applied anhydrous ammonia. *Soil Science Society of America Journal*, 68(2):545–551.

Li, Q. and Hu, G. (2020). Multistage stochastic programming modeling for farmland irrigation management under uncertainty. *PLOS one*, 15(6):e0233723.

Li, Q., Hu, G., Jubery, T. Z., and Ganapathysubramanian, B. (2017a). A farm-level precision land management framework based on integer programming. *PLOS one*, 12(3):e0174680.

Li, X., Kang, S., Niu, J., Du, T., Tong, L., Li, S., and Ding, R. (2017b). Applying uncertain programming model to improve regional farming economic benefits and water productivity. *Agricultural Water Management*, 179:352–365.

Liu, H., Zhang, W., Irwin, E., Kast, J., Aloysius, N., Martin, J., and Kalcic, M. (2020). Best management practices and nutrient reduction: An integrated economic-hydrologic model of the western lake erie basin. *Land Economics*, 96(4):510–530.

Liu, J., Men, C., Cabrera, V. E., Uryasev, S., and Fraisse, C. W. (2008). Optimizing crop insurance under climate variability. *Journal of Applied Meteorology and Climatology*, 47(10):2572–2580.

Lopez-Ponnada, E., Lynn, T., Peterson, M., Ergas, S., and Mihelcic, J. (2017). Application of denitrifying wood chip bioreactors for management of residential non-point sources of nitrogen. *Journal of Biological Engineering*, 11(1):1–14.

Masclaux-Daubresse, C., Daniel-Vedele, F., Dechorgnat, J., Chardon, F., Gaufichon, L., and Suzuki, A. (2010). Nitrogen uptake, assimilation and remobilization in plants: challenges for sustainable and productive agriculture. *Annals of Botany*, 105(7):1141–1157.

Mase, A. S., Gramig, B. M., and Prokopy, L. S. (2017). Climate change beliefs, risk perceptions, and adaptation behavior among Midwestern US crop farmers. *Climate Risk Management*, 15:8–17.

McMinimy, M., Angadjivand, S., Aussenberg, R., Billings, K., Bracmort, K., Casey, A., et al. (2019). The 2018 Farm Bill (PL 115–334): Summary and side-by-side comparison. Washington, DC: Congressional Research Service.

Medina, G., Isley, C., and Arbuckle, J. (2021). Promoting sustainable agriculture: Iowa stakeholders' perspectives on the US Farm Bill conservation programs. *Environment, Development and Sustainability*, 23(1):173–194.

Memmah, M.-M., Lescourret, F., Yao, X., and Lavigne, C. (2015). Metaheuristics for agricultural land use optimization. A review. *Agronomy for Sustainable Development*, 35(3):975–998.

Menapace, L., Colson, G., and Raffaelli, R. (2013). Risk aversion, subjective beliefs, and farmer risk management strategies. *American Journal of Agricultural Economics*, 95(2):384–389.

Mikkelsen, R., Schwab, G., and Randall, G. (2009). The four fertilizer rights: Selecting the right source. *Crops Soils*, 42(3):28–32.

Minnesota Pollution Control Agency (2014). The Minnesota nutrient reduction strategy. https://www.pca.state.mn.us/sites/default/files/wq-s1-80.pdf.

Mississippi River/Gulf of Mexico Watershed Nutrient Task Force (2008). Gulf hypoxia action plan 2008: For reducing mitigating, and controlling hypoxia in the northern Gulf of Mexico and improving water quality in the Mississippi River Basin. https://www.epa.gov/ms-htf/hypoxia-task-force-2008-action-plan-and-related-documents. Washington, D.C.

Moghaddam, K. S. and DePuy, G. W. (2011). Farm management optimization using chance constrained programming method. *Computers and Electronics in Agriculture*, 77(2):229–237.

Pannell, D. J. (2017). Economic perspectives on nitrogen in farming systems: managing trade-offs between production, risk and the environment. *Soil Research*, 55(6):473–478.

Peña-Haro, S., Pulido-Velazquez, M., and Llopis-Albert, C. (2011). Stochastic hydro-economic modeling for optimal management of agricultural groundwater nitrate pollution under hydraulic conductivity uncertainty. *Environmental Modelling & Software*, 26(8):999–1008.

Pepper, I. L., Gerba, C. P., Gentry, T. J., and Maier, R. M. (2011). *Environmental microbiology*. Academic Press.

Plastina, A. and Hart, C. (2018). Is ARC-CO acting as a safety net program? Evidence from Iowa. *Choices*, 33(1):1–10.

Polasky, S., Carpenter, S. R., Folke, C., and Keeler, B. (2011). Decision-making under great uncertainty: environmental management in an era of global change. *Trends in ecology & evolution*, 26(8):398–404.

Prokopy, L. S., Floress, K., Arbuckle, J. G., Church, S. P., Eanes, F. R., Gao, Y., Gramig, B. M., Ranjan, P., and Singh, A. S. (2019). Adoption of agricultural conservation practices in the United States: Evidence from 35 years of quantitative literature. *Journal of Soil and Water Conservation*, 74(5):520–534.

Rajsic, P. and Weersink, A. (2008). Do farmers waste fertilizer? A comparison of ex post optimal nitrogen rates and ex ante recommendations by model, site and year. *Agricultural Systems*, 97(1-2):56–67.

Rockafellar, R. T. (2007). Coherent approaches to risk in optimization under uncertainty. In *OR Tools and Applications: Glimpses of Future Technologies*, pages 38–61. Informs.

Sawyer, J. E. (2015). Nitrogen use in Iowa corn production.

Schnitkey, G. and Zulauf, C. (2016). The farm safety net for field crops. *Choices*, 31(316-2016-7846).

Setiyono, T., Yang, H., Walters, D., Dobermann, A., Ferguson, R., Roberts, D., Lyon, D., Clay, D., and Cassman, K. (2011). Maize-n: A decision tool for nitrogen management in maize. *Agronomy Journal*, 103(4):1276–1283.

Shahhosseini, M., Martinez-Feria, R. A., Hu, G., and Archontoulis, S. V. (2019). Maize yield and nitrate loss prediction with machine learning algorithms. *Environmental Research Letters*, 14(12):124026.

Singh, A. (2012). An overview of the optimization modelling applications. *Journal of Hydrology*, 466:167–182.

Soufizadeh, S., Munaro, E., McLean, G., Massignam, A., Van Oosterom, E., Chapman, S., Messina, C., Cooper, M., and Hammer, G. (2018). Modelling the nitrogen dynamics of maize crops–Enhancing the APSIM maize model. *European Journal of Agronomy*, 100:118–131.

Spiegel, A., Britz, W., Djanibekov, U., and Finger, R. (2020). Stochastic-dynamic modelling of farm-level investments under uncertainty. *Environmental Modelling & Software*, 127:104656.

Stein, L. Y. and Klotz, M. G. (2016). The nitrogen cycle. *Current Biology*, 26(3):R94–R98.

Sun, J., Liao, L.-Z., and Rodrigues, B. (2018). Quadratic two-stage stochastic optimization with coherent measures of risk. *Mathematical Programming*, 168(1):599–613.

Takle, E. S., Anderson, C. J., Andresen, J., Angel, J., Elmore, R. W., Gramig, B. M., Guinan, P., Hilberg, S., Kluck, D., Massey, R., et al. (2014). Climate forecasts for corn producer decision making. *Earth Interactions*, 18(5):1–8.

The Nature Conservancy (2021). 4R Plus: Nutrient management and conservation for healthier soils. https://4rplus.org/. Accessed: 2021-03-15.

Thorburn, P., Biggs, J., McMillan, L., Webster, T., Palmer, J., and Everingham, Y. (2020). Innovative economic levers: a system for underwriting risk of practice change in cane-farming. Technical report, National Environmental Science Program. Reef and Rainforest Research Centre Limited, Cairns (67pp.).

Turner, R. E. and Rabalais, N. N. (2004). Suspended sediment, C, N, P, and Si yields from the Mississippi River Basin. *Hydrobiologia*, 511(1-3):79–89.

Ullah, R., Shivakoti, G. P., Zulfiqar, F., and Kamran, M. A. (2016). Farm risks and uncertainties: Sources, impacts and management. *Outlook on Agriculture*, 45(3):199–205.

USDA (2020). Ag and food statistics: Charting the essentials, february 2020. https://www.ers.usda.gov/publications/pub-details/?pubid=96956.

USDA (2021). World agricultural supply and demand estimates. https://www.usda.gov/oce/commodity/wasde.

Waldman, K. B., Todd, P. M., Omar, S., Blekking, J. P., Giroux, S. A., Attari, S. Z., Baylis, K., and Evans, T. P. (2020). Agricultural decision making and climate uncertainty in developing countries. *Environmental Research Letters*, 15(11):113004.

Yan, Z. and Li, M. (2018). A stochastic optimization model for agricultural irrigation water allocation based on the field water cycle. *Water*, 10(8):1031.

Yoshida, Y., Flint, C. G., and Dolan, M. K. (2018). Farming between love and money: US Midwestern farmers' human–nature relationships and impacts on watershed conservation. *Journal of Environmental Planning and Management*, 61(5-6):1033–1050.

CHAPTER 2. LAND USE OPTIMIZATION FOR NUTRIENT REDUCTION UNDER STOCHASTIC PRECIPITATION RATES

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2.1. Abstract

A nutrient reduction strategy for Iowa identifies land use and conservation alternatives to reduce nutrient loss from agriculture and the resulting Gulf of Mexico hypoxia. From the viewpoint of a policy maker concerned with regional costs and benefits, we develop a land use optimization model to maximize profit while satisfying nutrient reduction constraints. Because uncertain precipitation levels affect both yields and nutrient loss, we formulate two variants of a multistage stochastic mixed-integer program with probabilistic scenarios for annual precipitation generated from a Markov chain model. Numerical sensitivity analyses on the recourse variant reveal complicated interactions among the nutrient reduction and labor availability constraints as well as crop prices. The chance-constrained variant provides needed flexibility in meeting nutrient reduction goals by neglecting low-probability precipitation outcomes. Case study results indicate that, although significant financial incentives might be required for landowners to implement optimal strategies, substantial reductions in nutrient loss can be achieved.

2.2. Introduction

Nitrogen (N) and phosphorus (P) are necessary agricultural nutrients but, when lost from the environment through runoff or leaching, may also negatively affect aquatic life by reducing the level of dissolved oxygen. Nitrogen (N) can be found in water bodies naturally in dissolved form and it primarily moves as nitrate-N in the water. Excess nitrate is discharged to streams through agricultural drainage systems. Phosphorus (P), on the other hand, is fixed to soil and naturally uncommon in surface water. It reaches waterways mostly on soil particles as erosion transports sediments (Minnesota Pollution Control Agency, 2008). Excess delivery of these nutrients to waterways enhance growth of plants and algae. This eutrophication causes hypoxia and presents a serious ecological threat (EPA, 2008). Hypoxia causes both economic and ecological problems. During hypoxic incidents, mobile aquatic animals are forced to change their habitat and move to waters with more oxygen while less mobile ones die. This alteration in aquatic life results in serious economic impacts. Both the fishing and tourism sectors suffer, though it is difficult to quantify the exact impact (Rabotyagov et al., 2014). In the US, the Gulf of Mexico provides more than 1.3 billion pounds of fish each year which is equivalent to more than $20 billion (Karnauskas et al., 2013). The tourism sector, which generates $20 billion each year (Karnauskas et al., 2013), also is affected negatively as unsightly algal blooms cause disturbing odors (Rabotyagov et al., 2014).

Nutrients lost from watersheds within the Mississippi River Basin move downstream and create the Gulf of Mexico dead zone, one of the largest in the world at nearly 9,000 square miles (EPA, 2017). The 2008 Gulf Hypoxia Action Plan (Mississippi River/Gulf of Mexico Watershed Nutrient Task Force, 2008) calls on the twelve states that border the Mississippi River for action to reduce the nutrient load in the Gulf. The plan aims to decrease the area of the Gulf with dissolved oxygen less than 2 mg/l to 1930 square miles. To reach that goal, the original plan set a target to reduce nutrients by about 30% but over the years subsequent studies revealed that a 45% reduction is necessary (Iowa State University et al., 2017). Several studies investigate Iowa's share of nutrients reaching the Gulf of Mexico (Goolsby et al., 2000; Jones et al., 2018; Libra et al., 2004; Turner and Rabalais, 2004). Although estimates differ, the studies all agree that Iowa contributes a considerable amount (20-40%) of the nutrients in the Gulf compared to the eleven other states along the Mississippi. A major statewide study established a strategy for reducing N loss by 41% and P loss by 29% (Iowa State University et al., 2017). This Iowa Nutrient Reduction

Strategy (INRS) summarizes ways to decrease nutrient concentrations in surface water originating from both point and non-point sources. Because 93% of the total nitrate-N load and 79% of total P load come from non-point sources in Iowa, particularly corn and soybean production, the strategy emphasizes land use and management practices to reduce nutrient loss from agriculture.

Nutrient reduction practices have long been studied empirically and independently (Schnepf and Cox, 2007). Aggregating different land use options for a region results in making several interrelated decisions. These include crop choices and rotations; in-field conservation practices such as reduced tillage or cover crops; edge-of-field practices such as filter strips, riparian buffers, or bioreactors; or wetland construction. To apply the results of these studies requires thousands of decisions even for a small watershed area. Moreover, the nutrient movement process is inherently stochastic. Precipitation is the major uncertain factor because it dictates hydrological processes that affect nutrient movement. The combinatorial nature of this problem renders it practically impossible to test all possible combinations of land use alternatives and best management practices. Therefore, an optimization model that accounts for uncertainty is necessary for achieving nutrient reduction goals economically.

Optimization methods have a long history of application in managing the use of land for crop production, which accounted for 10% of the earth's land surface at the end of the last century (Delcourt and Delcourt, 1988; Ramankutty and Foley, 1999). Traditionally, the goal was to maximize overall income but spatial criteria such as compactness were soon added. In recent years, social and governmental influences have motivated the consideration of additional cultural and ecological criteria (Memmah et al., 2015; Williams and ReVelle, 1998). As a result, a great variety of land use optimization studies have been proposed for various purposes. Nutrient reduction criteria are less commonly included but have drawn more interest recently. We briefly review land use optimization studies concerned with water quality and models with similar types of decision making structure as ours.

To the best of our knowledge, all the previous land use optimization models considering water quality impacts used a multi-objective approach and almost all of them combined metaheuristic search techniques with agricultural simulation tools to evaluate solution quality. Kaim et al. (2018) provided an exhaustive review of multi-criteria land use optimization studies while Memmah et al. (2015) surveyed the related metaheuristic procedures. Groot et al. (2007) and Groot et al. (2012) considered minimizing nitrogen loss from the soil as one component of a multi-objective function to increase the quality of agricultural operations. Groot et al. (2007) pursued agricultural income, landscape quality such as diversification of land uses, and reduction in nutrient loss. To find the optimal land use decisions for the multi-objective function, an iterative heuristic strategy was coupled with an evolutionary algorithm to explore Pareto optimality and rank candidate solutions. Groot et al. (2012) applied a similar approach to investigate potential farming operations with the goals of maximizing farming income and minimizing nitrogen loss in the soil. More recently, Whittaker et al. (2017) formulated a model predicated on the existence of a higher authority concerned with nutrient reduction in a similar way as in this paper. The study examined the relationship between the governmental authority and farmers by adopting a game theoretic approach. The governmental authority was responsible for setting a tax rate with two objectives: maximizing the profit and reducing nutrient load to streams. In their turn, farmers responded to the tax rate with land management decisions such as the use of labor and fertilizer to maximize their own profit. As a result, a bilevel structure with government decision on the upper level and farmer decisions on the lower level was formulated. To explore and evaluate solutions, Whittaker et al. (2017) and several other authors (Ahmadi et al., 2013; Panagopoulos et al., 2012, 2013; Rabotyagov et al., 2010) used a genetic algorithm to explore different land use practices while employing the Soil and Water Assessment Tool (SWAT), a detailed river basin simulation model, to evaluate fitness.

Although Stewart et al. (2004) considered neither nutrient reduction nor uncertainty, their study identified a similar decision making and data structure as defined in this paper, where a watershed is divided into cells and land use assignment decisions are made for each cell. A single objective was formulated to include multiple criteria, including total cost and spatial attributes, by assigning weights to each. A genetic algorithm was employed to solve the problem. Unlike most other published studies, Sadeghi et al. (2009) found an exact solution to a land use optimization problem incorporating environmental criteria. A watershed in Iran was designed to maximize net income and minimize gross erosion. A linear programming model was proposed to apportion the area among orchard, rangeland, irrigated farming and dry farming. The decisions to allocate cells to those four land use categories were made using a multi-objective mathematical programming software package called ADBASE (Steuer, 1992).

We have found only two studies that incorporate uncertainty explicitly in their models. Altinakar and Qi (2008) combined a multi-objective function that incorporates agricultural income and nutrient concentration levels with an agriculture simulation tool (AnnAGNPS) that evaluated nutrient transportation and nutrient loading to streams for each candidate solution. A tabu search framework with a fuzzy objective was adopted to solve the problem with uncertain parameter values. Klein et al. (2013) developed a procedure to find an optimal set of decisions among land use alternatives, soil management and fertilization options under changing climate conditions. Hundreds of solutions were generated by considering all possible combinations of decisions for two possible climate futures. A multi-criteria procedure was used with the CropSyst agricultural simulation tool to identify, for each climate future, a solution that would balance critical indicators such as yield, erosion and nitrate loss. Kaim et al. (2018) identified the integration of uncertainty into optimization models as a future research direction.

In this study, we focus our efforts on non-point sources and approach the land use optimization problem from the viewpoint of a policy maker concerned with regional costs and benefits. This policy maker has two goals: first, to maximize agricultural profit and second, to meet the nutrient reduction targets imposed by the Gulf Hypoxia Action Plan. Given that nutrient reduction targets have been established, we treat them as constraints and formulate the problem with a single objective to facilitate optimization under uncertainty. Whereas deterministic optimization models are formulated assuming all parameter values are known at the time of decision making, real world decisions have uncertain effects. Stochastic programming models explicitly include the uncertainty in parameter values by specifying a set of probabilistic scenarios for the uncertain parameter values as they unfold over time. By solving a deterministic equivalent with ordinary mathematical programming solvers, a solution that is feasible for all possible outcomes while optimizing the expected value of the objective function is identified. Stochastic programming models are commonly defined by stages where, at each stage, decisions are made based on data available at that time. After a decision is taken in a stage using the available information, the decisions in the following stages can take recourse to additional information as it is revealed. For introductorial tutorials of stochastic programming, we refer the reader to Higle (2005) and Shapiro and Philpott (2007).

Our land use optimization model accounts for spatial features of the land and the effects of uncertain precipitation levels over multiple years. Specifically, we build a multi-stage stochastic mixed-integer program for land use decisions to maximize the agricultural profits of a watershed while meeting target reductions in nitrate-N and P levels under uncertain precipitation rates. We formulate the problem at a watershed scale because individual watersheds can be combined easily to represent an entire river basin, and each watershed model can be solved separately since watershed decisions are mutually independent. We consider the whole watershed area as a single entity by prioritizing the total prosperity instead of individual benefits for farmers. This viewpoint aligns with the INRS where it is assumed that all Iowans work together to achieve the nutrient reduction goals (Iowa State University et al., 2017). Formulating the model from this perspective can inform policy decisions on state investments in supporting infrastructure, watershed prioritization, and the structure of landowner incentives.

While other studies relied on metaheuristics to solve their multi-objective models (Memmah et al., 2015), we demonstrate the ability of a commercial mixed-integer solver to obtain solutions in a reasonable amount of time. The results demonstrate the value of developing and solving the stochastic formulation. From traditional sensitivity studies, we find that labor availability and crop prices, which are both hard to estimate, have major impacts on land use decisions and profitability. We analyze and compare two constraint relaxation strategies for their effects on the expected profit. First, the results of simply relaxing the nutrient reduction targets reveal complicated interactions between the constraints and uncertain precipitation levels. Second, a chance-constrained formulation allows the decision-maker to specify a probability with which nutrient reduction targets are met in each year, granting the solver freedom to choose which low-probability outcomes will be ignored. Numerical results show that the chance-constrained formulation finds a more profitable way to achieve the same nutrient reduction amounts than the solution to a deterministic formulation based on expected precipitation rates. Hence, the chance-constrained formulation appears to be a promising way to incorporate flexibility in meeting the nutrient reduction targets. Finally, we illustrate how the model can be used to identify financial incentives for landowners to implement optimal strategies. Numerical results show that, although the financial burden to ensure such cooperation is significant, optimal strategies generate substantial reduction in nutrient loss.

The rest of the paper is organized as follows. In Section 2.3, we provide a detailed problem description and a multi-stage stochastic mixed-integer mathematical model for the problem. In Section 2.4 we specify the parameters for a watershed-scale computational study and in Section 2.5, we discuss the results of computational studies conducted to evaluate the performance of the proposed model. Finally, concluding remarks are provided in Section 2.6.

2.3. Model Definition

In this section, we provide a formal definition of the problem and the notation used in our model. We present both a deterministic mixed-integer programming model and two variations of stochastic programming for addressing N and P targets. The mathematical models for yield and nutrient reduction are constructed in part according to their formulations in an open source web platform called People in Ecosystems Watershed Integration (PEWI). PEWI is an interactive decision-making tool that helps its users to analyze land use alternatives and their ecological consequences (Chennault et al., 2016). The tool incorporates detailed information about several land use options and mathematical expressions that approximate total yield, total P delivery to streams and the nitrate-N contributions resulting from each land use alternative. The nomenclature of the model is provided in Table 2.2. For a detailed guide to parameters generated through PEWI and to understand how they are calculated, we refer the reader to Chennault (2014). It is important to underline that PEWI allows its users to conduct "what-if" analyses by presenting quantitative performance measures of proposed land use combinations. Our deterministic optimization model described in Section 2.3.2 adds the conversion of yield to profit and allows the use of commercial solvers that implicitly enumerate all land use combinations. We further enhance the model to explicitly incorporate uncertain precipitation levels over multiple years in the stochastic programming formulations given in Section 2.3.3.

2.3.1 Assumptions and Formulations Based on PEWI

Here, we summarize assumptions we have in common with PEWI. As that tool allows a user to select a land use alternative for each portion of a simulated watershed, we formulate an optimization problem from the viewpoint of a single decision maker who is responsible from making all land use decisions in a region. The watershed is divided into subwatersheds, which in turn are divided into smaller cells and we try to select best land use option for each cell among different alternatives to maximize overall profit without exceeding N and P loss standards. Land use alternatives considered in this paper are given in Table 2.1. Cells (sometimes called locations in the remainder of the paper) are assumed to be large enough to accommodate any land use alternative assigned.

Multiple physiographic features, such as water holding capacity of the soil or slope of the land, affect the actual impact of a wetland (Chennault et al., 2016). It is technically possible to highlight some locations in a region as better candidates to install a wetland for maximum impact. To simplify our model, in each subwatershed we assume some cells, more favorable to install a wetland, are separated from the rest. We call those cells the "strategic wetland locations" and we allow construction of a wetland only on those strategic cells. A wetland and its associated buffer are assumed to occupy one whole cell. According to Christianson et al. (2013), a wetland can treat a region up to hundred times its size. PEWI assumes that constructing a wetland in one cell of a subwatershed is adequate to treat that whole subwatershed, and having more than one wetland in a subwatershed does not provide any additional benefit beyond not having its land planted in row crop.

Nitrogen naturally exists in water bodies in dissolved form as a result of the nitrogen cycle. Therefore, without human interference and agricultural production, nitrate-N concentration naturally will not drop below a minimum level. Based on Randall et al. (1997), the minimum nitrate contribution of a subwatershed is 2 mg/L.

Table 2.1: Land use alternatives

Land use strategy	**Description**
Conventional Corn	Corn grain grown using conventional tillage
Conservation Corn	Corn grain grown using conservation practices including no-till, cover crops, buffers, grassed waterways and contouring
Conventional Soybean	Soybean grown using conventional tillage
Conservation Soybean	Soybean grown using conservation practices including no-till, cover crops, buffers, grassed waterways and contouring
Alfalfa	Perennial legume mainly used for grazing, hay or silage
Permanent Pasture	Practice of continuously grazing forage with few or no shifts between pastures
Rotational Grazing	Practice of frequent shifting cattle between pastures to improve forage
Switchgrass	Biomass crop harvested for producing biofuel or biopower
Fruits and Vegetables	A mixed land use including grapes, strawberries, green beans and winter squash
Wetland	Constructed wetlands designed to capture and contain nutrients

It is important to note that we assume nutrient loss from each cell is proportional to its area and total loss in the watershed is the sum of individual cell losses. Therefore, our model ignores the upstream-downstream relationship when calculating the nutrient loss by isolating each cell. Incorporating such dependency require an extremely data-intensive modeling approach and result in a highly nonlinear model.

Table 2.2: Nomenclature for the model

Sets	
$\mathcal{I}$	Set of subwatersheds ($\{1,\ldots,I\}$) – indexed by i
$\mathcal{J}_i$	Set of cells located in each subwatershed i ($\{1,\ldots,J_i\}$) – indexed by j
$\mathcal{K}$	Set of land use alternatives ($\{1,\ldots,K\}$) – indexed by k or l
$\mathcal{T}$	Set of decision stages ($\{1,\ldots,T\}$) – indexed by t
$\mathcal{T}'$	Set of decision stages ($\{2,\ldots,T\}$) – indexed by t
$\mathcal{U}$	Specific set of (i,j) which indicates strategic locations which are more beneficial to install wetlands
Parameters	
$Y_{ijk}(\omega_t)$	Yield of subwatershed i, cell j for land use k in period t (units of yield)
$N_{ijk}(\omega_{[t]})$	Nitrate-N contribution of subwatershed i, cell j for land use k in period t if there is no wetland in subwatershed i (mg/L)
$N^w_{ijk}(\omega_{[t]})$	Nitrate-N contribution of subwatershed i, cell j for land use k in period t if there is wetland in subwatershed i scenario s (mg/L)
$P_{ijlk}(\omega_t)$	Phosphorus loss of subwatershed i, cell j for consecutive selection of land use alternatives l and k respectively for periods $t-1$ and t (Mg/yr)
$P^w_{ij}(\omega_t)$	Phosphorus loss of subwatershed i, cell j if there is a wetland in period t (Mg/yr)
r_k	Base profit for land use k ($/unit of yield)
μ_k	Yield loss of not using rotation in consecutive periods for land use k (%)
F_{ij}	Fixed cost of installing a wetland in subwatershed i, cell j ($)
η	Target nitrate-N concentration (mg/L)
ρ	Target phosphorus loss (Mg/yr)
A_{ij}	Area of cell j in subwatershed i (acres)
n_k	Annual labor required for land use alternative k (hrs)
N	Total available labor force in the watershed in terms of hours per year (hrs)
b_t	Number of potential precipitation outcomes of ω_t in period t
H	Length of study horizon (years)
c_t	Cyclical multiplier
R_t	Expected profit in decision stage t
M	A sufficiently large number
Random Variables	
ω_t	Uncertain precipitation level in period t
$\omega_{[t]}$	History of precipitation levels up to period t: $\omega_{[t]} = (\omega_0, \omega_1, .., \omega_t)$ where ω_0 represents precipitation in the period before $t = 1$

2.3.2 Deterministic Model

Tillage and crop rotations have a critical impact on yield, and numerous studies in the literature over the past couple of decades analyzed that impact under different conditions. The general perception, with a few exceptions, agrees that tillage and rotation increase the crop yield (Lund et al., 1993; Meyer-Aurich et al., 2006; Al-Kaisi et al., 2015). Our model approximately captures the impact of tillage and other best management practices, as in PEWI, by including "conservation corn" and "conservation soybean" along with their conventional counterparts. Unlike PEWI, our model also incorporates the effect of rotation by introducing a yield loss multiplier as a penalty for not rotating crops. To maintain linearity, however, we model this effect only for pairs of successive periods; i.e., we neglect the compounding yield reduction that may result from planting the same crop for more than two years. Another added constraint, motivated by shortages experienced in Iowa, is a restriction on the ability of labor (Hertz and Zahniser, 2013).

It is important to note that yield, P loss and nitrate-N concentration are parameters that depend on the precipitation level (ω_t) of each period t. The deterministic formulation relies on an assumption that realizations of the precipitation random variable are known (i.e., can be forecast accurately) for each year in the study. Given these realizations, one can build a multi-period deterministic mixed integer programming (MIP) model using the decision variables:

$$x^1_{ijkt} = \begin{cases} 1, & \text{if land use } k \text{ is assigned to subwatershed } i\text{, cell } j \text{ given that there is a wetland} \\ & \text{in subwatershed } i \text{ in period } t \\ 0, & \text{otherwise} \end{cases}$$

$$x^2_{ijkt} = \begin{cases} 1, & \text{if land use } k \text{ is assigned to subwatershed } i\text{, cell } j \text{ given that there is no wetland} \\ & \text{in subwatershed } i \text{ in period } t \\ 0, & \text{otherwise} \end{cases}$$

$$z_{ijlkt} = \begin{cases} 1, & \text{if land use alternatives } l \text{ and } k \text{ are assigned to subwatershed } i, \text{ cell } j \\ & \text{for periods } t-1 \text{ and } t \text{ respectively} \\ 0, & \text{otherwise} \end{cases}$$

u^1_{it} = cumulative nitrate-N contribution of subwatershed i in period t if there is a wetland in subwatershed i

u^2_{it} = cumulative nitrate-N contribution of subwatershed i in period t if there is no wetland in subwatershed i

$$y_{ijt} = \begin{cases} 1, & \text{if a wetland is newly constructed in subwatershed } i, \text{ cell } j \text{ in period } t \\ 0, & \text{otherwise} \end{cases}$$

Note that the wetland land use option is distinguished from the rest of the land use alternatives and defined as a distinct decision variable because it plays a unique role by reducing nutrient loss without providing any profit. Also, to reflect subwatershed nitrate contribution successfully and to prevent a non-linear structure, we create two groups of decision variables. The first group, denoted as (x^1_{ijkt}, u^1_{it}), represents the condition of having at least one wetland in subwatershed i and the second group, denoted as (x^2_{ijkt}, u^2_{it}) represents the opposite case. This implementation is necessary to maintain a linear structure because installing a wetland in one of the cells of a subwatershed impacts the nitrate discharge of the entire subwatershed.

Using these decision variables, we develop the following mixed-integer linear programming model:

$$\begin{aligned} \text{Max} \quad & \sum_{i\in\mathcal{I}} \sum_{j\in\mathcal{J}_i} \sum_{k\in\mathcal{K}} \sum_{t\in\mathcal{T}} r_k Y_{ijkt}(\omega_t) \Big(x^1_{ijkt} + x^2_{ijkt} - \sum_{l\in\mathcal{K}} \mu_k z_{ijlkt} \Big) \\ & - \sum_{i\in\mathcal{I}} \sum_{j\in\mathcal{J}_i} \sum_{t\in\mathcal{T}} F_{ij} y_{ijt} - \epsilon \sum_{i\in\mathcal{I}} \sum_{t\in\mathcal{T}} \Big(u^1_{it} + u^2_{it} \Big) \end{aligned} \tag{2.1}$$

s.t.

$$\sum_{i\in\mathcal{I}} \Big(u^1_{it} + u^2_{it} \Big) \frac{\sum_{j\in\mathcal{J}_i} A_{ij}}{\sum_{i\in\mathcal{I}} \sum_{j\in\mathcal{J}_i} A_{ij}} - 2 \leq \eta \qquad \forall t \in \mathcal{T} \tag{2.2}$$

$$u^1_{it} \geq 2 \qquad \forall i \in \mathcal{I}, t \in \mathcal{T} \tag{2.3}$$

$$u^1_{it} \geq \sum_{j\in\mathcal{J}_i}\sum_{k\in\mathcal{K}} N^w_{ijkt}(\omega_{[t]})x^1_{ijkt} \qquad \forall i\in\mathcal{I}, t\in\mathcal{T} \tag{2.4}$$

$$u^2_{it} \geq 2 \qquad \forall i\in\mathcal{I}, t\in\mathcal{T} \tag{2.5}$$

$$u^2_{it} \geq \sum_{j\in\mathcal{J}_i}\sum_{k\in\mathcal{K}} N_{ijkt}(\omega_{[t]})x^2_{ijkt} \qquad \forall i\in\mathcal{I}, t\in\mathcal{T} \tag{2.6}$$

$$\sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i}\sum_{l\in\mathcal{K}}\sum_{k\in\mathcal{K}}\sum_{t\in\mathcal{T}} P_{ijlkt}(\omega_t)z_{ijlkt} + \sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i}\sum_{\delta=1}^{t} P^w_{ijt}(\omega_t)y_{ij\delta} \leq \rho \qquad \forall t\in\mathcal{T} \tag{2.7}$$

$$\sum_{k\in\mathcal{K}} x^1_{ijkt} + \sum_{k\in\mathcal{K}} x^2_{ijkt} + \sum_{\delta=1}^{t} y_{ij\delta} \leq 1 \qquad \forall i\in\mathcal{I}, j\in\mathcal{J}_i, t\in\mathcal{T} \tag{2.8}$$

$$\sum_{j\in\mathcal{J}_i}\sum_{k\in\mathcal{K}} x^1_{ijkt} \leq M \sum_{j\in\mathcal{J}_i}\sum_{\delta=1}^{t} y_{ij\delta} \qquad \forall i\in\mathcal{I}, t\in\mathcal{T} \tag{2.9}$$

$$\sum_{j\in\mathcal{J}_i}\sum_{k\in\mathcal{K}} x^2_{ijkt} \leq M\Big(1 - \sum_{j\in\mathcal{J}_i}\sum_{\delta=1}^{t} y_{ij\delta}\Big) \qquad \forall i\in\mathcal{I}, t\in\mathcal{T} \tag{2.10}$$

$$x^1_{ijkt} + x^2_{ijkt} + x^1_{ijl(t-1)} + x^2_{ijl(t-1)} - z_{ijlkt} - 1 \leq 0 \qquad \forall i\in\mathcal{I}, j\in\mathcal{J}_i, \forall l, k\in\mathcal{K}, t\in\mathcal{T}' \tag{2.11}$$

$$\sum_{l\in\mathcal{K}}\sum_{k\in\mathcal{K}} z_{ijlkt} \leq 1 \qquad \forall i\in\mathcal{I}, j\in\mathcal{J}_i, t\in\mathcal{T} \tag{2.12}$$

$$x^1_{ijk1} + x^2_{ijk1} = z_{ijkk1} \qquad \forall i\in\mathcal{I}, j\in\mathcal{J}_i, \forall k\in\mathcal{K} \tag{2.13}$$

$$\sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i}\sum_{k\in\mathcal{K}} n_k\Big(x^1_{ijkt} + x^2_{ijkt}\Big) \leq N \qquad \forall t\in\mathcal{T} \tag{2.14}$$

$$y_{ijt} = 0 \qquad \forall (i,j)\notin\mathcal{U} \tag{2.15}$$

$$y_{ijt} \in \{0,1\} \qquad \forall i\in\mathcal{I}, j\in\mathcal{J}_i, t\in\mathcal{T} \tag{2.16}$$

$$x^1_{ijkt}, x^2_{ijkt} \in \{0,1\} \qquad \forall i\in\mathcal{I}, j\in\mathcal{J}_i, \forall k\in\mathcal{K}, t\in\mathcal{T} \tag{2.17}$$

$$z_{ijlkt} \in \{0,1\} \qquad \forall i\in\mathcal{I}, j\in\mathcal{J}_i, t\in\mathcal{T} \tag{2.18}$$

$$u^1_{it}, u^2_{it} \geq 0 \qquad \forall i\in\mathcal{I}, t\in\mathcal{T} \tag{2.19}$$

Our objective function (2.1) includes three terms. The first term is the profit generated annually from crop production and calculated based on per unit profit of each crop alternative. It involves a potential yield loss ratio (μ_k) determined according to land use decisions in consecutive years. This ratio reflects a more realistic environment where not using rotation in successive periods may reduce the yield for some types of crops. The second term is a fixed wetland construction cost. The third term is a modeling construct with negligible magnitude that is added to obtain an accurate nitrate concentration, utilizing the maximization nature of our objective, in case Constraint (2.2) is not binding. Constraint (2.2) ensures that the target nitrate concentration is not exceeded. Constraints (2.3-2.4) represent the case of having at least one wetland in a subwatershed while Constraints (2.5-2.6) represent the case of not having any wetland in the subwatershed. Those constraints also ensure that nitrate-N concentration of a subwatershed cannot realistically drop below 2 mg/L. Constraint (2.7) guarantees that the target phosphorus loss is not exceeded. Constraint (2.8) assigns only a single land use alternative to each location. Constraints (2.9-2.10) employ a large number, M, to ensure that the correct group of decision variables is selected for each subwatershed where x^1_{ijkt} may take positive values if a wetland exists in subwatershed i and x^2_{ijkt} may take positive values otherwise. Constraint (2.11) investigates which land use alternatives are assigned to a specific location in consecutive periods. Constraint (2.12) allows the selection of a single land use combination for consecutive periods. In Constraint (2.13), we assume our model is initialized without any land use rotation from the previous period. Constraint (2.14) restricts the availability of labor. Constraint (2.15) allows wetland construction only on strategic locations. Finally, the remaining constraints enforce sign and binary restrictions.

2.3.3 Stochastic Programming

Stochastic programs are mathematical models to optimize under uncertainty where random variables may be incorporated into the objective function or constraints. Precipitation is the uncertain element in our model, and it is incorporated both into the objective and in some of the constraints, as yields and nutrient losses depend on stochastic precipitation levels. Therefore, the general structure of the problem can be considered as a variant of a stochastic assignment problem where we assign a land use alternative to each cell to maximize overall profit with nutrient reduction constraints and by taking the random precipitation variables into consideration. Our multi-period stochastic land use optimization model can be structured with $T + 1$ stages as shown in Figure 2.1, where each stage consists of one period.

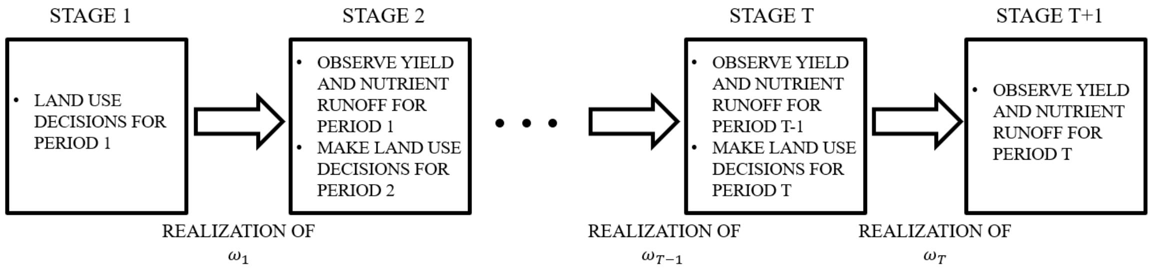

Figure 2.1: Stage representation

Assuming we have a finite number, b_t, of realizations for the random precipitation level ω_t in period t, the scenario set $\mathcal{S} = \{1, ..., S\}$ consists of scenario paths s, each of which represents a sequence of precipitation levels in periods $t \in \mathcal{T}$. We denote the precipitation in period t for scenario s as ω_t^s. Scenario s occurs with probability $p(s)$. Panel (a) of Figure 2.2 illustrates a scenario tree representation of an instance with $T = 2$ periods and $b_t = 3$ precipitation outcomes for each t: High, Medium, Low. In the scenario representation depicted in panel (b), we create a copy of each decision variable for each scenario path. The dashed ovals in panel (b) represent non-anticipativity, corresponding to the nodes of the scenario tree in panel (a), and imply that it is not possible to anticipate the future. Therefore decisions taken at each stage for nodes which belong to the same dashed oval should be identical for all scenarios.

Let $\theta_{ijkt}(s) = \left(x^1_{ijkt}(s), x^2_{ijkt}(s), y_{ijt}(s)\right)$ represent the whole group of decision variables for scenario s. This notation makes it appear that decisions can depend on scenario data, including future realizations of the uncertain precipitation. To force each decision to depend only on information available when the decision is made, we include non-anticipativity constraints (2.34) in the formulation below, which correspond to agreement of decisions within the dashed ovals of Figure 2.2(b).

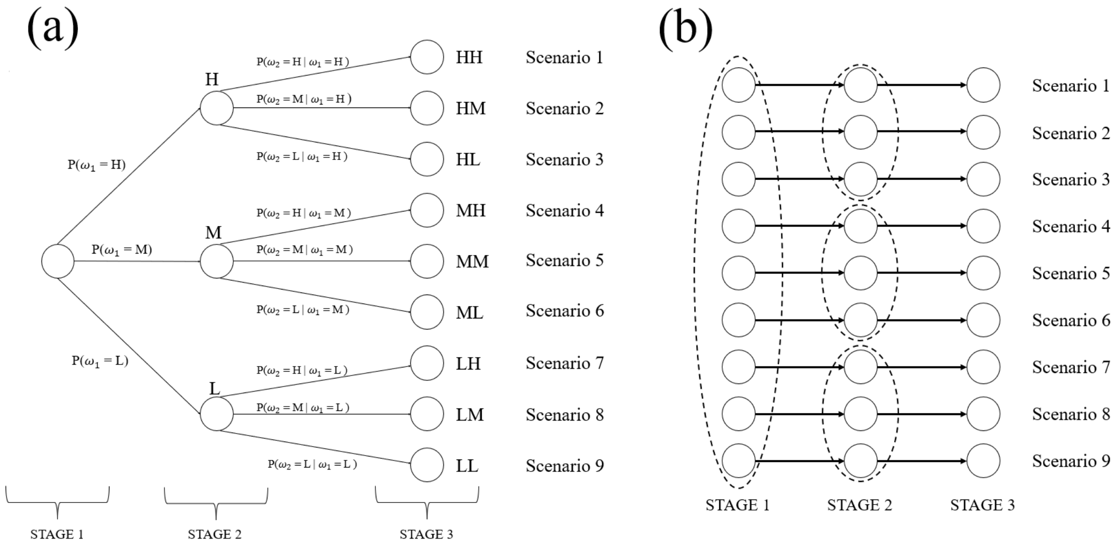

Figure 2.2: (a) Scenario tree representation; (b) Scenario formulation assuming 3 precipitation levels in each of 2 periods

2.3.3.1 Recourse Formulation

The scenario representation of a multi-stage recourse stochastic program can be formulated as follows:

$$\begin{aligned}
\text{Max} \quad & \sum_{s\in\mathcal{S}}\sum_{t\in\mathcal{T}} p(s)\Bigg[\sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i}\sum_{k\in\mathcal{K}} r_k Y_{ijk}(\omega_t^s)\Big(x_{ijkt}^1(s)+x_{ijkt}^2(s) \\
& \quad -\sum_{l\in\mathcal{K}}\mu_k z_{ijlkt}(s)\Big) - \sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i} F_{ij}y_{ijt}(s) \\
& \quad -\epsilon\sum_{i\in\mathcal{I}}\Big(u_{it}^1(s)+u_{it}^2(s)\Big)\Bigg]
\end{aligned} \tag{2.20}$$

s.t.

$$\sum_{i\in\mathcal{I}}\Big(u_{it}^1(s)+u_{it}^2(s)\Big)\frac{\sum_{j\in\mathcal{J}_i}A_{ij}}{\sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i}A_{ij}} - 2 \le \eta \qquad \forall t\in\mathcal{T}, s\in\mathcal{S} \tag{2.21}$$

$$u_{it}^1(s) \ge 2 \qquad \forall i\in\mathcal{I}, t\in\mathcal{T}, s\in\mathcal{S} \tag{2.22}$$

$$u_{it}^1(s) \ge \sum_{j\in\mathcal{J}_i}\sum_{k\in\mathcal{K}} N_{ijk}^w(\omega_{[t]}^s)x_{ijkt}^1(s) \qquad \forall i\in\mathcal{I}, t\in\mathcal{T}, s\in\mathcal{S} \tag{2.23}$$

$$u_{it}^2(s) \ge 2 \qquad \forall i\in\mathcal{I}, t\in\mathcal{T}, s\in\mathcal{S} \tag{2.24}$$

$$u^2_{it}(s) \geq \sum_{j\in\mathcal{J}_i}\sum_{k\in\mathcal{K}} N_{ijk}(\omega^s_{[t]})x^2_{ijkt}(s) \qquad \forall i\in\mathcal{I}, t\in\mathcal{T}, s\in\mathcal{S} \tag{2.25}$$

$$\sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i}\sum_{l\in\mathcal{K}}\sum_{k\in\mathcal{K}} P_{ijlk}(\omega^s_t)z_{ijlkt}(s) + \sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i}\sum_{\delta=1}^{t} P^w_{ij}(\omega^s_t)y_{ij\delta}(s) \leq \rho \qquad \forall t\in\mathcal{T}, s\in\mathcal{S} \tag{2.26}$$

$$\sum_{k\in\mathcal{K}} x^1_{ijkt}(s) + \sum_{k\in\mathcal{K}} x^2_{ijkt}(s) + \sum_{\delta=1}^{t} y_{ij\delta}(s) \leq 1 \qquad \forall i\in\mathcal{I}, j\in\mathcal{J}_i, t\in\mathcal{T}, s\in\mathcal{S} \tag{2.27}$$

$$\sum_{j\in\mathcal{J}_i}\sum_{k\in\mathcal{K}} x^1_{ijkt}(s) \leq M\sum_{j\in\mathcal{J}_i}\sum_{\delta=1}^{t} y_{ij\delta}(s) \qquad \forall i\in\mathcal{I}, t\in\mathcal{T}, s\in\mathcal{S} \tag{2.28}$$

$$\sum_{j\in\mathcal{J}_i}\sum_{k\in\mathcal{K}} x^2_{ijkt}(s) \leq M\Big(1-\sum_{j\in\mathcal{J}_i}\sum_{\delta=1}^{t} y_{ij\delta}(s)\Big) \qquad \forall i\in\mathcal{I}, t\in\mathcal{T}, s\in\mathcal{S} \tag{2.29}$$

$$x^1_{ijkt}(s) + x^2_{ijkt}(s) + x^1_{ijlt}(s) + x^2_{ijlt}(s) - z_{ijlkt}(s) - 1 \leq 0 \qquad \forall i\in\mathcal{I}, j\in\mathcal{J}_i, \forall l,k\in\mathcal{K}, t\in\mathcal{T}', s\in\mathcal{S} \tag{2.30}$$

$$\sum_{l\in\mathcal{K}}\sum_{k\in\mathcal{K}} z_{ijlkt}(s) \leq 1 \qquad \forall i\in\mathcal{I}, j\in\mathcal{J}_i, t\in\mathcal{T}, s\in\mathcal{S} \tag{2.31}$$

$$x^1_{ijk1}(s) + x^2_{ijk1}(s) = z_{ijkk1}(s) \qquad \forall i\in\mathcal{I}, j\in\mathcal{J}_i, \forall k\in\mathcal{K}, s\in\mathcal{S} \tag{2.32}$$

$$\sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i}\sum_{k\in\mathcal{K}} n_k\Big(x^1_{ijkt}(s) + x^2_{ijkt}(s)\Big) \leq N \qquad \forall t\in\mathcal{T}, s\in\mathcal{S} \tag{2.33}$$

$$\theta_{ijkt}(s) - \theta_{ijkt}(s') = 0 \qquad \forall i\in\mathcal{I}, k\in\mathcal{K}, j\in\mathcal{J}_i,\ t, s, s' \text{ for which } \omega^s_{[t-1]} = \omega^{s'}_{[t-1]} \tag{2.34}$$

$$y_{ijt}(s) = 0 \qquad \forall (i,j)\notin\mathcal{U}, s\in\mathcal{S} \tag{2.35}$$

$$y_{ijt}(s) \in \{0,1\} \qquad \forall i\in\mathcal{I}, j\in\mathcal{J}_i, t\in\mathcal{T}, s\in\mathcal{S} \tag{2.36}$$

$$x^1_{ijkt}(s), x^2_{ijkt}(s) \in \{0,1\} \qquad \forall i\in\mathcal{I}, j\in\mathcal{J}_i, \forall k\in\mathcal{K}, t\in\mathcal{T}, s\in\mathcal{S} \tag{2.37}$$

$$z_{ijlkt}(s) \in \{0,1\} \qquad \forall i\in\mathcal{I}, j\in\mathcal{J}_i, t\in\mathcal{T}, s\in\mathcal{S} \tag{2.38}$$

$$u_{it}^1(s), u_{it}^2(s) \geq 0 \qquad \forall i \in \mathcal{I}, t \in \mathcal{T}, s \in \mathcal{S} \tag{2.39}$$

Constraint (2.34) is the only new constraint added to the deterministic model introduced in Section 2.3.2. This constraint enforces non-anticipativity and ensures that decisions in one period do not depend on unknown outcomes in later periods.

2.3.3.2 Cyclical Recourse Formulation

Recal that we use mathematical expressions defined in PEWI (Chennault et al., 2016) to estimate nutrient loss and yield of each land use alternative. Those expressions hypothesize that nutrient loss for a given year depends on the precipitation levels of the most recent pair of consecutive years. That is, the nutrient loss of the current year is calculated based on the current year's annual precipitation, which is not known when the land use decision is made, and the observed precipitation in the previous year. We model annual precipitation as a Markov chain, where one year's precipitation level depends only on the precipitation in the previous year. Moreover, we incorporate the effect of rotating crops in our model only for pairs of successive years. These three model assumptions produce a cyclical pattern of land use decisions after the first stage. Specifically, we observe similar land use decisions in all even numbered years (2,4,6,..) and all odd-numbered years (3,5,7,..) excluding the first year. We illustrate this cyclical decision pattern surfacing in our numerical results in Section 2.5.

Wetland construction is generally a long term decision. In the literature, studies investigating wetland installation decisions commonly consider planning horizons of 50 years. However, extending a scenario tree over a long time horizon results in an enormous number of scenarios and renders the stochastic program intractable to solve. On the other hand, solving the model for shorter planning horizons does not allow the benefit of a wetland to outweigh its large land acquisition and installation cost. Therefore, we suggest an alternative recourse formulation that takes advantage of the land use cyclical pattern to investigate a longer planning horizon.

To do so, we introduce new decision variables, R_t, which represent the expected profit in each decision stage $t = 1, 2, 3$. The cyclical recourse objective (2.40) is formed by modifying Equation

(2.21) to include the land use decisions of only three stages, where the second stage represents all even years and the third stage represents all odd years after the first year. That is, R_1 is the expected profit in the first year based on the the initial precipitation level and first-stage decisions, R_2 is the expected profit of an even year, based on second stage decisions, and R_3 is the expected profit of an odd year, based on third stage decisions.

$$\text{Max} \quad \sum_{s\in\mathcal{S}}\sum_{t\in\mathcal{T}} p(s)\Big[-\sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i} F_{ij}y_{ijt}(s) - \epsilon\sum_{i\in\mathcal{I}}\Big(u^1_{it}(s)+u^2_{it}(s)\Big)\Big] + R_1 + c_2R_2 + c_3R_3 \tag{2.40}$$

Also, an additional constraint (2.41) is included to calculate the expected profit in each decision stage t, where we define cyclical multipliers, c_t, for even and odd years as follows:

$$c_2 = \begin{cases} \frac{H-1}{2}, & \text{if planning horizon } H \text{ is an odd number} \\ \frac{H}{2}, & \text{otherwise} \end{cases}$$
$$c_3 = \begin{cases} \frac{H-1}{2}, & \text{if planning horizon } H \text{ is an odd number} \\ \frac{H}{2}-1, & \text{otherwise} \end{cases}$$

$$\sum_{s\in\mathcal{S}} p(s)\Big[\sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i}\sum_{k\in\mathcal{K}} r_kY_{ijk}(\omega^s_t)\Big(x^1_{ijkt}(s)+x^2_{ijkt}(s)-\sum_{l\in\mathcal{K}}\mu_k z_{ijlkt}(s)\Big)\Big] = R_t \quad \forall t=1,2,3 \tag{2.41}$$

In the cyclical recourse model, Equation (2.40) replaces (2.21) and (2.41) is appended to the constraints in Section 2.3.3.1 with $\mathcal{T}=\{1,2,3\}$.

2.3.3.3 Chance-constrained Formulation

The recourse formulations in Sections 2.3.3.1 and 2.3.3.2 ensure that nutrient restrictions are met for all scenarios. In this section, we provide a different approach to our problem by making sure that the probability of meeting nutrient restrictions at each period is above some minimum level. Therefore, those constraints now hold each year with some specified probability. In our model, we consider nitrate-N and P loss restrictions separately, and ensure that those restrictions are met with some predefined probabilities α_t and γ_t, respectively, for all t. Therefore, we update Constraint (2.21) and Constraint (2.26) accordingly:

$$P\left(s \in \mathcal{S} : \sum_{i\in\mathcal{I}} \left(u^1_{it}(s) + u^2_{it}(s)\right) \frac{\sum\limits_{j\in\mathcal{J}_i} A_{ij}}{\sum\limits_{i\in\mathcal{I}}\sum\limits_{j\in\mathcal{J}_i} A_{ij}} - 2 \le \eta\right) \ge \alpha_t \qquad \forall t \in \mathcal{T} \tag{2.42}$$

$$P\left(s \in \mathcal{S} : \sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i}\sum_{l\in\mathcal{K}}\sum_{k\in\mathcal{K}} P_{ijlk}(\omega^s_t) z_{ijlkt}(s) + \sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i}\sum_{\delta=1}^{t} P^w_{ij}(\omega^s_t) y_{ij\delta}(s) \le \rho\right) \ge \gamma_t \quad \forall t \in \mathcal{T} \tag{2.43}$$

Those constraints can be reformulated as linear mixed-integer by introducing new binary variables β^s_t and ν^s_t and a big number M as follows:

$$\sum_{i\in\mathcal{I}} \left(u^1_{it}(s) + u^2_{it}(s)\right) \frac{\sum\limits_{j\in\mathcal{J}_i} A_{ij}}{\sum\limits_{i\in\mathcal{I}}\sum\limits_{j\in\mathcal{J}_i} A_{ij}} - 2 \le \eta + M(1 - \beta^s_t) \quad \forall t \in \mathcal{T}, s \in \mathcal{S} \tag{2.44}$$

$$\sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i}\sum_{l\in\mathcal{K}}\sum_{k\in\mathcal{K}} P_{ijlk}(\omega^s_t) z_{ijlkt}(s) + \sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i}\sum_{\delta=1}^{t} P^w_{ij}(\omega^s_t) y_{ij\delta}(s) \le \rho + M(1 - \nu^s_t) \quad \forall t \in \mathcal{T}, s \in \mathcal{S} \tag{2.45}$$

$$\sum_{s\in\mathcal{S}} p_s \beta^s_t \ge \alpha_t \quad \forall t \in \mathcal{T} \tag{2.46}$$

$$\sum_{s\in\mathcal{S}} p_s \nu^s_t \ge \gamma_t \quad \forall t \in \mathcal{T} \tag{2.47}$$

We simply replace Constraints (2.21) and (2.26) with Constraints (2.44-2.47) to create our chance-constrained model. Likewise, we obtain a cyclical chance-constrained formulation by applying the same changes and by additionally making the same modifications as in Section 2.3.3.2.

2.4. Computational Study

Computational experiments are performed on watershed instance generated by Chennault et al. (2016) for PEWI. The virtual watershed instance implemented in that tool is shaped according to typical landscape and soil properties of Iowa. It consists of 21 subwatersheds and 593 cells where the area of each cell is roughly equal to 10 acres. Parameters including yield $Y_{ijk}(\omega_t)$, nitrate concentration $N_{ijk}(\omega_{[t]})$ and phosphorus loss $P_{ijlk}(\omega_t)$ are obtained directly from PEWI.

To our knowledge, limited quantitative data on the number of available agricultural workers exists. A significant portion of agricultural workers in Iowa are migrants who work seasonally. Therefore, labor surveys may not always be accurate (Kandel, 2015). Thus, it is difficult to estimate a realistic numerical value for the total labor availability (N), especially at a watershed level. The latest USDA farm labor report (USDA, 2018) divides the United States into regions according to agricultural laborshed and provides exhaustive information about agricultural workers in each identified region. Because our watershed instance is based on Iowa, we use the Cornbelt 2 region (which includes Iowa and Missouri) to estimate the value of N. According to the study, the weekly average number of hours worked in agriculture in the US in 2018 was 40.4 hours, and there were only 21,000 hired workers in Cornbelt 2. However, this report may not include seasonal workers, and to reflect a practical restriction, it is critical to focus on busy seasons. Edwards and Plastina (2016) estimates that the average number of full-time laborer equivalents in Iowa is 4.4 workers per harvesting operation. Also, the watershed instance generated by PEWI approximately contains 18 farms considering the average size of each farm in Iowa (Thessen et al., 2018). Assuming there are 4.4 full-time equivalent workers available per farm, and a full-time laborer works 40.4 hours per week, we estimate the weekly available labor force as 3200 hours. Therefore N is set to 166,400 hours per year. Acknowledging the crudeness of this approximation, in Section 2.5, we conduct sensitivity analyses on this parameter value.

To estimate profit (r_k) and required labor hours (n_k) of each land use alternative, we utilize several different sources. Table 2.3 summarizes those parameters and the sources of the information. Fruit and vegetable crops are considered to be grapes, green beans, strawberries and winter squash for consistency with PEWI. Estimates of annual averages for for r_k and n_k are given in Table 2.3.

Table 2.3: Profit and labor hours estimates

Land use Type	Profit (r_k)	Labor Hours (n_k)	Sources
Corn	\$1.2/bushel	2.8 hrs/acre	(Johanns, 2018; Plastina, 2018)
Soybean	\$4.2/bushel	2.2 hrs/acre	(Johanns, 2018; Plastina, 2018)
Alfalfa	\$50/ton	2.5 hrs/acre	(Biensen, 2018; Plastina, 2018)
Pasture-Grazing	\$60/head	6 hrs/acre	(Ellis and Schulz, 2018; University of Minnesota, 2010) (Holmgren and Feuz, 2015; Paine and Gildersleeve, 2011)
Switchgrass	\$30/ton	4.2 hrs/acre	(Duffy, 2018; Jacobs et al., 2016; Quals, 2009)
Fruits and Veggies	\$0.82/pound	132 hrs/acre	(Center for Crop Diversification, 2017; Chase, 2018) (Nordquist et al., 2011; Yeh et al., 2014)

Drinking water is considered safe for human consumption if the nitrate level is less than 10 mg/L (Tang et al., 2018). EPA (2013) on the other hand, suggests that the nitrate level in surface water should be between 2 mg/L and 6 mg/L for a healthy environment. Data gathered between 2000-2002 shows that the nitrate concentration of individual watersheds in Iowa varies between 3.5-15.4 ppm while their average is 8.78 ppm (Libra et al., 2004). Likewise, phosphorus load to streams ranges from 0.18 to 3.4 pounds/acre with an average of 0.75 pounds/acre. For a relative comparison, the watershed instance used in this study is around 5930 acres and total phosphorus load may range from 0.13 to 11 Mg/year. According to Iowa State University et al. (2017), Iowa must achieve reductions of 41% for nitrogen and 29% for phosphorus. If we consider average nitrate concentration and phosphorus load along with the size of our watershed, the target nitrate concentration should be approximately 5 ppm and that for phosphorus load should be 2 Mg/yr. Along with these baseline values, in Section 2.5, we investigate how different nitrate concentration (η) and phosphorus load (ρ) target values impact the total profit.

The yield loss due to not rotating corn or soybean crops in successive years is assumed to be 10 percent for each (Iowa State University et al., 2017; Meyer-Aurich et al., 2006).

Conservation land use alternatives for both corn and soybean involve combined implementation of no-till, cover crops, buffers, grassed waterways and contouring, which may decrease crop yield. Here, an 8% yield reduction is estimated to occur as a result of selecting the conservation alternatives (Iowa State University et al., 2017; Meyer-Aurich et al., 2006).

To estimate wetland construction cost, we use the information provided from Tyndall and Bowman (2016). Because we expect a wetland to treat an entire subwatershed, measuring 282 acres on average, the cost of constructing a wetland to treat this area is approximately \$15,000. Also, we include land acquisition cost by using per acre state average in 2018 in state of Iowa (Zhang, 2018) which is approximately equal to \$7,200 per acre. Therefore, for a ten-acre cell, we approximate a \$87,000 wetland construction cost in total.

From analysis of historical annual precipitation data in Iowa from 1893 to 2018, we find a small correlation in successive years with negligible correlations across longer time lags. Therefore, we assume the annual precipitation level is Markovian. To explore an effective discretization, we consider two Markov chain models for precipitation. The first has $b_t = 3$ precipitation levels for each t as shown in Table 2.4. The second model has the $b_t = 7$ states for all t, taken directly from PEWI, shown in Table 2.5. To estimate transition probabilities, we applied k-nearest neighbor clustering on the historical data and the frequency of transitions among these states. The resulting transition probability matrices are also provided in Tables 2.4 and 2.5. We use the smaller Markov chain with $b_t = 3\ \forall t \in \{1, 2, 3\}$ as our baseline case.

Table 2.4: State space and precipitation transition probabilities for Markov chain model 1

State Space		Transition Probabilities			
Precipitation (cm/yr)	Type		71.6	81.7	92.6
71.6	Dry	71.6	0.2500	0.6250	0.1250
81.7	Normal	81.7	0.1899	0.6329	0.1772
92.6	Wet	92.6	0.0909	0.6364	0.2727

2.5. Results and Discussion

In this section, we describe computational tests performed to answer questions under six main categories: (i) How do parameters that are hard to estimate affect the solution? (ii) What is the economic benefit of relaxing nutrient reduction targets? (iii) What is the value of granting flexibility to policy makers to meet nutrient reduction goals with probabilities (α_t, γ_t) less than one? (iv) How does precipitation uncertainty affect optimal land use assignments and to what

Table 2.5: State space and precipitation transition probabilities for Markov chain model 2

State Space		Transition Probabilities							
Precipitation (cm/yr)	Type		62.4	71.6	77.2	81.7	87.2	92.6	114.6
62.4	Very Dry	62.4	0.3000	0.1000	0.0000	0.2000	0.2000	0.1000	0.1000
71.6	Dry	71.6	0.0714	0.0714	0.1429	0.2857	0.3571	0.0714	0.0000
77.2	Dry-Normal	77.2	0.0400	0.1600	0.2000	0.2700	0.2000	0.1100	0.0200
81.7	Normal	81.7	0.0800	0.1600	0.2400	0.1300	0.1600	0.2100	0.0200
87.2	Normal-Wet	87.2	0.0769	0.0769	0.3077	0.1154	0.1923	0.1538	0.0769
92.6	Wet	92.6	0.0526	0.0526	0.1579	0.2105	0.2105	0.1053	0.2105
114.6	Very Wet	114.6	0.0000	0.0000	0.1667	0.3333	0.1667	0.3333	0.0000

extent does multistage stochastic programming improve the decision making? (v) How does employing a finer discretization of annual precipitation levels impact the results? (vi) How could landowners be encouraged to cooperate with optimal strategies and what is the financial burden of such cooperation? We use IBM ILOG CPLEX as the optimization engine and perform the experiments on a machine with Intel Core i7-7700HQ @ 2.80 GHz processor and 16 GB RAM.

2.5.1 Cyclical Land Use Decisions

First we demonstrate the cyclical land use decision pattern by comparing the results of the original recourse formulation with $T = 5$ and the cyclical recourse formulation with $T = 3$, $H = 5$, using the three-state Markov chain. Table 2.6 summarizes the expected land use decisions at each stage. In the original recourse formulation, similar expected land use decisions are observed in years 2 and 4 as well as in years 3 and 5. The second stage decisions from the cyclical formulation approximately match the even-year decisions while the third stage decisions from cyclical formulation echo the odd-year results of the original recourse model. Here, as in all the following tables, the percentages represent probability-weighted average proportions of the land devoted to each land use alternative. Similar results, not shown, are found for the seven-state Markov chain.

Wetland construction decisions are not short term decisions. When the study horizon is longer, the benefits of installing a wetland accrue over additional periods, allowing more time to absorb their costs. For the remainder of the paper, we continue to use the cyclical formulations so

Table 2.6: Expected land use assignments in odd and even years for the original recourse model with $T = 5$ vs. the cyclical recourse model with $T = 3$, $H = 5$ for Markov chain model 1

Land Use Alternative	Original Recourse				Cyclical Recourse	
	Stage 2	Stage 3	Stage 4	Stage 5	Stage 2	Stage 3
Wetland	0.51%	0.51%	0.51%	0.51%	0.51%	0.51%
Conventional Corn	8.17%	0.90%	8.02%	0.78%	8.22%	0.85%
Conservation Corn	4.88%	0.00%	4.90%	0.00%	4.77%	0.00%
Conventional Soybean	18.18%	27.41%	18.24%	27.23%	18.34%	27.59%
Conservation Soybean	7.85%	10.04%	7.67%	10.20%	7.64%	10.76%
Alfalfa	58.56%	59.29%	58.80%	59.43%	58.67%	58.44%
Permanent Pasture	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Rotational Grazing	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Switchgrass	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Fruits and Veggies	1.85%	1.85%	1.85%	1.85%	1.85%	1.85%

that we can consider a planning horizon of 50 years. This approach provides a more accurate economic analysis without excessively increasing the problem complexity.

The full results of the cyclical recourse model are presented in Table 2.7 for our baseline case. The land use percentages summarize the decisions for all non-leaf nodes in the scenario tree with $T = 3$ and $b_t = 3$ for all t. We observe that finalizing the construction decisions of wetlands in the first period is always more beneficial than installing them in later stages since it brings a higher benefit-cost ratio. Depending on the evolution of precipitation levels, most of the land is devoted to alfalfa, conventional soybean and conservation soybean, with both conventional and conservation corn substituted in year 2. Throughout our computational tests, permanent pasture and rotational grazing are never assigned to any cell with our current estimated parameter values described in Section 2.4. Therefore, we exclude those land use alternatives from all tables of results in the remainder of this section. Because it is cumbersome to present the full multi-stage solution, most of the rest of the results presented are limited to the expected land use decisions and the optimal expected profits over the whole study horizon.

We compute the expected land use proportion of alternative k in stage t as shown in Equation (2.48). To summarize the expected land use decisions over the whole study horizon, we use Equation (2.49).

Table 2.7: Land use assignments from the cyclical recourse formulation with $\eta = 5$ ppm and $\rho = 2$ Mg/yr for the baseline case

Land use Alternative	Stage 1	Stage 2			Stage 3								
		H	M	L	HH	HM	HL	MH	MM	ML	LH	LM	LL
Wetland	1.52%	1.52%	1.52%	1.52%	1.52%	1.52%	1.52%	1.52%	1.52%	1.52%	1.52%	1.52%	1.52%
Conventional Corn	0.00%	13.32%	16.19%	4.72%	0.00%	0.00%	0.00%	0.00%	0.00%	1.35%	0.00%	0.00%	1.35%
Conservation Corn	0.00%	5.56%	4.55%	9.27%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Conventional Soybean	32.72%	17.88%	16.86%	14.67%	28.16%	32.72%	26.64%	32.21%	32.72%	29.51%	31.20%	32.72%	29.51%
Conservation Soybean	9.95%	6.58%	6.07%	19.22%	15.01%	9.95%	20.74%	11.30%	9.95%	14.67%	12.82%	9.95%	14.67%
Alfalfa	53.96%	53.29%	52.95%	48.74%	53.46%	53.96%	49.24%	53.12%	53.96%	51.10%	52.61%	53.96%	51.10%
Permanent Pasture	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Rotational Grazing	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Switchgrass	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Fruits and Veggies	1.85%	1.85%	1.85%	1.85%	1.85%	1.85%	1.85%	1.85%	1.85%	1.85%	1.85%	1.85%	1.85%

$$\chi(t,k) = \frac{\sum_{s\in\mathcal{S}}\sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}} p(s)\left(x^1_{ijkt}(s) + x^2_{ijkt}(s)\right)}{\sum_{i\in\mathcal{I}} J_i} \quad \forall t \in \mathcal{T}, k \in \mathcal{K} \tag{2.48}$$

$$X(k) = \frac{\chi(1,k) + c_2\chi(2,k) + c_3\chi(3,k)}{H} \quad \forall k \in \mathcal{K} \tag{2.49}$$

2.5.1.1 Sensitivity of Parameter Estimates

In view of the difficulty of estimating parameter values as described in Section 2.4, we explore the impact of variations in those parameter values on the results. Labor availability (N) at a watershed level is particularly difficult to estimate but dramatically restricts the land use design of the watershed. Table 2.8 indicates how the first stage decisions and expected profit vary with the value of N. We analyze alternative cases first by both reducing and increasing the baseline N value by 25% and 50%.

Table 2.8: Impact of changing labor availability from its baseline value

Land Use Alternative	50%	75%	**100%**	125%	150%
Wetland	1.85%	1.69%	1.52%	1.52%	1.52%
Conventional Corn	5.69%	7.65%	5.63%	8.04%	5.67%
Conservation Corn	5.94%	1.03%	3.10%	0.00%	5.24%
Conventional Soybean	19.95%	27.46%	24.86%	26.85%	24.19%
Conservation Soybean	18.01%	8.69%	10.91%	9.49%	9.36%
Alfalfa	41.87%	52.13%	52.13%	51.74%	51.16%
Switchgrass	0.00%	0.00%	0.00%	0.00%	0.00%
Fruits and Veggies	0.84%	1.35%	1.85%	2.36%	2.87%
Expected Annual Profit ($1000)	1,812	2,193	2,522	2,845	3,165

As the labor availability in the watershed area increases, the percentage of land devoted to fruits and vegetables also increases because of its high profitability compared to other land use alternatives. Yet, it uses a huge portion of the available labor, and the other land use assignment decisions take shape accordingly.

Profit estimates summarized in Table 2.3 are the other critical parameter values. With the baseline profit values for each land use alternative, our model prefers the soybean alternatives over corn and a significant alfalfa assignment is also made. However, market trends considerably affect profit levels. Here by taking market conditions from the previous year into account, we investigate an alternative realistic price example in which corn profit is increased by 5% and alfalfa profit is reduced by 15%. Table 2.9 presents the change in first stage decisions and expected profit under this price regime.

Table 2.9: Expected land use decisions and expected annual profit under alternative prices for Markov chain model 1

Land Use Alternative	Baseline Prices	Alternative Prices
Wetland	1.52%	1.69%
Conventional Corn	5.63%	17.90%
Conservation Corn	3.10%	25.72%
Conventional Soybean	24.86%	6.86%
Conservation Soybean	10.91%	4.26%
Alfalfa	52.13%	41.71%
Switchgrass	0.00%	0.00%
Fruits and Veggies	1.85%	1.85%
Expected Annual Profit ($1000)	2,522	2,488

It is evident that the land use assignments are greatly affected by these prices. Instead of selecting soybean as in the original baseline price strategy, the model prefers corn. Also, alfalfa assignments are decreased, which results in even more land devoted to corn. These decisions require more wetlands and a greater emphasis on conservation rather than conventional management to meet the nutrient reduction targets.

2.5.1.2 Relaxation of Nutrient Reduction Goals

Our baseline case is constructed from the nutrient reduction goals identified by the 2008 Gulf Hypoxia Action Plan. This plan requires a 45% nutrient reduction and Iowa State University et al. (2017) claims that Iowa as a whole must achieve 41% N and 29% P reductions to meet this objective. This amount is approximately equivalent to a nitrate-N concentration of 5 mg/L and P load of 2 Mg/yr for our watershed instance. In this section, we explore the economic impacts of alternative nutrient reduction aims for both nitrate-N concentration and P load. In Table 2.10 and Table 2.11, the changes in expected land use decisions resulting from alternative target nitrate-N concentrations and P loads are provided. Also, Figures 2.3 and 2.4 illustrate the change in expected annual profit with alternative nitrate-N and P targets.

Table 2.10: Impact of changing target nitrate-N on $X(k)$ for Markov chain model 1

Land Use Alternative	3 mg/L	4 mg/L	**5 mg/L**	6 mg/L	7 mg/L	8 mg/L
Wetland	1.35%	1.52%	1.52%	1.35%	1.69%	1.69%
Conventional Corn	3.01%	5.17%	5.63%	6.35%	5.51%	7.70%
Conservation Corn	2.23%	4.17%	3.10%	8.22%	10.56%	14.78%
Conventional Soybean	9.30%	21.80%	24.86%	30.19%	35.13%	33.62%
Conservation Soybean	15.54%	3.08%	10.91%	7.28%	15.91%	19.44%
Alfalfa	66.70%	62.41%	52.13%	44.52%	28.34%	20.92%
Switchgrass	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Fruits and Veggies	1.85%	1.85%	1.85%	1.85%	1.85%	1.85%
Expected Annual Profit ($1000)	2,409	2,478	2,522	2,550	2,595	2,629

Table 2.11: Impact of changing target P level on $X(k)$ for Markov chain model 1

Land Use Alternative	1 Mg/yr	1.5 Mg/yr	**2 Mg/yr**	3 Mg/yr	4 Mg/yr
Wetland	1.69%	1.52%	1.52%	1.52%	1.69%
Conventional Corn	0.00%	0.34%	5.63%	4.57%	4.61%
Conservation Corn	23.91%	20.69%	3.10%	3.12%	2.03%
Conventional Soybean	0.00%	0.67%	24.86%	31.23%	33.14%
Conservation Soybean	34.94%	34.11%	10.91%	3.00%	1.12%
Alfalfa	15.68%	40.81%	52.13%	54.70%	55.56%
Switchgrass	10.79%	0.00%	0.00%	0.00%	0.00%
Fruits and Veggies	1.85%	1.85%	1.85%	1.85%	1.85%
Expected Annual Profit ($1000)	2,252	2,455	2,522	2,527	2,529

It is easily seen that as the η value increases, the percentage of land devoted to alfalfa decreases. As we allow more nitrate runoff, nitrogen stops being the limiting factor. Consequently, the land use percentage for corn and soybean increase. Similarly, as ρ is increased,

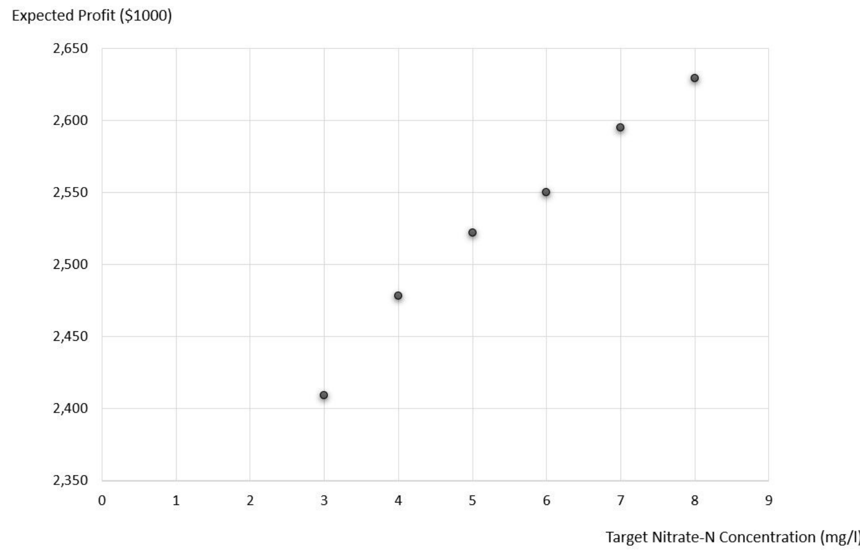

Figure 2.3: Expected annual profit with different targets Markov chain model 1

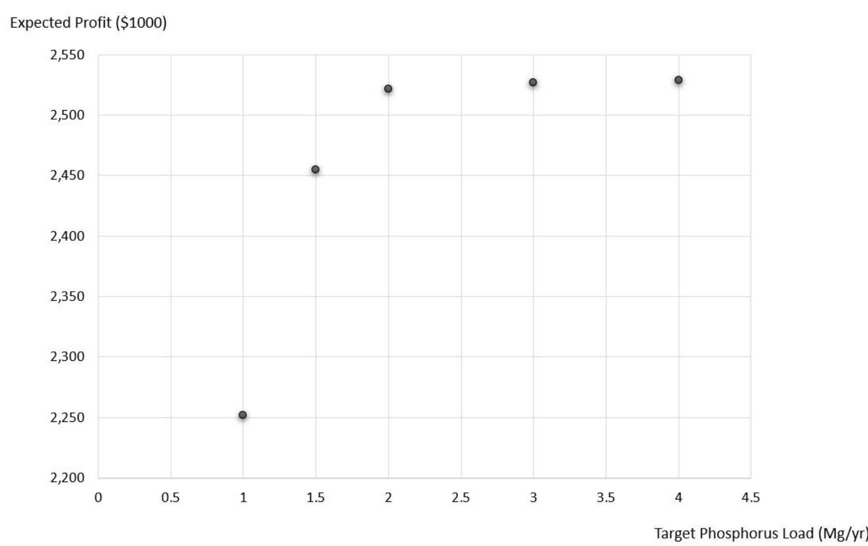

Figure 2.4: Expected annual profit with different nitrate-N targets for Markov chain model 1

the relaxation of the phosphorus constraint compels nitrate to again be the limiting factor and results in an increase in alfalfa. Allowing ρ greater than 2 Mg/yr without changing η results in only a small profit increase, indicating that the nitrate-N constraint controls the land use allocations while the P constraint is not binding. Overall, it appears that the nitrogen goal is the more restrictive one. If the policy maker is able to alter the nutrient reduction goals, it is more valuable to focus first on the nitrate-N level.

2.5.1.3 Cyclical Recourse vs. Cyclical Chance-Constrained Formulation

A comparison between the results of the cyclical recourse and chance-constrained formulation exposes the effect of allowing flexibility in satisfying the nutrient reduction constraints. In the recourse formulation, nutrient reduction targets are enforced for every possible precipitation outcome each year; i.e., the requirements are met with probability one in every year t and scenario s. The chance-constrained formulation in Section 2.3.3.3 allows this probability to be altered for either nutrient in any year. This allows the policy maker to effectively ignore some low probability outcomes which negatively impact both profit and nutrient levels. In this section, we analyze how decisions and annual expected profit are affected as we change the probabilities of nutrient reduction constraint satisfaction. The results quantify the value of flexibility. In Table 2.12, expected land use decisions and annual profit of the baseline case for alternative values of $\alpha_t = \gamma_t$ for all t are provided. The case where the probability is set to 100% is equivalent to the recourse formulation.

As we lower the probability of satisfying both nutrient reduction constraints in all periods, expected alfalfa cultivation over scenarios is slightly decreased and that portion of land is allocated to corn and soybean which results in a higher annual profit.

Table 2.12: Expected land use decisions of baseline case with different values of $\alpha_t = \gamma_t$ for all t

Land Use Alternative	100%	95%	90%	85%	80%	75%	70%
Wetland	1.52%	1.69%	1.52%	1.52%	1.69%	1.52%	1.52%
Conventional Corn	5.63%	5.32%	4.87%	3.45%	6.30%	4.58%	5.68%
Conservation Corn	3.10%	3.87%	4.54%	7.21%	4.60%	6.42%	5.31%
Conventional Soybean	24.86%	28.93%	27.14%	30.11%	31.80%	31.11%	33.81%
Conservation Soybean	10.91%	6.41%	8.09%	6.57%	5.16%	7.09%	4.40%
Alfalfa	52.13%	51.93%	51.98%	49.29%	48.60%	47.42%	47.42%
Switchgrass	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Fruits and Veggies	1.85%	1.85%	1.85%	1.85%	1.85%	1.85%	1.85%
Expected N Concentration over scenarios (ppm)	5.00	5.07	5.10	5.20	5.24	5.28	5.31
Expected P Load over scenarios (Mg/yr)	2.00	2.04	2.07	2.08	2.15	2.22	2.30
Expected Annual Profit ($1000)	2,522	2,529	2,534	2,537	2,539	2,543	2,545

2.5.1.4 Impact of Precipitation Uncertainty

The chance-constrained formulation also helps to demonstrate how incorporating uncertainty in the model improves the decision making. To assess the value of formulating and solving the multi-stage stochastic program, we investigate the impact of ignoring precipitation uncertainty.

First, we solve the cyclical single scenario model by setting the precipitation level in each year to its expected value. As a result, we obtain the results presented in Table 2.13.

Table 2.13: Expected value solution for $T = 3$, $H = 50$

Land use Alternative	Stage 1	Stage 2	Stage 3
Wetland	1.52%	1.52%	1.52%
Conventional Corn	0.00%	4.44%	0.00%
Conservation Corn	0.00%	4.90%	0.00%
Conventional Soybean	34.74%	28.42%	34.74%
Conservation Soybean	8.09%	6.41%	8.09%
Alfalfa	53.79%	52.45%	53.79%
Switchgrass	0.00%	0.00%	0.00%
Fruits and Veggies	1.85%	1.85%	1.85%
Nitrate-N feasibility	88.1%	72.6%	68.9%
Phosphorus load feasibility	88.1%	76.1%	69.7%

If we attempt to fix the decision variables to these values into our cyclical recourse stochastic programming formulation, we find the model to be infeasible; i.e., we do not meet nitrogen and phosphorus goals in every scenario s. Table 2.13 also provides information about frequency of meeting nitrogen and phosphorus goals at each stage according to scenario probabilities p_s.

To make a fair comparison between the expected value and stochastic programming formulations, we first fix the decision variables to their values in the expected value solution while solving the cyclical chance-constrained formulation with the probabilities of constraint satisfaction set to the percentage values provided in Table 2.13 for each stage and nutrient type. That is we set $\alpha_1 = 0.881$, $\alpha_2 = 0.726$, $\alpha_3 = 0.689$, $\gamma_1 = 0.881$, $\gamma_2 = 0.761$ and $\gamma_3 = 0.693$. In this way, we conserve feasibility for the expected value solution and observe a resulting annual expected profit of \$2,534 (in thousands of dollars). Second, we solve the chance-constrained formulation by using the same probability values again without fixing any values of decision variables. The resulting annual expected profit in thousands of dollars is increased by 0.3% to \$2,541. While this increase is admittedly small, it does demonstrate that allowing flexibility in how nutrient reduction goals are met over time and uncertain precipitation outcome can increase the profitability of land use decisions.

2.5.1.5 Impact of Precipitation Outcomes

Given the value of the multi-stage stochastic solution demonstrated in Section 2.5.1.4, it is natural to ask whether expanding the instance to include more finely discretized precipitation levels is worth the computational effort. Our baseline case includes 27 scenarios. Increasing b_t from 3 to 7 with $T = 3$ increases this number to 343. Table 2.14 presents the results of increasing the instance size in dimension. In all tests, the optimality gap for the mixed-integer programming solver was set to 1%; i.e., the solver was instructed to continue iterations until the value of the solution found could be guaranteed to be within 1% of the optimal value. However, the computation time limit was set to 12 hours. After investigated the computational burden of cyclical chance-constrained problem, we observe that our model manages to reach a 0.67% optimality gap within 641.2 s when Markov chain model 1 is used. On the other hand, when

Markov chain model 2 is used instead, the optimality gap can be narrowed only to 2.01% within the 12 hour time limit.

Table 2.14: Impact of changing the outcome number for cyclical recourse problem

Land Use Alternative	Markov chain model 1	Markov chain model 2
Wetland	1.52%	1.52%
Conventional Corn	5.63%	5.74%
Conservation Corn	3.10%	3.21%
Conventional Soybean	24.86%	22.56%
Conservation Soybean	10.91%	13.74%
Alfalfa	52.13%	51.37%
Switchgrass	0.00%	0.00%
Fruits and Veggies	1.85%	1.85%
Expected Annual Profit ($1000)	2,522	2,520
Computational Time (s)	566.3	5421.6
Optimality Gap %	0.52%	0.97%

It is evident that the problem becomes considerably harder to solve as the total number of scenarios increases. In our test runs, when different numbers of precipitation outcomes were examined, we observed no significant change in expected land use or annual profit.

2.5.1.6 Value of Installing Wetlands and Cost of Meeting Nutrient Restrictions

In this section, we first solve the cyclical recourse formulation without permitting the construction of wetlands in any cells. By doing so, we calculate the amount of additional profit enabled by wetlands under the nutrient reduction constraints. We call this additional profit the value of installing wetlands, and it helps us to investigate how much incentive should be considered for landowners of the cells where wetlands are optimally constructed to meet the nutrient reduction goals. Secondly, we solve the cyclical recourse formulation assuming the policy maker is not trying to satisfy any of nutrient reduction requirements. That is, we maximize profit using the recourse model ignoring the nutrient reduction constraints. This helps us to identify the required regional investments and incentives to encourage landowners to cooperate and achieve the nutrient reduction goals.

Table 2.15 summarizes the results. The additional watershed annual profit of $337,000, that could be earned by ignoring the nutrient reduction constraints, corresponds to a suggested annual compensation of $570 for each ten-acre cell as incentive for adopting the socially-optimal land use decision. On the other hand, the reduction in annual profit of $124,000, that results from preventing the construction of the nine watersheds in the optimal solution, could be seen as a suggested transfer among landowners within the watershed. The owner of each of those nine cells should be paid $13,780 for sacrificing revenue from that land while enabling the neighboring landowners to earn more profit than they could without the benefit of the wetlands. Finally, note that even though the cost of fulfilling nutrient requirements is quite high, without any reduction constraints the resulting nutrient losses are substantially higher than the goals set in the Gulf Hypoxia Action Plan. Adding more spatial granularity while considering conservation practices separately in the model could moderate those results by capturing the ability of precision agricuture to simultaneously increase profit and reduce nutrient loss (Muth, 2014).

Table 2.15: Value of Installing Wetlands and Meeting Nutrient Restrictions

Land Use Alternative	Base Model	No Wetlands	No Nutrient Restriction
Wetland	1.52%	0.00%	0.00%
Conventional Corn	5.63%	0.00%	38.79%
Conservation Corn	3.10%	3.18%	0.00%
Conventional Soybean	24.86%	2.23%	54.68%
Conservation Soybean	10.91%	23.32%	0.00%
Alfalfa	52.13%	67.81%	4.68%
Switchgrass	0.00%	0.00%	0.00%
Fruits and Veggies	1.85%	1.85%	1.85%
Expected N Concentration (ppm)	5.00	5.00	24.53
Expected P Load (Mg/yr)	2.00	1.64	6.52
Expected Annual Profit ($1000)	2,522	2,398	2,859

2.6. Conclusion

In this study, we focused on the land use optimization of a watershed. We approached the problem from the perspective of a policy maker who is responsible for making land use decisions in a region. Such a policy maker must consider regional benefits but also fulfill the nutrient reduction requirements imposed by a higher authority. Besides, the decision maker must incorporate several factors including the planning horizon and uncertain precipitation which affects yield and nutrient loss considerably. Therefore, we built a multi-period stochastic mixed-integer program for land use decisions to maximize the agricultural profits of a watershed while meeting target reductions in nitrate-N and P levels under uncertain precipitation rates. We constructed the mathematical model based on watershed information collected from People in Ecosystems Watershed Integration (PEWI) (Chennault et al., 2016). The problem is inherently NP-hard because it is generalizes the stochastic assignment problem. Through an extensive computational study using the CPLEX commercial optimization software, we explored several questions which can facilitate the policy maker's work, identify crucial points in decision making and assist higher authorities or landowners with proper use of funding and incentives.

The formulation incorporated several parameters that are hard to estimate but have high impact on the optimal solutions. One is the total available labor force in the watershed, for which there are limited quantitative data due to migrant character of many agricultural workers. The other set of critical parameters are the profits of each land use alternative. In future work it would be worthwhile to consider explicitly modeling uncertainty in crop prices in addition to precipitation levels.

Nitrate-N concentration, P load and yield of each land use alternative depend on stochastic annual precipitation levels. In Section 2.5.1.4, we demonstrate that it is not possible to either reach an optimal profit or actually meet nutrient reduction goals by implementing a solution derived without considering precipitation uncertainty. Therefore, stochastic programming is needed to achieve optimality while meeting reduction targets.

The two variants of the multi-stage stochastic program provide insight into strategies for relaxing nutrient reduction goals. The simple strategy of relaxing the targets increases the profit of the watershed area as expected. Our results indicate that, under the current reduction goals identified by the 2008 Gulf Hypoxia Action Plan and Iowa Nutrient Reduction Strategy, nitrogen tends to be the limiting factor compared to phosphorus. Therefore, if there will be any concessions, nitrate-N constraint relaxation should be considered first. However, it is important to note that those results may be specific to the watershed instance examined. Further tests are required using different watershed data. The second relaxation strategy investigated in this study is to decrease the probability with which nutrient reduction targets are met. Instead of meeting nutrient reduction goals in every year and possible scenario with certainty, this strategy allows policy makers to ignore some scenarios with low probability outcomes that negatively impact both expected profit and nutrient levels. The chance-constrained formulation outperforms the solution to the deterministic expected value formulation by providing a more profitable way to achieve the same nutrient reduction amounts and incorporate flexibility for policy makers in meeting reduction targets.

Our model prioritizes the total prosperity instead of individual benefits of landowners through planning of a benevolent policy maker. Even if this viewpoint aligns with the INRS where statewide cooperation is assumed to achieve the nutrient reduction goals, the major concern is to ensure the cooperation of each landowner in order to implement socially optimal strategies. We investigate the amount of incentives required to ensure compliance of each landowner. Our results indicate that, although the expected compensation per landowner is admittedly not small, the resulting nutrient reduction is quite significant. However, it is necessary to expand the watershed analysis statewide to investigate to what extent Iowa can follow the optimal reduction strategies with reasonable economic sacrifices.

The current formulation can further be expanded by increasing the number land use options while elaborating individual conservation practices. Expanding the number of land use alternatives or adding more parameters modeled as random variables might require the use of decomposition methods for solving the resulting, larger scale, stochastic programs.

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2.7. References

Ahmadi, M., Arabi, M., Hoag, D. L., and Engel, B. A. (2013). A mixed discrete-continuous variable multiobjective genetic algorithm for targeted implementation of nonpoint source pollution control practices. *Water Resources Research*, 49(12):8344–8356.

Al-Kaisi, M. M., Archontoulis, S. V., Kwaw-Mensah, D., and Miguez, F. (2015). Tillage and crop rotation effects on corn agronomic response and economic return at seven Iowa locations. *Agronomy Journal*, 107(4):1411–1424.

Altinakar, M. S. and Qi, H. (2008). Numerical-simulation based multiobjective optimization of agricultural land-use with uncertainty. In *World Environmental and Water Resources Congress 2008: Ahupua'A*, pages 1–10.

Biensen, N. (2018). Iowa hay summary. Technical report, USDA Market News.

Center for Crop Diversification (2017). 2017 vegetable and melon budgets. University of Kentucky.

Chase, C. (2018). Iowa fruit and vegetable production budgets. *Ag Decision Maker A1-17*. Iowa State University Extension and Outreach.

Chennault, C. M. (2014). People in ecosystems/watershed integration: Visualizing ecosystem services tradeoffs in agricultural landscapes. Master's thesis, Iowa State University.

Chennault, C. M., Schulte, L. A., and Tyndall, J. C. (2016). People in ecosystems/watershed integration: A web-based learning tool for evaluating ecosystem service tradeoffs from watersheds. *Journal of Soil and Water Conservation*, 71(2):31A–36A.

Christianson, L., Tyndall, J., and Helmers, M. (2013). Financial comparison of seven nitrate reduction strategies for Midwestern agricultural drainage. *Water Resources and Economics*, 2:30–56.

Delcourt, H. R. and Delcourt, P. A. (1988). Quaternary landscape ecology: relevant scales in space and time. *Landscape Ecology*, 2(1):23–44.

Duffy, M. (2018). Estimated costs for production, storage and transportation of switchgrass. *Ag Decision Maker A1-22*. Iowa State University Extension and Outreach.

Edwards, W. and Plastina, A. (2016). Grain harvesting equipment and labor in Iowa. Technical report, Iowa State University, Department of Economics.

Ellis, S. and Schulz, L. (2018). Livestock enterprise budgets for Iowa. *Ag Decision Maker B1-21*. Iowa State University Extension and Outreach.

EPA (2008). Hypoxia 101. https://www.epa.gov/ms-htf/hypoxia-101. Mississippi River/Gulf of Mexico Hypoxia Task Force.

EPA (2013). Total nitrogen. https://www.epa.gov/sites/production/files/2015-09/documents/totalnitrogen.pdf. Office of Water.

EPA (2017). Northern Gulf of Mexico hypoxic zone. https://www.epa.gov/ms-htf/northern-gulf-mexico-hypoxic-zone. Mississippi River/Gulf of Mexico Hypoxia Task Force.

Goolsby, D. A., Battaglin, W. A., Aulenbach, B. T., and Hooper, R. P. (2000). Nitrogen flux and sources in the Mississippi River basin. *Science of the Total Environment*, 248(2-3):75–86.

Groot, J. C., Oomen, G. J., and Rossing, W. A. (2012). Multi-objective optimization and design of farming systems. *Agricultural Systems*, 110:63–77.

Groot, J. C., Rossing, W. A., Jellema, A., Stobbelaar, D. J., Renting, H., and Van Ittersum, M. K. (2007). Exploring multi-scale trade-offs between nature conservation, agricultural profits and landscape quality—a methodology to support discussions on land-use perspectives. *Agriculture, Ecosystems & Environment*, 120(1):58–69.

Hertz, T. and Zahniser, S. (2013). Is there a farm labor shortage? *American Journal of Agricultural Economics*, 95(2):476–481.

Higle, J. L. (2005). Stochastic programming: Optimization when uncertainty matters. In *Tutorials in Operations Research*, chapter Chapter 2, pages 30–53. INFORMS.

Holmgren, L. and Feuz, D. (2015). 2015 costs and returns for a 200 cow, cow-calf operation, Northern Utah. https://digitalcommons.usu.edu/cgi/viewcontent.cgi?article=1716&context=extension_curall. Utah State University Extension.

Iowa State University, Iowa Department of Agriculture and Land Stewardship, and Iowa Department of Natural Resources (2017). Iowa nutrient reduction strategy: A science and technology-based framework to assess and reduce nutrients to Iowa waters and the Gulf of Mexico. http://www.nutrientstrategy.iastate.edu/sites/default/files/documents/2017%20INRS%20Complete_Revised%202017_12_11.pdf.

Jacobs, K. L., Mitchell, R., and Hart, C. E. (2016). To grow or not to grow: A tool for comparing returns to switchgrass for bioenergy with annual crops and CRP. *Ag Decision Maker A1-27*. Iowa State University Extension and Outreach.

Johanns, A. (2018). Iowa cash corn and soybean prices. *Ag Decision Maker A2-11*. Iowa State University Extension and Outreach.

Jones, C. S., Nielsen, J. K., Schilling, K. E., and Weber, L. J. (2018). Iowa stream nitrate and the Gulf of Mexico. *PLOS ONE*, 13(4):1–17.

Kaim, A., Cord, A. F., and Volk, M. (2018). A review of multi-criteria optimization techniques for agricultural land use allocation. *Environmental Modelling & Software*, 105:79–93.

Kandel, W. (2015). Hired farmworkers a major input for some US farm sectors. *Amber Waves*, 6(2).

Karnauskas, M., Schirripa, M. J., Kelble, C. R., Cook, G. S., and Craig, J. K. (2013). Ecosystem status report for the Gulf of Mexico. NOAA Technical Memorandum NMFS-SEFSC-653.

Klein, T., Holzkämper, A., Calanca, P., Seppelt, R., and Fuhrer, J. (2013). Adapting agricultural land management to climate change: a regional multi-objective optimization approach. *Landscape Ecology*, 28(10):2029–2047.

Libra, R. D., Wolter, C. F., and Langel, R. J. (2004). Nitrogen and phosphorus budgets for Iowa and Iowa watersheds. Iowa Geological Survey Technical Information Series 47.

Lund, M., Carter, P., and Oplinger, E. (1993). Tillage and crop rotation affect corn, soybean, and winter wheat yields. *Journal of Production Agriculture*, 6(2):207–213.

Memmah, M.-M., Lescourret, F., Yao, X., and Lavigne, C. (2015). Metaheuristics for agricultural land use optimization. A review. *Agronomy for Sustainable Development*, 35(3):975–998.

Meyer-Aurich, A., Janovicek, K., Deen, W., and Weersink, A. (2006). Impact of tillage and rotation on yield and economic performance in corn-based cropping systems. *Agronomy Journal*, 98(5):1204–1212.

Minnesota Pollution Control Agency (2008). Nutrients: Phosphorus, nitrogen sources, impact on water quality. https://www.pca.state.mn.us/sites/default/files/wq-iw3-22.pdf.

Mississippi River/Gulf of Mexico Watershed Nutrient Task Force (2008). Gulf hypoxia action plan 2008: For reducing mitigating, and controlling hypoxia in the northern Gulf of Mexico and improving water quality in the Mississippi River Basin. https://www.epa.gov/ms-htf/hypoxia-task-force-2008-action-plan-and-related-documents. Washington, D.C., USA.

Muth, D. (2014). Profitability versus environmental performance: Are they competing? *Journal of Soil and Water Conservation*, 69(6):203A–206A.

Nordquist, D., McCamant, T., Moynihan, M., and Kuntz, G. (2011). Minnesota specialty crops, an analysis of profitability and performance 2008-2011. Minnesota Department of Agriculture.

Paine, L. and Gildersleeve, R. (2011). A summary of beef grazing practices in Wisconsin. https://fyi.uwex.edu/grazres/files/2011/05/2011-Beef-Grazing-Summary-FINAL.pdf. Wisconsin Department of Agriculture, Trade, and Consumer Protection, Madison.

Panagopoulos, Y., Makropoulos, C., and Mimikou, M. (2012). Decision support for diffuse pollution management. *Environmental Modelling & Software*, 30:57–70.

Panagopoulos, Y., Makropoulos, C., and Mimikou, M. (2013). Multi-objective optimization for diffuse pollution control at zero cost. *Soil Use and Management*, 29:83–93.

Plastina, A. (2018). Estimated costs of crop production in Iowa, 2018. *Ag Decision Maker A1-20*. Iowa State University Extension and Outreach.

Quals, J. (2009). Swithchgrass production decision tool. Technical report, University of Tennessee, Department of Agricultural and Resource Economics.

Rabotyagov, S., Kling, C., Gassman, P., Rabalais, N., and Turner, R. (2014). The economics of dead zones: Causes, impacts, policy challenges, and a model of the Gulf of Mexico hypoxic zone. *Review of Environmental Economics and Policy*, 8(1):58–79.

Rabotyagov, S. S., Jha, M., and Campbell, T. D. (2010). Nonpoint-source pollution reduction for an Iowa watershed: An application of evolutionary algorithms. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie*, 58(4):411–431.

Ramankutty, N. and Foley, J. A. (1999). Estimating historical changes in global land cover: Croplands from 1700 to 1992. *Global biogeochemical cycles*, 13(4):997–1027.

Randall, G., Huggins, D., Russelle, M., Fuchs, D., Nelson, W., and Anderson, J. (1997). Nitrate losses through subsurface tile drainage in conservation reserve program, alfalfa, and row crop systems. *Journal of Environmental Quality*, 26(5):1240–1247.

Sadeghi, S., Jalili, K., and Nikkami, D. (2009). Land use optimization in watershed scale. *Land Use Policy*, 26(2):186–193.

Schnepf, M. and Cox, C., editors (2007). *Environmental benefits of conservation on cropland : the status of our knowledge.* Soil and Water Conservation Society, Ankeny, Iowa.

Shapiro, A. and Philpott, A. (2007). A tutorial on stochastic programming. https://www2.isye.gatech.edu/people/faculty/Alex_Shapiro/TutorialSP.pdf. Georgia Institute of Technology, School of Industrial and Systems Engineering.

Steuer, R. E. (1992). Manual for the ADBASE multiple objective linear programming package. Department of Management Science and Information Technology, University of Georgia.

Stewart, T. J., Janssen, R., and van Herwijnen, M. (2004). A genetic algorithm approach to multiobjective land use planning. *Computers & Operations Research*, 31(14):2293–2313.

Tang, C., Lade, G. E., Keiser, D., Kling, C., Ji, Y., and Shr, Y.-H. (2018). Economic benefits of nitrogen reductions in Iowa. https://www.card.iastate.edu/products/publications/texts/water-quality-report.pdf. Iowa State University.

Thessen, G., Hamer, H., and Johnson, J. (2018). Iowa agricultural statistics. Technical report, USDA, National Agricultural Statistics Service.

Turner, R. E. and Rabalais, N. N. (2004). Suspended sediment, C, N, P, and Si yields from the Mississippi River Basin. *Hydrobiologia*, 511(1-3):79–89.

Tyndall, J. and Bowman, T. (2016). Iowa nutrient reduction strategy best management practice cost overview series: Constructed wetlands. https://www.nrem.iastate.edu/bmpcosttools/files/page/files/2016%20Cost%20Sheet%20for%20Constructed%20Wetlands.pdf. Department of Ecology and Natural Resource management, Iowa State University.

University of Minnesota (2010). Labor hour estimates. https://www.cffm.umn.edu/finpackkb/pubs/FINPACK_Labor_Hours.pdf. FINPACK, Center for Farm Financial Management.

USDA (2018). Farm labor. Technical report, National Agricultural Statistics Service.

Whittaker, G., Färe, R., Grosskopf, S., Barnhart, B., Bostian, M., Mueller-Warrant, G., and Griffith, S. (2017). Spatial targeting of agri-environmental policy using bilevel evolutionary optimization. *Omega*, 66:15–27.

Williams, J. C. and ReVelle, C. S. (1998). Reserve assemblage of critical areas: a zero-one programming approach. *European Journal of Operational Research*, 104(3):497–509.

Yeh, A. D., Gómez, M. I., and White, G. B. (2014). Cost of establishment and production of v. vinifera grapes in the Finger Lakes region of New York-2013. Cornell University, New York.

Zhang, W. (2018). 2018 Farmland value survey. *Ag Decision Maker C2-70.* Iowa State University Extension and Outreach.

CHAPTER 3. FARM MANAGEMENT OPTIMIZATION UNDER UNCERTAINTY WITH IMPACTS ON WATER QUALITY AND ECONOMIC RISK

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3.1. Abstract

Farm management decisions under uncertainty are important not only for farmers trying to maximize their net income but also for policymakers responsible for incentives and regulations to achieve environmental goals. We focus on corn production as a significant contributor to the US Midwest economy. Nitrogen is one of the key nutrients needed to increase production efficiency, but its leaching and loss as nitrate through subsurface flow and agricultural drainage systems poses a threat to water quality. We build a novel two-stage stochastic mixed-integer program to find the annual farm management decisions that maximize the expected farm profit. A decomposition-based solution strategy is suggested to reduce the computational complexity resulting from the predominance of binary variables and complicated constraints. Case study results indicate that farmers may compensate for the additional risks associated with nutrient reduction strategies by increasing the planned nitrogen application rate. Significant financial incentives would be required for farmers to achieve substantial reductions in nitrate loss by fertilizer management alone. The complicated interactions between fertilizer management and crop insurance decisions observed in the numerical study suggest that crop insurance programs can affect water quality by influencing the adoption of environmentally beneficial practices.

3.2. Introduction

Farm management is a complex process that is exposed to a wide range of risks and uncertainties. Each year, farmers make several management decisions with the goal to maximize net income, but their profits are also subject to weather and market conditions beyond their control. Planting time and fertilizer management are critical decisions that influence the farm yield. However, uncertain growing season precipitation and temperature can also significantly affect the yield, so that farmers cannot know the yield outcome of their decisions with certainty in advance. Furthermore, both planting and fertilizer application require suitable field moisture conditions, the lack of which may prevent execution of management decisions as planned. To mitigate economic risk, farmers may purchase crop insurance with benefits that depend on the uncertain yield and price at harvest time, as well as the specific terms of the plan purchased.

The interaction of farm management decisions and weather uncertainty also poses environmental risks. In the US Midwest, agriculture's impact on water quality is a major concern. Nitrogen (N) is one of the key nutrients needed in agricultural production. Ideally, crops can be fed with enough nutrients at the right time to ensure healthy plant growth. The soil naturally holds many nutrients, but if it lacks enough nutrients to match the required plant uptake, the farm's yield will suffer. Farmers commonly apply fertilizer to the soil to compensate for its nutrient deficiencies. Because N is water-soluble, it is easily washed away by water moving through agricultural drainage systems due to precipitation or irrigation. Nitrate-N loss from farmland causes nutrient loads in waterways and depletes the oxygen level in surface waters, a phenomenon known as hypoxia. Nitrate within the Mississippi River basin moves downstream and creates the Gulf of Mexico dead zone, one of the largest in the world at nearly 9,000 square miles (EPA, 2017). Although estimates differ, several studies agree that Iowa contributes a considerable amount (20-40%) of the nutrients in the Gulf compared to the eleven other states along the Mississippi River (Goolsby et al., 2000; Jones et al., 2018; Turner and Rabalais, 2004). In a major statewide study updated annually since 2012, Iowa State University et al. (2017) summarize ways to decrease N concentration in surface water and reveal that a 45% reduction in

N loss statewide is required to achieve environmental goals set by the Mississippi River/Gulf of Mexico Watershed Nutrient Task Force (2008). However, practices to reduce nutrient loss remain voluntary, with effects are subject to the same weather uncertainty that affects profit.

Uncertainty is therefore not only a serious concern for farmers, but is also an important consideration for policymakers and social planners with environmental concerns. In the US, several agricultural conservation policies and state regulations concern nutrient management. Those preventive measures aim to promote and incentivize nutrient reduction practices to improve water quality. According to the most recent (2018) U.S. Farm Bill, the budget allocated to the popular conservation programs will continue to increase gradually until 2023 (McMinimy, 2019). Farmer concerns about uncertainty and the resulting risk are also acknowledged in the legislation, as some of the income support direct payments are converted to insurance subsidies.

Policy makers commonly measure the potential effectiveness of a conservation program according to the types and amounts of payments required for farmers to adopt nutrient reduction practices that they otherwise would not (Claassen et al., 2014). However, determining additionality (i.e., whether a subsidy causes adoption of a practice) is not a simple task, as various risk perceptions and attitudes lead to different decisions under uncertainty. Income risk is one of the primary reasons for farmers' neglect of environmental practices (Bosch and Pease, 2000; Minnesota Pollution Control Agency, 2014; Marra et al., 2003; Greiner et al., 2009). In the agronomy literature, farmers' behavior has even prompted debate about farmer rationality (Arbuckle Jr et al., 2015; Howley et al., 2015). Farmers who do not adopt nutrient reduction practices argue that incentives do not cover the additional costs and effort required to follow those practices. Environmentalists commonly cite experimental tests to validate additional economic benefits. Those experiments are usually observed under specific weather and soil conditions and do not reflect how a small change in any component would impact the outcome. Even the studies that explicitly aim to investigate the uncertainties interpret the final results in terms of expected conditions only. Regardless, those studies fall short of representing underlying risks from the farmer's perspective. To develop effective policies and promote nutrient reduction practices, social planners must first understand optimal farm management decisions under uncertainty. Based on that understanding, it may be possible to judge the effectiveness of existing policies, such as whether the current incentive rates are enough to accomplish the social goals, or how policies can be improved. Although farmers may not necessarily follow the management decisions found to be optimal in a model, optimization results can provide some motivation for policies as well insights into farmer responses to those policies.

To explore the nitrate water pollution impacts of farm management under a profit maximization goal, this study focuses on corn production in Iowa. The production of corn, also known as maize, in the US has trended upward since the 1930s (USDA and NASS, 2020). Improved farm management strategies and technological advances that have boosted yield per acre (Shahhosseini et al., 2020) are the primary factors behind the long-term growth to meet the increasing global demand. Today, corn enjoys the highest demand of any grain product and represents more than 40% of all grain production worldwide (USDA, 2020). The US, as the world leader in corn production, meets more than 30% of the global corn demand, while the state of Iowa is the biggest corn supplier in the US. Although farmers have faced some struggles in recent years, agriculture is still a major contributor to Iowa's economy by accounting for around 20% of jobs.

We explore the uncertainty in corn production from a farmer's viewpoint. We investigate the major annual farm-level decisions, including planting time, fertilizer application rate and timing, and crop insurance purchase, to maximize the expected farm profit. The agricultural economics literature includes many investigations of the economic consequences of individual management decisions and their interactions with some uncertain elements, as described in Section 3.4.1. However, those studies are neither comprehensive nor concerned with optimization. Of the numerous articles on farming decisions from the operations research perspective (Moghaddam and DePuy, 2011; Capitanescu et al., 2017), none investigate the annual management decisions of a Midwest farmer growing a grain product under real-world uncertainties. To fill this gap, we propose a novel two-stage stochastic program for optimal annual farm management. The case study and numerical instances represent the state of Iowa but the model can be parameterized for any state in the US Midwest. Numerical solutions reveal useful information about a farmer's management behavior under uncertainty and provide valuable input to social planners concerned with environmental issues. We consider five major questions: (i) What are the optimal annual farming decisions under uncertainty? (ii) What financial incentives would be needed to achieve N reduction targets by fertilizer management alone? (iii) What are the expected profit tradeoffs for meeting various water quality goals through fertilizer management alone? (iv) What is the combined effect of fertilizer management and crop insurance decisions on farm profitability and water quality? (v) What types of information are needed to improve research on how to achieve environmental goals via management practices?

Our numerical results suggest that current N reduction targets for Iowa cannot be achieved by focusing only on N management practices, as Iowa has naturally high organic matter levels, which means that the potential for N losses is high even without any fertilizer application. We demonstrate that crop rotation improves the farmer's profit and reduces the necessary incentive rates to improve water quality. We are aware of only one recent study in the literature that considers insurance programs as a means to achieve environmental goals (Thorburn et al., 2020). However, uncertainty is one of the biggest concerns in agriculture, and insurance programs are the primary economic tools available to farmers to mitigate the resulting risk. Therefore, this paper explicitly explores the interaction between N management and crop insurance. We demonstrate that fertilizer management and insurance policy selection decisions are highly interrelated. Specifically, we observe that crop insurance has a complementary role in reducing the N application rate, with positive environmental impact. On the other hand, for very low N application rates, the availability of crop insurance reduces the motivation to adopt environmentally beneficial N application timing practices. The complicated and contradictory interactions display the need for more extensive investigations of insurance programs and their impact on environmental practices. Finally, our results indicate that N is a risk-reducing factor, in that the additional risk associated with a nutrient reduction practice may be mitigated by applying more fertilizer to the soil. However, the existing agronomy data representing the farm yield and N loss generated through field trials are not adequate to inform policy-making. Agronomic research currently emphasizes the investigation of individual elements (decisions, uncertainties, and other known factors) as independent entities while overlooking more complex interactions. A more extensive investigation into farmer decision-making under uncertainty requires more comprehensive information about interactions among these elements. The rest of the paper is organized as follows. In Section 3.3, we review the related studies in the literature. Section 3.4 contains a detailed problem description and a two-stage stochastic programming formulation. In Section 3.5, we specify the parameters used in the computational study and in Section 3.6, we present the numerical results. Finally, concluding remarks are provided in Section 3.7.

3.3. Literature Review

Optimization models of agricultural management have been formulated frequently. Singh (2012) provides a detailed survey. Those applications broadly include resource management, cropping pattern optimization, groundwater and irrigation management, and increasing production efficiency. Although some of them concern farm management, each study's content and methods vary widely due to the investigation of different crops, objectives, and assumptions. To the best of our knowledge, the existing literature does not investigate a US Midwest farmer's annual management decisions for growing a grain product under real-world uncertainties to the extent discussed in this paper. In this section, we describe the existing literature most similar to this paper.

Bloemhof-Ruwaard and Hendrix (1996) is one of the first papers to investigate the relationship between land management and fertilizer application to maximize farming profits. A bilinear model is formulated to make land management and fertilizer application decisions considering manure application limits imposed by the government to reduce negative environmental impacts. Li et al. (2017) build an integer program to investigate irrigation water allocation and seed selection decisions to maximize annual farm profit. Liu et al. (2008) optimize crop insurance decisions of a cotton and peanut farm in Florida under weather uncertainty to minimize the expected loss using a CVaR constraint. The study also includes crop allocation and binary planting decisions. Moghaddam and DePuy (2011) explore the stochastic nature of farming yield due to weather uncertainty on a hay farm. The study also includes environmental policies to improve water quality in the form of chance constraints. Hyytiäinen et al. (2011) include nitrogen balance equations in the soil in a stochastic dynamic program to compare split and spring fertilizer application under a pollution tax. The available N amount in the soil and crops is introduced as a state variable, while transition probabilities are obtained through simulation using weather data and fertilizer related decisions as input. The study suggests that split application performs better under the pollution tax while spring application is better without any taxation. Peña-Haro et al. (2011) investigate fertilizer application and irrigation rate decisions to maximize the agricultural profits without exceeding nitrate leaching standards. Functions for crop yield and nitrate leached are imported from an agro-simulation tool. Most recently, Capitanescu et al. (2017) investigate the crop allocation and rotation decisions over a multi-year planning horizon to maximize the farm profit based on environmental constraints generated according to the water-food-energy nexus.

In the agronomy literature, numerous studies look for optimal N application rates (Rware et al., 2016; Sexton et al., 1996; Yong et al., 2018). However, those studies rely on previous empirical tests to identify the best alternative among the limited number of experiments and do not seek optimality in the mathematical programming sense. Researchers commonly use popular crop simulation tools to estimate several outputs, including yield and N loss, and couple those simulation models with genetic algorithms to select management practices that increase profit and improve water quality simultaneously (Kaini et al., 2012; Srivastava et al., 2002; Geng et al., 2019). In recent years researchers have applied machine learning models to predict yield and N loss, acknowledging the limitation of experimental tests and simulation-based estimations (Chlingaryan et al., 2018; Puntel et al., 2016; Shahhosseini et al., 2019; Archontoulis et al., 2020).

However, those models have yet to be integrated with agricultural decision making in optimization models.

3.4. Model Definition

In this section, we formulate a stochastic mixed-integer mathematical program for the farmer's annual decision problem. Full nomenclature of the model is presented in Table 3.1.

3.4.1 Major Farming Decisions

We first introduce the major farming decisions investigated in this study. We discuss the importance of each decision and present a decision timeline illustrating the annual corn production calendar involving those decisions. The decisions involve fertilizer application rate, fertilizer timing, planting time, and finally, insurance plan selection.

3.4.1.1 Fertilizer Decisions

Nutrients are essential for agricultural production. In this study, we specifically focus on N and its underground movement as nitrate-N. Because crops cannot take in N directly from the air, having enough N in the soil is a necessity for healthy crop growth. In a soil network, some portion of N supply occurs through natural processes (mineralization and nitrification of soil organic matter) as nitrate-N. The remaining N supply can be provided through alternative sources, including synthetic fertilizers and manures, in which all forms of N will be transformed into nitrate-N as a result of nitrification (Randall and Mulla, 2001). Because nitrate-N easily moves with water, it is susceptible to leaching. The resulting loss causes N loads in waterways and negatively impacts the water quality by contributing to eutrophication (Iowa State University et al., 2017). Nitrate-N loss through drainage systems is highly dependent on precipitation rates and available nitrate-N amount in the soil (Lawlor et al., 2008).

Farmers apply fertilizer to the soil to replenish the missing N and prevent a potential yield loss. Each year, farmers face two critical fertilizer application decisions that will impact the

Table 3.1: Nomenclature for the model

Sets	
$\mathcal{I}$	Set of nitrate timing alternatives {1(fall), 2(spring), 3(split), 4(sidedress)} – indexed by i
$\mathcal{J}$	Set of planting time windows {1(optimal), 2(delayed)} – indexed by j
$\mathcal{S}$	Set of all future scenarios ($\{1, \ldots, S\}$) – indexed by s
$\mathcal{S}'$	Scenario group where soil conditions are not suitable for fieldwork in early spring which will delay planting time with spring and split application – indexed by s
$\mathcal{L}$	Number of piecewise functions generated based on yield and N Rate relation illustrated in Figure 3.3 ($\{1, \ldots, L\}$) – indexed by l
$\mathcal{V}$	Set of insurance coverage alternatives ($\{1, \ldots, V\}$) – indexed by v
B	Set of unfavorable outcomes of τ_1 that define $\mathcal{S}'$
Decision Variables	
x_i	Binary decision for nitrate timing alternative i Equal to 1 if timing alternative i is selected, otherwise equal to 0
z_j^s	Binary decision for a specific planting time j under scenario s Equal to 1 if planting window i is selected, otherwise equal to 0
t	N application rate (lbs/acre)
u_1	Impact of N application rate to yield (percent of maximum yield)
u_2^s	Impact of N application rate to yield for split applications (percent of maximum yield)
α_{ij}^s	Binary decision representing combination of fertilizer and planting timing decisions Equal to 1 if both x_i and z_j^s are also equal to 1 at the same time
y_{v1} and y_{v2}	Binary variable representing coverage level selection for insurance plans Equal to 1 if a coverage level v is chosen, otherwise equal to 0
σ_1^s and σ_2^s	Indemnity paid by insurance protection plans
w_{ij}^s	A continuous variable introduced for linearization purposes Equal to u_1 if α_{ij}^s is 1, otherwise equal to 0
$q_1^s, q_2^s, q_3^s, q_4^s$	Disjunctive variables used for big-M reformulation while formulating insurance options
π	Expected farm profit
Parameters	
g	Cost of N application ($/lbs)
p^s	Probability of scenario s
a_l, b_l	Constants of piecewise linear function l generated according with respect to Figure 3.3
c_{v1}	Insurance premium cost for yield protection plan for coverage option v ($/acre)
c_{v2}	Insurance premium cost for revenue protection plan for coverage option v ($/acre)
r_0	Projected corn price ($/bu)
H	Maximum achievable yield of the farm (bu/acre)
μ	Historical average yield of the farm (bu/acre)
f_v	Coverage rate for coverage option v
M	A sufficiently large number
β_{ij}^s	Fraction of maximum yield realized on scenario s based on combinations of decisions i, j
k_i^s	Portion of N being able to applied to soil during growing season in scenario s (%)
I^s	Scenario dependent binary parameter Equal to 1 if $\tau_1 \in B$ in scenario s, otherwise equal to 0
Random Variables	
ω	Uncertain precipitation level during crop growing season (inches)
γ	Uncertain temperature level during crop growing season (°F)
r^s	Uncertain crop price at the harvest time ($/bu)
τ_1	Days suitable for fieldwork during early spring for N application
τ_2	Days suitable for fieldwork during summer sidedressing

harvested crop yield and also have environmental consequences: (i) rate; i.e., the amount applied per unit of land area, and (ii) timing. The amount of N taken up by crops during the growing season varies according to the growth stage of the plant. Ideally, one needs to match the required N uptake at each stage by ensuring the N availability in the soil during the uptake timings to achieve maximum yield potential. Corn growth stages are defined as vegetative (V) stages and reproductive stages. The V stages are denoted by Vn, where n represents the number of visible leaf collars.

Most farmers traditionally prefer applying N to the soil either during the fall or in the spring before planting. Cao et al. (2018) surveys historical fertilizer application timing in US. The most recent data on N application timing for corn in US were collected in 2010. Of the Iowa respondents to this survey, 31% applied N in the fall, while more than 50% favored spring pre-plant application. Sidedressing strategies generally were not preferred by the farmers. Similarly, according to Bierman et al. (2012), the occurrence of fall, spring and sidedressing N application in Minnesota was 32.5%, 58.8%, and 8.7%, respectively, in 2009. The main concern with fall application is the unavailability of N in the soil in the spring and throughout the growing season. Some N loss is expected during the winter, with rate of this N loss depending on the winter precipitation. Spring application lowers the expected N loss because the duration of time between N application and uptake by the plant is significantly shorter. However, spring application poses another risk. If the soil is not suitable for fieldwork in the early spring pre-plant time due to high soil moisture, then it will not be possible to apply the fertilizer without avoiding planting delay. Such delay could reduce the maximum yield potential. A third alternative, sidedressing, became popular in the last couple of decades as a result of nutrient reduction efforts. This alternative involves the application of some portion of N during the pre-planting window and applying the rest by sidedressing after planting during the summer, commonly within the V6-V8 growth stages of corn, with the idea of feeding N at the right time to reduce nitrogen loss to the environment and achieve a higher yield outcome (Nleya et al., 2016). The V6-V8 growth stages are expected to occur around June, depending on planting time, and each stage lasts two to three weeks. In this study, we investigate two sidedressing strategies: (i) split (40% pre-plant and 60% summer sidedress), and (ii) full summer sidedress. Sidedressing risks, however, may be even higher than those of spring application. First, a split application still could cause a planting delay due to the spring feed of the first portion of N. Second, if the soil is not suitable for fieldwork during the summer feed of the second portion of N by sidedress, there will be no choice but to apply less fertilizer to the soil than what was intended. Therefore, nitrate management is a complex process in which fertilizer rate and application timing decisions not only play a crucial role in the farmers' profitability but also have a notable impact on nitrate loss.

In the remainder of this paper, we denote the fertilizer application rate decision by a continuous decision variable, t, and fertilizer timing decisions by binary variables x_i where $i \in \mathcal{I} = \{1(\text{fall}), 2(\text{spring}), 3(\text{split}), 4(\text{full summer sidedress})\}$.

3.4.1.2 Planting Time

Planting can start when the soil is warm enough, not too wet, and not too dry. Those conditions are necessary for planting and other field operations, but there are also other considerations. The main goal when selecting planting time is to ensure that the time between planting and the end of the growing season is long enough so that crops can mature enough before harvesting (Elmore, 2013). For example, in colder climates, corn is expected to mature more slowly and harvest must occur earlier. Previous research investigates the impact of planting time on yield at different locations (Baum et al., 2020; Abendroth et al., 2017). For most locations, optimal planting windows (the period between first and last date to plant to obtain maximum yield) have been identified. In Iowa they can range between early April and mid-May, depending on the region. If farmers cannot plant during their specific location's planting window due to some delay, the crop will not reach its maximum yield potential. Fertilizer applications other than sidedressing can cause such delays in planting because they require similar soil conditions as planting and other field operations, and must be completed before planting operations start.

To represent planting time, we denote decisions by binary variables, z_j, where $j = 1$ represents the optimal planting window recommended by agronomists while $j = 2$ corresponds to a planting delay.

3.4.1.3 Crop Insurance Plan Selection

Uncertainties, including weather and thereby yield, market prices, and policies, significantly affect the farm income. Crop insurance is popular among farmers because it potentially reduces their risk exposure (Antón et al., 2013; Moschini and Hennessy, 2001). Farmers can purchase the insurance policies subsidized by the federal government for protection against a potential crop loss due to unexpected weather conditions and/or revenue loss due to unexpected price changes. Producers can pay the premium for their selected policy to receive an indemnity payment for covered loss.

We consider two common crop insurance plans, yield protection and revenue protection, and denote those choices by binary variables, y_{v1} and y_{v2}, respectively, where $v \in \mathcal{V}$ indicates the selected coverage level. Detailed explanation about the insurance plans is provided in Section 3.4.4.1.

3.4.1.4 Timeline

Figure 3.1 shows the timeline of the farmer's decisions investigated in this study. Commonly, after the harvesting in the fall, a farmer must finalize fertilizer rate and application timing decisions without full information on random weather events and crop harvest prices. It is logical to expect that, if the farmer prefers a fall application, they can revisit the fertilizer decisions made during fall and modify them in springtime based on observed fall and winter precipitation. That is, the farmer can opt to apply fertilizer again in spring and/or in summer considering the N loss between fall and spring. To the best of our knowledge, however, there are no empirical studies in the literature that quantify the unique impact of fall precipitation on either N loss or yield. Therefore, in this study, we ignore the potential alteration of fertilizer decisions made in fall because of this lack of data.

Just before spring begins, March 15 is the deadline for all insurance plan purchases for corn in the US. The length of optimal planting windows is expected to be no less than three weeks (Elmore, 2012). This length can be longer depending on the unique climate and weather conditions. If fall fertilizer application is selected ($x_1 = 1$), planting operations can start as soon as the soil becomes suitable for fieldwork. As with most field operations, the length of planting time depends on several factors such as total acres to be covered, implement width and speed, or daily working hours (Edwards, 2015). However, planting time traditionally is not considered as a time-consuming process that could force a planting delay on its own (Irwin and Hubbs, 2018). Therefore, because in this model we only consider planting and fertilizing farming operations, we assume fall fertilizer application will not cause any potential delay in planting.

Because spring and split applications occur just before planting, those management decisions can delay planting depending on weather conditions (Scharf et al., 2002). For this reason, the soil's suitability for fieldwork in the first two weeks of April is important. We denote the total number of days suitable for fieldwork in early spring by τ_1 and represent its set of values unfavorable for timely planting by B.

Since farmers cannot know the weather conditions before making the fertilizer timing decisions, they take a risk of planting delay and resulting loss of yield by choosing spring or split applications in exchange for a potentially lower N loss, which can help to increase the yield and reduce the N cost (Randall et al., 2008; Gramig et al., 2017; Sawyer et al., 2016). Likewise, if split application is chosen, the remaining fertilizer application is planned to be completed in summer. This implies a second time window in which the soil is required to be dry enough for fieldwork. Unlike with early spring applications, if summer fertilizer sidedressing cannot be completed during the V6-V8 stages window, the uncompleted portion of the fertilizer will be missing (Gramig et al., 2017). Finally, uncertain precipitation and temperature during the growing season, from planting time in early spring until harvesting time in fall, as well as crop price at harvest, affect the farmer's harvest time revenue.

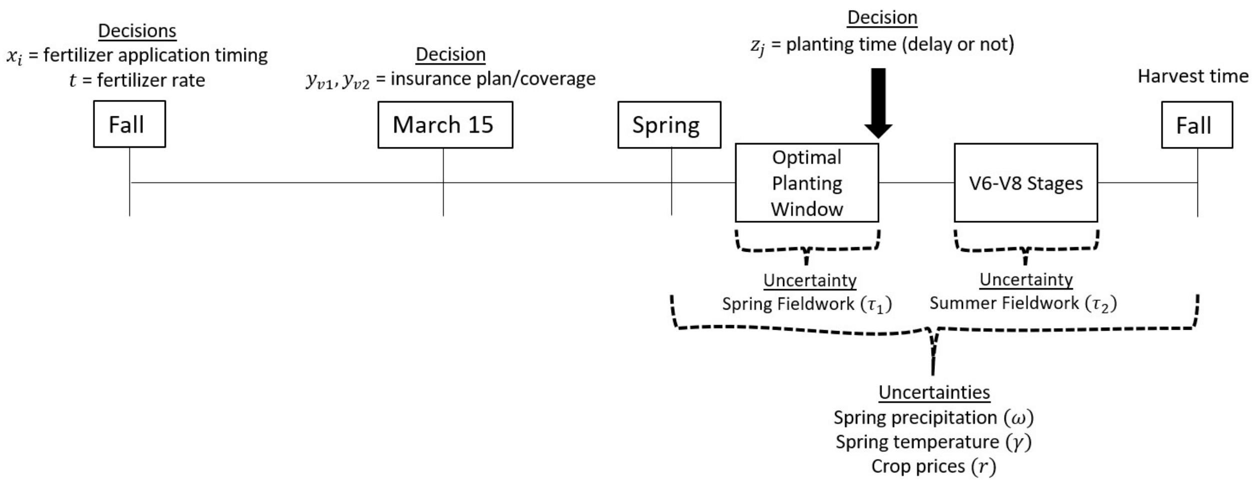


Figure 3.1: Farmer's decision model timeline

3.4.2 Available Information and Assumptions

Crop yield depends on several factors, including farm management decisions, weather conditions, and soil properties. Agronomists investigate their impact on crop yield through exhaustive analysis and empirical tests over various sites and conditions (Iowa State University, 2020; Randall and Mulla, 2001; Randall et al., 2008; Sawyer et al., 2016). However, it is highly challenging to observe all those conditions simultaneously and investigate complicated interactions. Thus, the literature largely consists of empirical studies investigating the impact of those factors disjointly by analyzing only one or two selected factors at a time. Accordingly, despite the interactions in the effects of farmer decisions and weather uncertainties on yield, we collect our data from distinct studies and treat their impact on yield as mutually independent. An alternative approach would be to estimate yield and N loss simultaneously through either numerical crop simulation tools (Archontoulis et al., 2020; Stockle et al., 1994) or machine learning approaches (Chlingaryan et al., 2018; Shahhosseini et al., 2019).

3.4.2.1 The Impact of N Application Rate on Yield

The online Corn Nitrogen Rate Calculator tool provides reliable information showing the impact of N rate on yield based on research trials (Sawyer et al., 2020). The tool generates data points indicating the percent of maximum yield given different N application rates for six midwestern states (Illinois, Iowa, Michigan, Minnesota, Ohio, and Wisconsin). Generated data points for Iowa, with integer-valued N application rates between 0 and 240 lbs/acre, are illustrated in Figure 3.3. Note that the N rate achieving 100% of the maximum yield is not necessarily the best selection for a farmer because maximum return to N (MRTN), the N rate where the economic net return to N application is maximized, can be different when fertilizer prices are taken into account (Sawyer et al., 2006). The tool currently does not elaborate on how precipitation affects the relationship between N rate and yield. Previous experiments demonstrate the need for N rate at higher than MRTN, yet current research is not reliable enough to indicate how much additional N would be needed (Sawyer, 2019). To preserve the linearity of the optimization model, we generate piecewise linear functions to approximate the data points displayed in Figure 3.3.

3.4.2.2 The Impact of Planting and N Application Time Decisions on Yield

Optimal planting windows differ based on geographical region. Previous research includes elaborate experimental tests investigating how different time windows affect yields (Abendroth et al., 2017; Kucharik, 2008). Depending on the region, one can categorize planting windows based on their yield outcomes. Similarly, various studies examine the impact of N application timing on yield (Sawyer et al., 2016; Randall et al., 2008; Randall and Mulla, 2001). Using the information available in the literature, we define $\beta_{ij}(\omega, \gamma)$, as a fraction of maximum yield, to indicate the combined impact of the decisions, where i represents one of the N application timings considered in this study and j denotes the planting window. Harvested crop yield depends not only on those decisions but also on uncertain weather conditions. The random variables, ω and γ, symbolize the observed average growing season precipitation and temperature, respectively. We assume that fall fertilizer application is the default selection, and $\beta_{1,1}(\omega, \gamma) = 1$ under ideal weather conditions.

The cost of specialized equipment needed for sidedressing application is not considered in this study.

3.4.2.3 The Impact of Precipitation and Temperature on Yield

Weather conditions influence both yield and hydrological processes, including N loss, by surface runoff and leaching. The weather effect on yield and N loss can be investigated under two time phases. The first phase goes from fall harvesting time until spring and the second spans spring until the next harvest.

In the literature, the fall fertilizer application is generally expected to result in lower yield and higher N loss compared to other applications. That is because additional N added to the soil during fall increases the chance of leaching, as no plant N uptake occurs until springtime. Experimental results support such claims and, as discussed in Section 3.4.2.2, we already take into account this particular yield impact through the parameter $\beta_{ij}(\omega, \gamma)$. This leaching rate, however, depends on fall precipitation. In reality, if the fall precipitation is significantly low in a given year, similar yield and N rates are expected from both fall and spring applications (and vice versa, high fall precipitation or mild winter can spike the N loss significantly during fall). Unfortunately, the experimental tests collected from the literature to calculate $\beta_{ij}(\omega, \gamma)$ do not include this inherent uncertainty. As a result, we lack enough information to calculate the impact of fall precipitation on N leaching and yield, and the fall precipitation uncertainty is not considered in this study.

Growing season weather uncertainty, on the other hand, is considered. In the literature, various studies examine the effect of precipitation and temperature during the growing season on yield (Li et al., 2019; Yamoah et al., 2000; Xu et al., 2016), and we account for the impact of those uncertainties multiplicatively, as they are independent of the investigated decisions.

3.4.3 Deterministic Model

If the weather during the growing season and crop price at harvest time were known, a farmer could optimize management decisions according to the model below. Because there is no risk exposure, insurance is unnecessary.

We denote the crop yield by $A(x, z, t)$, where x and z are binary vectors while t is a continuous variable. Denoting a maximum achievable crop yield of a single farm by H, the yield can be calculated as follows:

$$A(x, z, t) = H \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}} \beta_{ij}(\omega, \gamma)\alpha_{ij} u(t) \tag{3.1}$$

$$x_i + z_j \geq 2\alpha_{ij} \qquad \forall i \in \mathcal{I}, j \in \mathcal{J} \tag{3.2}$$

where $u(t)$ is the percent of maximum yield given fertilizer application rate t (Section 3.4.2.1), and α_{ij} is another binary variable that equals 1 if and only if $x_i = z_j = 1$. Note that Equation (3.1) is a bilinear expression where α_{ij} is binary and t is continuous. Because the objective is to maximize the yield and revenue, we can linearize this expression by replacing $\alpha_{ij} u(t)$ with a continuous decision variable w_{ij} and appending Constraints (3.3) and (3.4):

$$u(t) - (1 - \alpha_{ij}) \leq w_{ij} \leq \alpha_{ij} \qquad \forall i \in \mathcal{I}, j \in \mathcal{J} \tag{3.3}$$

$$w_{ij} \leq u(t) \qquad \forall i \in \mathcal{I}, j \in \mathcal{J} \tag{3.4}$$

The right hand inequality of Constraint (3.3) ensures w_{ij} will equal 0 if α_{ij} is 0. Equation (3.4) and left hand inequality of Equation (3.3) together force w_{ij} to equal $u(t)$ if α_{ij} equals 1.

Recall that a split application or a full summer N sidedress may prevent the farmer from applying all of the intended fertilizer, depending on suitability of soil conditions for fieldwork. For that reason, we define decision variables u_1 and u_{2i} to replace $u(t)$, where u_1 denotes the percent of maximum yield obtained for fall and spring N applications, and u_{2i} indicates the percent of maximum yield achieved with split and full summer sidedress applications.

The farmer's deterministic mixed-integer program solved in fall, assuming full knowledge of growing season precipitation and temperature, corn harvest price and fieldwork suitability both in early spring and summer, is:

$$\text{Max (\$/acre)} \quad -gt + rH \sum_{i\in\mathcal{I}} \sum_{j\in\mathcal{J}} \beta_{ij}(\omega,\gamma) w_{ij} \tag{3.5a}$$

s.t.

$$\sum_{i\in\mathcal{I}} x_i = 1 \tag{3.5b}$$

$$\sum_{j\in\mathcal{J}} z_j = 1 \tag{3.5c}$$

$$x_i + z_1 \leq 2 - I\{\tau_1 \in B\} \qquad \forall i \in \{2,3\} \tag{3.5d}$$

$$x_i + z_j \geq 2\alpha_{ij} \qquad \forall i \in \mathcal{I}, j \in \mathcal{J} \tag{3.5e}$$

$$\sum_{i\in\mathcal{I}} \sum_{j\in\mathcal{J}} \alpha_{ij} = 1 \tag{3.5f}$$

$$u_1 \leq a_l + b_l t \qquad \forall l \in \mathcal{L} \tag{3.5g}$$

$$u_{2i} \leq a_l + b_l k_i(\tau_2) t \qquad \forall i \in \{3,4\}, l \in \mathcal{L} \tag{3.5h}$$

$$u_1 - (1-\alpha_{ij}) \leq w_{ij} \leq \alpha_{ij} \qquad \forall i \in \{1,2\}, j \in \mathcal{J} \tag{3.5i}$$

$$w_{ij} \leq u_1 \qquad \forall i \in \{1,2\}, j \in \mathcal{J} \tag{3.5j}$$

$$u_{2i} - (1-\alpha_{ij}) \leq w_{ij} \leq \alpha_{ij} \qquad \forall i \in \{3,4\}, j \in \mathcal{J} \tag{3.5k}$$

$$w_{ij} \leq u_{2i} \qquad \forall i \in \{3,4\}, j \in \mathcal{J} \tag{3.5l}$$

$$0 \leq t \leq t_{max} \tag{3.5m}$$

$$x_i, z_j, \alpha_{ij} \in \{0,1\} \qquad \forall i \in \mathcal{I}, j \in \mathcal{J} \tag{3.5n}$$

$$u_1, w_{ij} \geq 0 \qquad \forall i \in \mathcal{I}, j \in \mathcal{J} \tag{3.5o}$$

$$u_{2i} \geq 0 \qquad \forall i \in \{3,4\} \tag{3.5p}$$

The first term in the objective function (3.5a) represents the cost of using fertilizer rate t. The second term is the revenue obtained from selling harvested crop. Note that other costs of farming operations are excluded, under the assumption that they will not be affected by these management decisions. Constraints (3.5b)-(3.5f) involve fertilizer application timing, planting timing and their interactions. Equations (3.5b) and (3.5c), respectively, ensure that only one of the fertilizer timing and planting windows is selected. Recall that if spring or split application is selected and the soil is not suitable for fieldwork in early spring, the farmer must delay the planting operation. Constraint (3.5d) enforces this logic. The set of unfavorable τ_1 values which will delay the planting operation is denoted by B. The binary parameter $I\{\tau_1 \in B\}$ equals 1 if $\tau_1 \in B$, and 0 otherwise. Equation (3.5e) guarantees α_{ij} equals 1 if both fertilizer application time $x_i = 1$ and planting time $z_j = 1$. Equation (3.5f) ensures only a single $\alpha_{ij} = 1$. To approximate the percent of maximum yield given a fertilizer rate t, we substitute piecewise linear functions for the data points shown in Figure 3.3. Equation (3.5g) defines the piecewise linear functions used to estimate the concave relationship between N rate and percent of maximum yield while Equation (3.5h) additionally takes into account the possibility of not being able apply all of the planned N with sidedress applications. The parameter $k_i(\tau_2)$ is the portion of N applied to soil calculated based on total workdays available for fieldwork during V6-V8 stages. This portion may be different for split and full summer sidedress applications. Therefore, the calculation of u_{2i} involves how much N is actually able to be applied to the soil for a given weather condition. Constraints (3.5i) to (3.5l) are used to linearize the bilinear terms. Equation (3.5m) defines the bounds for N application rate and the remaining constraints are the sign and binary restrictions on the decision variables.

Note that before introducing w_{ij} and constraints (3.5i) - (3.5l), the objective function would have bilinear terms $\alpha_{ij}u_1$, and $\alpha_{ij}u_{2i}$, while all constraints are linear expressions. A branch-and-cut solution procedure would create subproblems by fixing discrete variables to binary values. With all α_{ij} fixed to 0 or 1, the objective function would be linear. Then, if the fertilizer timing decision is $x_1 = 1$ or $x_2 = 1$, an optimal solution exists at one of the breakpoints for u_1 as a function of t. However, if $x_3 = 1$ or $x_4 = 1$ and the corresponding value of $k_i(\tau_1) < 1$, then a breakpoint combination of t and respective u_{2i} may not be optimal. However, restricting attention to breakpoint values of t proves to be a useful heuristic, as illustrated in Section 3.6.2.

3.4.4 Stochastic Program

The farm management decisions and growing season weather together determine the crop yield. Because farmers make fertilizer management decisions without full information on random weather events, the crop yield is the major uncertain element in this study. To summarize the connections between management decisions and uncertainties:

- Growing season average precipitation and temperature directly impact yield.
- The lack of enough days suitable for fieldwork during early spring causes planting delay if the spring or split fertilizer application decision was made during fall.
- The farmer will not be able to apply some portion of planned summer sidedress if there are not enough days suitable for fieldwork during summer.
- Crop yield uncertainty (depending on growing season weather), and harvest-time crop price uncertainty significantly affect the farmer's profit (generated by the combination of crop sale revenue and crop insurance).

Therefore, the average growing season precipitation, ω, the average growing season temperature, γ, the corn harvest price, r, the number of suitable workdays in early spring, τ_1, and the number of suitable workdays in summer during the V6-V8 stages of the crop growth, τ_2, are the uncertain elements in our model.

In the deterministic model, the crop yield is calculated using Equation (3.1). Note that $\beta_{ij}(\omega, \gamma)$ is the only parameter in that equation, and the first uncertain parameter of the stochastic program. The second uncertain parameter is the corn price, r, at harvest time. The third uncertain parameter used in model (3.5) is $I\{\tau_1 \in B\}$, an indicator takes the value of 1 if $\tau_1 \in B$, causing a planting delay. Finally, the fourth and fifth uncertain parameters are $k_2(\tau_2)$ and $k_3(\tau_2)$. Those parameters represent the portion of N that can be applied to soil the during the growing season, and depend on uncertain element τ_2.

We structure a two-stage stochastic program by splitting the farmer's timeline into two periods, (i) from fall until spring, and (ii) from spring until harvest time in fall. Figure 3.2 depicts the decisions and recourse actions at each stage. The first stage involves fertilizer application timing, fertilizer rate and insurance planning decisions. Because the optimal planting windows are already identified, the planting time is a simple recourse action in the second stage after the realization of whether or not a planting delay occurs. After all uncertainties are realized, the resulting yield and revenue are observed.

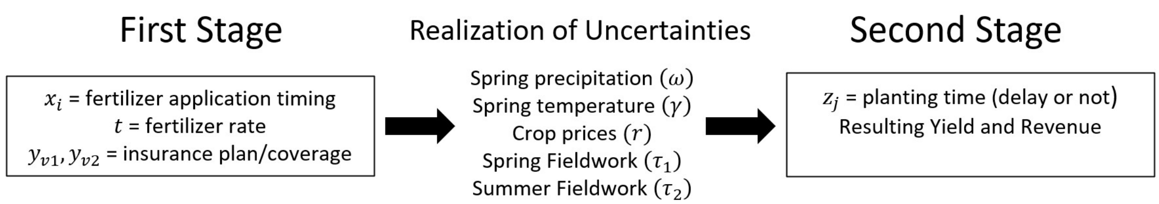


Figure 3.2: Staged Representation of Farmer's Problem

Assuming we have a finite number of realizations for each of the random variables $(\omega, \gamma, r, \tau_1, \tau_2)$, we can define the scenario set $\mathcal{S} = \{1, \ldots, S\}$ that consists of scenarios s, each of which represents a particular combination of realizations. As a result, we rewrite the parameters $\beta_{ij}(\omega, \gamma, \tau_1)$, r, $I\{\tau_1 \in B\}$, and $k_i(\tau_2)$ as β_{ij}^s, r^s, I^s, and k_i^s respectively.

3.4.4.1 Modeling Insurance

We consider the two most common crop insurance plans: (i) yield protection, and (ii) revenue protection. Each alternative has options in the set $\mathcal{V} = \{1, 2, ..., 8\}$ corresponding to coverage levels $\{50\%, 55\%, ..., 85\%\}$, respectively. The premium rates for each plan and coverage level depend on several factors including the producer's county, their historical 10-year average yield, the yield trend, and the size of the farm (acres).

The yield protection plan offers a production based guarantee. The indemnity payment of this option, denoted by σ_1, is calculated as:

$$\sigma_1 = \max\Big(\mu f_v r_0 - r_0 A, \quad 0\Big) \tag{3.6}$$

where r_0 is the projected corn price, f_v is the coverage percentage, μ is the actual production history (average yield) for the farm, and A is the actual yield realized at harvest.

The revenue protection plan offers a revenue guarantee, and also takes harvest price uncertainty into account. The indemnity payment of this plan, denoted by σ_2, is calculated as:

$$\sigma_2 = \max\Big(\mu f_v r_0 - rA, \quad \mu f_v r - rA, \quad 0\Big) \tag{3.7}$$

where r is the uncertain actual harvest price.

We define the binary decision variables, y_{v1} and y_{v2}, for the yield protection and revenue protection plan, respectively, to indicate which coverage level, $v \in \mathcal{V}$, is selected by the farmer. A two-stage insurance benefit model is formulated as follows:

$$\text{Max (\$/acre)} \quad -\sum_{v\in\mathcal{V}} \Big(c_{v1}y_{v1} + c_{v2}y_{v2}\Big) + \sum_{s\in\mathcal{S}} p^s\Big(\sigma_1^s + \sigma_2^s\Big) \tag{3.8a}$$

s.t.

$$\sigma_1^s \geq \sum_v \mu f_v r_0 y_{v1} - r_0 A^s \qquad \forall s \in \mathcal{S} \tag{3.8b}$$

$$\sigma_1^s \leq \sum_v \mu f_v r_0 y_{v1} - r_0 A^s + M q_1^s \qquad \forall s \in \mathcal{S} \tag{3.8c}$$

$$\sigma_1^s \leq M(1 - q_1^s) \qquad \forall s \in \mathcal{S} \tag{3.8d}$$

$$\sigma_2^s \geq \sum_v \mu f_v r_0 y_{v2} - r^s A^s \qquad \forall s \in \mathcal{S} \tag{3.8e}$$

$$\sigma_2^s \leq \sum_v \mu f_v r_0 y_{v2} - r^s A^s + M q_2^s \qquad \forall s \in \mathcal{S} \tag{3.8f}$$

$$\sigma_2^s \geq \sum_v \mu f_v r^s y_{v2} - r^s A^s \qquad \forall s \in \mathcal{S} \tag{3.8g}$$

$$\sigma_2^s \leq \sum_v \mu f_v r^s y_{v2} - r^s A^s + M q_3^s \qquad \forall s \in \mathcal{S} \tag{3.8h}$$

$$\sigma_2^s \leq M q_4^s \qquad \forall s \in \mathcal{S} \tag{3.8i}$$

$$q_2^s + q_3^s + q_4^s = 2 \qquad \forall s \in \mathcal{S} \tag{3.8j}$$

$$\sigma_1^s, \sigma_2^s \geq 0 \qquad \forall s \in \mathcal{S} \tag{3.8k}$$

$$\sum_v \Big(y_{v1} + y_{v2}\Big) \leq 1 \tag{3.8l}$$

$$y_{v1}, y_{v2} \in \{0,1\} \qquad \forall v \in \mathcal{V} \qquad (3.8m)$$

$$q_1^s, q_2^s, q_3^s, q_4^s \in \{0,1\} \qquad \forall s \in \mathcal{S} \qquad (3.8n)$$

The parameter c_{v1} is the insurance premium for the yield protection plan, while c_{v2} denotes the insurance premium of the revenue protection plan, with coverage level v. Accordingly, the first two terms in the objective function represent the cost of the insurance alternative selected. The third and fourth terms of the objective are the expected indemnity payments for the yield and revenue protection plan, respectively. The random crop yield harvested at the end of growing season is denoted by A^s while r^s is the random crop selling price. To calculate the yield protection plan indemnity, σ_1, we introduce a new binary disjunctive variable q_1^s, and disjunctive constraints (3.8b)-(3.8d) by using a big-M reformulation. Similarly disjunctive variables, q_2^s, q_3^s, and q_4^s, and constraints (3.8e)-(3.8j) are introduced to calculate the revenue protection plan indemnity. The role of the disjunctive variables and constraints (3.8b)-(3.8d) can be explained as follows:

1. If $q_1^s = 0$, the yield protection plan is purchased for some v $\left(\sum_v y_{v1} = 1\right)$ and the first term of (3.6) is greater than zero $\left(\text{i.e., } \sum_v \mu f_v r_0 y_{v1} - r_0 A^s > 0 \text{ for some } s\right)$. That means the farmer will receive some indemnity payment. Note that when $\sum_v \mu f_v r_0 y_{v1} - r_0 A^s > 0$ for some s, q_1^s cannot be equal to 1, because constraints (3.8b) and (3.8d) will conflict. Constraint (3.8c) ensures that the insurance model is not unbounded by ensuring that the indemnity payment equals $\sum_v \mu f_v r_0 y_{v1} - r_0 A^s$.

2. If $q_1^s = 1$, this could indicate that either

   (a) The farmer did not purchase the yield protection plan, or

   (b) The farmer purchased yield protection insurance for some v $\left(\sum_v y_{v1} = 1\right)$; however, the first term in equation (3.6) is less than zero $\left(\text{i.e., } \sum_v \mu f_v r_0 y_{v1} - r_0 A^s < 0 \text{ for some } s\right)$.

   In either case, $\sum_v \mu f_v r_0 y_{v1} - r_0 A^s < 0$. Therefore, q_1^s cannot equal 0, because constraint (3.8c) could not be satisfied.

3. Note that if $\sum_v \mu f_v r_0 y_{v1} - r_0 A^s = 0$ for some s $\Big($which can only happen if $\sum_v y_{v1} = 1\Big)$, q_1^s could take either value of 0 or 1 without any impact on the solution.

Similarly, binary disjunctive variables q_2^s, q_3^s, q_4^s and constraints (3.8e)-(3.8j) are introduced to calculate revenue protection plan indemnity, σ_2, with respect to Equation (3.7). The logic of those variables and constraints are summarized as follows:

1. If $q_2^s = 0, q_3^s = 1,$ and $q_4^s = 1$, the revenue protection plan is purchased for some v, and the first term in equation (3.7) is the largest $\Big($i.e., $\sum_v \mu f_v r_0 y_{v2} - r^s A^s$ is larger than the other two terms for this $s\Big)$. Note that when $\sum_v \mu f_v r_0 y_{v2} - r^s A^s$ is the largest term, q_3^s must be 1 to satisfy constraint (3.8h), and q_4^s must be 1 to satisfy constraint (3.8i). Since constraint (3.8j) enforces the model to allow only one of q_2^s, q_3^s, q_4^s to be 0 for each s, q_2^s must equal 0 to so that constraint (3.8f) prevents the model from being unbounded.

2. If $q_3^s = 0, q_2^s = 1,$ and $q_4^s = 1$, the revenue protection plan is purchased for some v, and the second term in equation (3.7) is largest $\Big($i.e, $\sum_v \mu f_v r^s y_{v2} - r^s A^s$ is the maximum for this $s\Big)$. This logic is similar to that described in item 1.

3. If $q_4^s = 0, q_2^s = 1,$ and $q_3^s = 1$, then either

   (a) The revenue protection plan is purchased for some v, and third term in equation (3.7) is the largest (i.e., the other two terms are negative; the logic is similar to that described in item 1), or

   (b) The revenue protection plan is not purchased. In that case, both the first and second terms of equation (3.7) are negative. To satisfy constraints (3.8f) and (3.8h), both q_2^s and q_3^s must equal 1. Constraint (3.8j) then forces q_4^s to equal 0.

Constraint (3.8k) ensures that the insurance indemnities are nonnegative, while constraint (3.8l) ensures that only one insurance plan is selected. Finally, constraints (3.8m) and (3.8n) are binary restrictions.

3.4.4.2 Two-Stage Stochastic Program for the Full Problem

The insurance model described in the previous section does not include the impact of fertilizer management or planting time on the actual yield realized at harvest. In this section, we combine all decisions presented in Figure 3.2, and build a two-stage stochastic programming model of the farmer's annual overall decision problem. Model (3.9) combines all constraints presented in sections 3.4.3 and 3.4.4.1. When calculating indemnities for both insurance plans, we replace the observed actual yield A^s mentioned in section 3.4.4.1 with $A^s(x,z,t) = H \sum\limits_{i\in\mathcal{I}} \sum\limits_{j\in\mathcal{J}} \beta_{ij}^s w_{ij}^s$.

$$\text{Max (\$/acre)} \qquad \pi = -gt - \sum_{v\in\mathcal{V}} \Big(c_{v1}y_{v1} + c_{v2}y_{v2}\Big) + \sum_{s\in\mathcal{S}} p^s \Big[Hr^s \sum_{i\in\mathcal{I}} \sum_{j\in\mathcal{J}} \beta_{ij}^s w_{ij}^s + \sigma_1^s + \sigma_2^s\Big] \tag{3.9a}$$

s.t.

$$t \leq t_{max} \tag{3.9b}$$

$$\sum_{i\in\mathcal{I}} x_i = 1 \tag{3.9c}$$

$$\sum_{v} \Big(y_{v1} + y_{v2}\Big) \leq 1 \tag{3.9d}$$

$$u_1 - b_l t \leq a_l \qquad \forall l \in \mathcal{L} \tag{3.9e}$$

$$u_{2i}^s - b_l k_i^s t \leq a_l \qquad \forall i \in \{3,4\}, l \in \mathcal{L}, s \in \mathcal{S} \tag{3.9f}$$

$$\sum_{j\in\mathcal{J}} z_j^s = 1 \qquad \forall s \in \mathcal{S} \tag{3.9g}$$

$$x_i + z_1^s + \leq 2 - I^s \qquad \forall s \in \mathcal{S}', i \in \{2,3\} \tag{3.9h}$$

$$x_i + z_j^s - 2\alpha_{ij}^s \geq 0 \qquad \forall i \in \mathcal{I}, j \in \mathcal{J}, s \in \mathcal{S} \tag{3.9i}$$

$$\sum_{i\in\mathcal{I}} \sum_{j\in\mathcal{J}} \alpha_{ij}^s = 1 \qquad \forall s \in \mathcal{S} \tag{3.9j}$$

$$u_1 - (1 - \alpha_{ij}^s) \leq w_{ij}^s \leq \alpha_{ij}^s \qquad \forall i \in \{1,2\}, j \in \mathcal{J}, s \in \mathcal{S} \tag{3.9k}$$

$$w_{ij}^s - u_1 \leq 0 \qquad \forall i \in \{1,2\}, j \in \mathcal{J}, s \in \mathcal{S} \tag{3.9l}$$

$$u_{2i}^s - (1 - \alpha_{ij}^s) \leq w_{ij}^s \leq \alpha_{ij}^s \qquad \forall i \in \{3,4\}, j \in \mathcal{J}, s \in \mathcal{S} \tag{3.9m}$$

$$w_{ij}^s - u_{2i}^s \leq 0 \qquad \forall i \in \{3,4\}, j \in \mathcal{J}, s \in \mathcal{S} \tag{3.9n}$$

$$\sigma_1^s - \mu r_0 \sum_v f_v y_{v1} + H r_0 \sum_{i\in\mathcal{I}} \sum_{j\in\mathcal{J}} \beta_{ij}^s w_{ij}^s \geq 0 \qquad \forall s \in \mathcal{S} \tag{3.9o}$$

$$\sigma_1^s - \mu r_0 \sum_v f_v y_{v1} + H r_0 \sum_{i\in\mathcal{I}} \sum_{j\in\mathcal{J}} \beta_{ij}^s w_{ij}^s - M q_1^s \leq 0 \quad \forall s \in \mathcal{S} \tag{3.9p}$$

$$\sigma_1^s - M(1 - q_1^s) \leq 0 \qquad \forall s \in \mathcal{S} \tag{3.9q}$$

$$\sigma_2^s - \mu r_0 \sum_v f_v y_{v2} + H r^s \sum_{i\in\mathcal{I}} \sum_{j\in\mathcal{J}} \beta_{ij}^s w_{ij}^s \geq 0 \qquad \forall s \in \mathcal{S} \tag{3.9r}$$

$$\sigma_2^s - \mu r_0 \sum_v f_v y_{v2} + H r^s \sum_{i\in\mathcal{I}} \sum_{j\in\mathcal{J}} \beta_{ij}^s w_{ij}^s - M q_2^s \leq 0 \quad \forall s \in \mathcal{S} \tag{3.9s}$$

$$\sigma_2^s - \mu r^s \sum_v f_v y_{v2} + H r^s \sum_{i\in\mathcal{I}} \sum_{j\in\mathcal{J}} \beta_{ij}^s w_{ij}^s \geq 0 \qquad \forall s \in \mathcal{S} \tag{3.9t}$$

$$\sigma_2^s - \mu r^s \sum_v f_v y_{v2} + H r^s \sum_{i\in\mathcal{I}} \sum_{j\in\mathcal{J}} \beta_{ij}^s w_{ij}^s - M q_3^s \leq 0 \quad \forall s \in \mathcal{S} \tag{3.9u}$$

$$\sigma_2^s - M q_4^s \leq 0 \qquad \forall s \in \mathcal{S} \tag{3.9v}$$

$$q_2^s + q_3^s + q_4^s = 2 \qquad \forall s \in \mathcal{S} \tag{3.9w}$$

$$t \geq 0, u_1 \geq 0 \tag{3.9x}$$

$$x_i, y_{v1}, y_{v2} \in \{0, 1\} \qquad \forall i \in \mathcal{I}, v \in \mathcal{V} \tag{3.9y}$$

$$u_{2i}^s \geq 0 \qquad \forall i \in \{3, 4\}, s \in \mathcal{S} \tag{3.9z}$$

$$w_{ij}^s, \sigma_1^s, \sigma_2^s \geq 0 \qquad \forall i \in \mathcal{I}, j \in \mathcal{J}, s \in \mathcal{S} \tag{3.9aa}$$

$$z_j^s, \alpha_{ij}^s, q_1^s, q_2^s, q_3^s, q_4^s \in \{0, 1\} \qquad \forall i \in \mathcal{I}, j \in \mathcal{J}, s \in \mathcal{S} \tag{3.9ab}$$

3.4.5 Fertilizer Rate Decomposition

Our computational experiments demonstrate that the two-stage stochastic mixed-integer program (3.9) is computationally expensive due to its disjunctive and linearization constraints, and the predominance of binary variables. In the literature, different formulation and solution strategies are suggested to overcome the difficulty of dealing with linearization (Adams and Sherali, 1990; Gupte et al., 2013) and disjunctive constraints (Sherali and Shetty, 2012). Our preliminary results show that the optimality gap of model (3.9) exceeds 80% after 12 hours of solution effort by CPLEX. In this section, we provide an alternative solution strategy using the unique structure that results from the assumptions made.

Among all the continuous variables (t, u_1,u_{2i}^s, and w_{ij}^s) in the two-stage stochastic model (3.9), t is the only actual decision made by the farmer. The auxiliary variables, u_1 and u_{2i}^s, simply represent the impact of t on yield according to the piecewise linear approximation, and w_{ij}^s is a variable introduced for the purpose of linearization. Therefore, if t is fixed, all the remaining non-auxiliary decision variables are binary.

For a given fixed N application rate t', let the parameters $\zeta_{ijv1}^s(t')$ and $\zeta_{ijv2}^s(t')$ denote the recourse indemnities for yield and revenue protection plans respectively:

$$\zeta_{ijv1}^s(t') = \max\Big(\mu f_v r_0 - A_{ij}^s(t') r_0, \quad 0\Big) \quad \forall i, j, v, s \tag{3.10}$$

$$\zeta_{ijv2}^s(t') = \max\Big(\mu f_v r_0 - A_{ij}^s(t') r^s, \quad \mu f_v r^s - A_{ij}^s(t') r^s, \quad 0\Big) \quad \forall i, j, v, s \tag{3.11}$$

where $A_{ij}^s(t')$ is a parameter representing the actual yield at harvest for N application time i and planting time j in scenario s. Recall that the insurance indemnities are calculated using decision variables σ_1^s and σ_2^s in models (3.8) and (3.9). By fixing t to a value t', we simply convert the decision variables σ_1^s and σ_2^s into parameters $\zeta_{ijv1}^s(t')$ and $\zeta_{ijv2}^s(t')$.

Similarly, we introduce binary decision variables η_{ijve}^s, where $e = 1$ represents the yield protection plan and $e = 2$ corresponds to the revenue protection plan. Decision variable η_{ijve}^s equals 1 if the protection plan e is selected with N application time i, planting time j and coverage level v, and 0 otherwise.

Then an alternative formulation, assuming the N rate decision t has been made, is:

$$\text{Max (\$/acre)} \qquad \rho(t') = -\sum_{v\in\mathcal{V}} \Big(c_{v1} y_{v1} + c_{v2} y_{v2}\Big) + \tag{3.12a}$$

$$\sum_{s\in\mathcal{S}} p^s \left[\sum_{i\in\mathcal{I}} \sum_{j\in\mathcal{J}} \left(A_{ij}^s(t') r^s \alpha_{ij}^s + \sum_{v\in\mathcal{V}} \Big(\zeta_{ijv1}^s(t') \eta_{ijv1}^s + \zeta_{ijv2}^s(t') \eta_{ijv2}^s \Big) \right) \right]$$

s.t.

$$(3.9c), (3.9d), (3.9g), (3.9h), (3.9i), (3.9j), (3.9y), (3.9ab) \tag{3.12b}$$

$$x_i + z_j^s + y_{v1} - 3\eta_{ijv1}^s \geq 0 \qquad \forall i \in \mathcal{I} \tag{3.12c}$$

$$x_i + z_j^s + y_{v2} - 3\eta_{ijv2}^s \geq 0 \qquad \forall i \in \mathcal{I} \tag{3.12d}$$

$$\sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}} \sum_{v \in \mathcal{V}} \left(\eta_{ijv1}^s + \eta_{ijv2}^s \right) \leq 1 \qquad \forall s \in \mathcal{S} \tag{3.12e}$$

$$\eta_{ijv1}^s, \eta_{ijv2}^s \in \{0, 1\} \qquad \forall i \in \mathcal{I} \tag{3.12f}$$

The first term in the objective function (3.12a) represents the first stage costs, and corresponds to insurance premiums paid. The remaining terms are revenues from harvested yield and insurance. Note that, since the yield impact of t' and insurance indemnities of insurance decisions are now calculated as parameters in the form of ζ_{ijv1}^s and ζ_{ijv2}^s, no linearization or disjunctive constraints are required in this model. As a result, constraints (3.9c),(3.9d),(3.9g), (3.9h), (3.9i), (3.9j), (3.9y), and (3.9ab) are retained in model (3.12) while the remaining constraints from model (3.9) are replaced by constraints (3.12c)-(3.12f).

Using the simplified formulation, we decompose the problem by separating the fertilizer rate decision t from all the other decisions, and solve it using Algorithm 1:

Algorithm 1 Fertilizer rate decomposition

```
Initiate BestResult = 0
for t'=0, t' ≤ t_max, t' = t'_next, t'_next ∈ T'_cand do
    Solve model (3.12) using t'
    NewResult = ρ(t') − gt'
    if NewResult > BestResult then
        BestResult = NewResult and t* = t'
    end if
end for
```

Because the values for percent of maximum yield are identified for only a finite number of integer-valued t, one alternative to use Algorithm 1 is to enumerate over all t from 0 to t_{max}. Alternatively, we can use the L linear segments as described in section 3.4.4.2 and model (3.9) to approximately solve the model (3.12). In this heuristic approach we consider a set T'_{cand} that includes only the $L+1$ breakpoints of the piecewise linear function. Instead of solving model (3.12) in step 3 of Algorithm (1), we solve the model (3.9) after fixing $t = t' \in T'_{cand}$. As discussed in section 3.4.3, equation (3.9f) is the only constraint that may prevent one of the breakpoint t values of the concave piecewise linear function from being optimal in (3.9). In section 3.6.1, we show that using this heuristic approach significantly improves the computation time with a small optimality gap when L is a small number. Furthermore, by increasing L, it is possible to come arbitrarily close to optimality without significantly increasing the computational time. In the remainder of the paper, this heuristic approach used to solve model (3.9) is referred to as the piecewise linear (PL) approximation heuristic.

3.5. Computational Study

The study is designed to represent a typical corn farm in Iowa, where typically corn is grown in rotation with soybeans but sometimes is repeated year after year.

The impact of the nitrogen application rate on yield is reflected in our model based on data points illustrated in Figure 3.3. We assume that this relationship of yield to N rate holds for fall N application. We use this information in two different ways. First, we generate piecewise linear (PL) functions representing this data to preserve the linearity of the main model as illustrated in Figure 3.3. We also explore the results by trying all potential fertilizer application rate points using Algorithm 1. To generate PL functions, we use the formulation of Jekel and Venter (2019) to identify the locations of a specified number of breakpoints that minimize the overall sum of squared differences between original data points and the PL approximation. For illustration, we generate three linear pieces as shown in Figure 3.3. However, we also explore how increasing the number of linear segments affects the quality of the results of the heuristic approach discussed in Section 3.4.5. Note that we do not allow the percent of maximum yield to exceed 100%. That is, if the PL approximation exceeds 100% at any point, we replace the approximated function value with 100%.

The cost of N fertilizer depends on the source, which can be urea, anhydrous ammonia, or urea ammonium nitrate (UAN; Sawyer et al. (2016)). In 2019, the cheapest anhydrous ammonia price was approximately \$0.30 - \$0.35 per lb N, while the most expensive UAN prices varied in

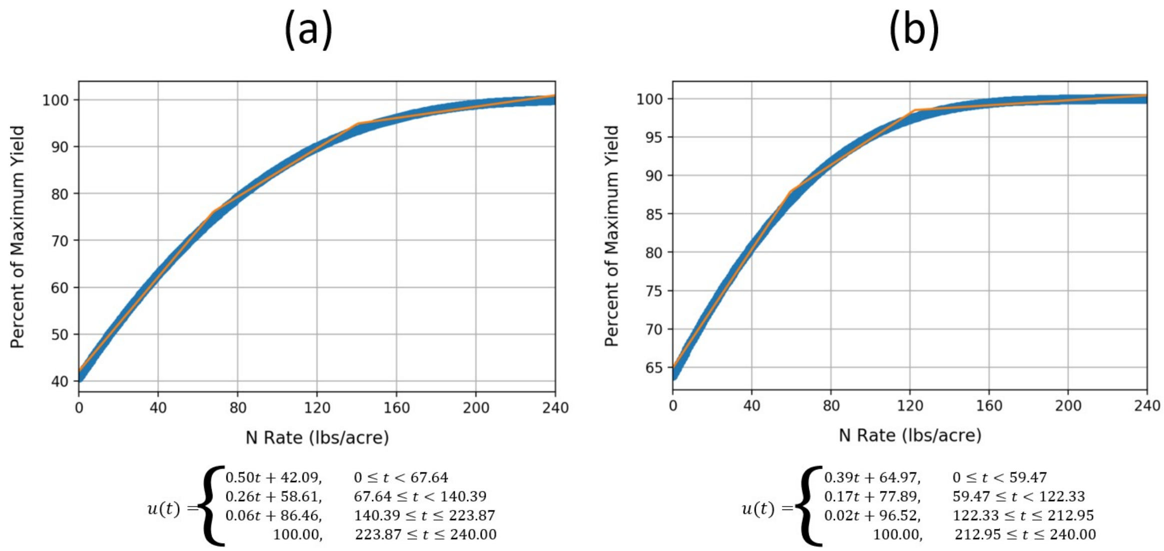


Figure 3.3: Impact of N rate on yield as discrete points and piecewise linear approximation with $L = 3$. (a) Corn-corn rotation (b) Soybean-corn rotation (Sawyer et al., 2020)

the range of \$0.45 - \$0.50 per lb N. (In 2020, the pandemic caused anhydrous prices to fall as low as \$0.26 per lb N, and UAN dropped to \$0.40 per lb N.) To reflect typical conditions, we assume fertilizer cost to be \$0.40 per lb N.

Crop insurance premiums are calculated based on several factors, including the insured land area (acres); the projected price at harvest, as determined by the US Department of Agriculture Risk Management Agency and known to farmers when choosing a policy; the historical crop yield of the farm and trend (up to 10 years); and the county average yield. In Table 3.2, we present the key parameters used to formulate the model and generate crop insurance premiums for our baseline case. Because insurance premiums can be higher if the farm has had an increasing yield trend or yield expectation is significantly higher than the county average, we also generate alternative corn premiums where trend-adjusted crop yield for the next year is 10% higher. Although a considerable number of assumptions were necessary to generate insurance premiums, their baseline values are at the low end and alternative values are at the high end of the likely ranges.

Table 3.2: Crop insurance premiums per acre, approximated using Enterprise units, for Story County, Iowa. In the baseline case the yield trend is flat while in the alternative case the annual yield increase is 10%.

	Baseline Case		Alternative Case	
$\boldsymbol{f_v}$	c_{v1}	c_{v2}	c_{v1}	c_{v2}
50%	\$0.21	\$0.22	\$0.27	\$0.30
55%	\$0.27	\$0.30	\$0.39	\$0.48
60%	\$0.37	\$0.45	\$0.53	\$0.71
65%	\$0.5	\$0.66	\$0.76	\$1.10
70%	\$0.68	\$0.93	\$1.02	\$1.76
75%	\$1.04	\$1.68	\$1.66	\$3.38
80%	\$1.94	\$3.64	\$3.00	\$6.82
85%	\$3.83	\$8.10	\$5.66	\$14.08

In this case study, we assume that, under fall N application, both historical yield average (μ) and maximum achievable yield (H) equal 180 bu/acre. That is, we assume the farmer already utilizes their farm to its full potential and the investigated farm has a flat yield trend. We use the most recent projected corn price ($r_0 = \$3.88$) announced to farmers by the Risk Management Agency for 2020. Based on this information, the estimated premiums are obtained using a crop insurance decision support tool (Schnitkey, 2019).

Spring and sidedress applications are expected to result in higher yields due to their lower potential for N loss. We approximate the yield impact of N application timing decisions using field test results of Iowa State University et al. (2017); Randall et al. (2008). Accordingly, spring, split (40% preplant + 60% sidedress) and full summer sidedress applications are assumed to add +6%, +10% and +13%, respectively, to the yield relative to fall application.

To generate scenarios, r^s, for harvest corn prices, we use the past five years' official harvest prices (determined based on average futures price of Chicago Board of Trade in October for December) to calculate insurance indemnities. Because corn prices in the early 2010s were significantly higher than in the late 2010s, we limit the number of recent years to reflect the current corn market conditions. Since harvest prices for 2016 and 2017 were the same, the data-driven price scenarios are \$3.83, \$3.49, \$3.68 and \$3.90, with respective probabilities of 0.2, 0.4, 0.2 and 0.2.

The effect of growing season (May - October) mean temperature on yield is based on crop simulation model predictions (Xu et al., 2016). A normal distribution provides the best continuous fit to historical temperature means from 1894 to 2019 (Figure 3.4). Discrete scenarios consisting of z values equal to -1.029, 0 and 1.029, with respective probabilities of 0.3035, 0.3930 and 0.3035, are proved to be an optimal three-point approximation to a standard normal distribution (Pflug, 2001). However, approximately 5% of the temperature data corresponds to abnormally high growing season averages above 70°F. Therefore, we also include a worst-case temperature alternative with probability 0.05. We normalize the probabilities provided by Pflug (2001) to sum to 0.95 and, thus, generate four probabilistic outcomes for mean growing-season temperature, as shown in Table 3.3. Note that only higher-than-average temperatures diminish the yield.

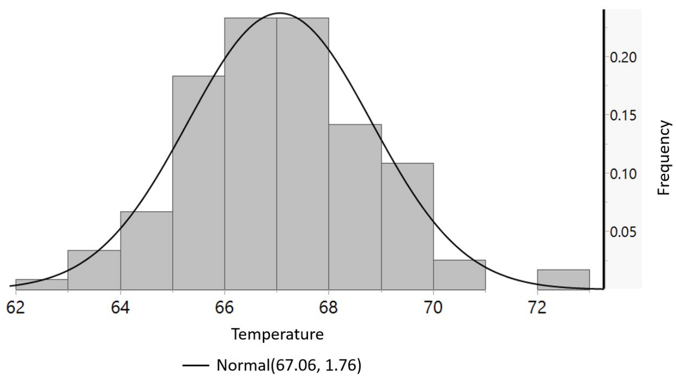


Figure 3.4: Frequency of temperature averages (°F) for Iowa from 1894 to 2019 between May and October

Table 3.3: Growing season mean temperature outcomes (γ)

	Low	Medium	High	Worst
Value	65.26°F	67.06°F	68.87°F	72.02°F
Probability	0.29	0.37	0.29	0.05
Yield Impact	-	-	-2.62%	-8.00%

Li et al. (2019) demonstrates that, in the Midwest, prediction model estimates given growing season precipitation from May to August are significantly different from actual yield observations. The study generates 14 bins of standardized precipitation intensity with width 0.5σ and tails defined as $< -2.5\sigma$ and $> +3.5\sigma$, and summarize the observed yields at each bin in the Midwest. Considering the similarities in yield outcomes and low probability of occurrence in certain categories, we aggregated the potential growing season precipitation outcomes to four as shown in Table 3.4. The probability of occurrence for each discrete scenario directly reflects historical growing season precipitation in Iowa between May and August from 1980 to 2019. The yield impact of each discrete outcome is simply the weighted average of the selected precipitation intensity range calculated according to the yield impact information of bin provided by Li et al. (2019). Finally, the probability of occurrence for each bin is generated based on Iowa precipitation data.

Table 3.4: Growing season precipitation outcomes (ω)

	Very Dry	Dry	Regular	Wet
Standardized value range	$(-\infty, -2\sigma]$	$(-2\sigma, \sigma]$	$(\sigma, 2\sigma)$	$[2\sigma, \infty)$
Probability	0.025	0.100	0.825	0.050
Yield impact, Iowa	-25.18%	-7.87%	-	-33.05%

Optimal crop planting dates depend on weather and soil conditions. Previous studies show that optimal planting dates vary across Iowa, ranging from mid-April until the second week of May, depending on the location (Elmore, 2012; Abendroth et al., 2017). However, except for the southern parts of the state, any planting after May 1 commonly results in lower yields. Therefore, in the case study, we assume that the farmer strives to complete any springtime farming operations before May 1, and failure to do so results in a 5% yield reduction. Because spring farming operations include not only fertilizer application but also other activities such as planting, we assume any fertilizer application should be completed within the first three weeks of April to avoid a planting delay. Weather and soil conditions are again the main factors determining whether a day is suitable for fieldwork depending on the emerging soil moisture at a given date. For a suitable fieldwork day, the soil must be not wet but also not too dry. The number of days, D, needed to apply fertilizer depends on several factors and is approximated by Hanna (2016) using equation (3.13).

$$D = \frac{\text{field size(acre)}}{\text{daily working hours} \times \text{field capacity(acre/hrs)}} \tag{3.13}$$

Field size represents the total area which needs to be covered during the fertilizer application, and the formula for estimating the field capacity is:

$$\text{field capacity(acre/hrs)} = \frac{\text{width(ft)} \times \text{speed(mph)} \times \text{field efficiency(\%)}}{\frac{\text{43,560(sq ft/acre)}}{\text{5280(ft/mile)}}} \tag{3.14}$$

Here, "width" refers to actual implement width, "speed" represents how fast the machinery can travel while performing the operation, and finally "field efficiency" represents the percent of effective working time by taking into account the time lost while turning around, slowing down, etc. Assuming 10 working hours per day, a 1000-acre farm will need approximately 10 working days to apply the fertilizer if the width of the implement, speed and field efficiency are 20 ft, 5 mph and 0.8 respectively. In the case study, we assume $D = 10$. However, we recognize this number may vary greatly depending on the unique conditions of the investigated farm.

Hanna (2014) summarizes the probabilities of a day to be suitable for fieldwork in Iowa, by week, from April until October. According to the study, the probabilities that a given day in the first, second, and third week of April is suitable for field work are 0.33, 0.43, and 0.45, respectively. We average the weekly probabilities over this three-week window and approximate the number of days suitable for fieldwork as binomial:

$$\Pr(\tau_1 \in B) \equiv \Pr(\tau_1 \geq D) = \sum_{d=D}^{21} \binom{21}{d} 0.4^d 0.6^{(21-d)} \tag{3.15}$$

In the case study, we assume that the number of days needed to apply the fertilizer, D, is equal to 10 (see the supplement for more information), and $\Pr(\tau_1 \geq 10) = 0.32$. Hence, we generate two discrete outcomes for τ_1 where, if the farmer selects spring or split application, a planting delay will occur with probability 0.68, or will not occur otherwise.

On the other hand, recall that if some portion of the fertilizer is planned to be applied during summer and there are not enough suitable workdays during this summer feed, there will be no choice but to apply less fertilizer to the soil than the preselected value of t. We assume that this summer N application will occur before the start of the V8 stage. The corn growth stage calendar depends on the planting date and weather conditions observed in a given year. The Corn Split N decision support tool (Gramig et al., 2017) estimates the V8 stage date for May 1 planting as approximately June 14. By using this approximation, we assume that the fertilizer application should be completed approximately two weeks before this date. By following the same logic used for spring application, we use the average probability (approximately 0.65) for a day to be suitable for fieldwork during the first two weeks of July from Hanna (2014), and calculate the potential outcomes for τ_2 as presented in Table 3.5. Note that we neglect potential outcomes with probability very close to 0.

Table 3.5: τ_2 outcomes where $D = 10$

	Value of τ_2	Probability	k_3^s	k_4^s
Outcome 1	5	$\Pr(\tau_2 = 5) = 0.017$	94%	50%
Outcome 2	6	$\Pr(\tau_2 = 6) = 0.048$	100%	60%
Outcome 3	7	$\Pr(\tau_2 = 7) = 0.103$	100%	70%
Outcome 4	8	$\Pr(\tau_2 = 8) = 0.172$	100%	80%
Outcome 5	9	$\Pr(\tau_2 = 9) = 0.217$	100%	90%
Outcome 6	$\geq$10	$\Pr(\tau_2 \geq 10) = 0.438$	100%	100%

Since we collected information related to random variables, ω, γ, r^s, τ_1 and τ_2, independently, we assume that they are mutually independent. Accordingly, we generate 768 combinations ($4 \times 4 \times 4 \times 2 \times 6$) as scenarios by multiplying the marginal probabilities. Similarly, realized yield β_{ij}^s is computed based on the respective yield impacts of each random component of scenario s, along with decisions x_i and z_j. Assuming the impacts of all decisions and uncertainties constituting a scenario path s, are independent of each other and multiplicative due to limited available information to reflect interactions among them, we calculate β_{ij}^s by multiplying the yield factors of i, j, γ and ω with a baseline $u(t)$ rate of 1.

3.6. Results and Discussion

In this section, we summarize the results of our computational runs by describing: (i) the computational performance and solution quality of the suggested models and the heuristic, and a suitable granularity for the PL approximation; (ii) optimal results for the baseline case and how different N application rates affect the profit and other management decisions; (iii) how higher crop insurance premiums affect the results; (iv) the water quality implications; and (v) the interactions between N management and crop insurance; specifically, how crop insurance programs affect environmentally beneficial N management practices.

We implemented the proposed models in Java and use IBM ILOG CPLEX as the optimization engine. We performed the computational experiments on a machine with Intel Core i7-7700HQ @ 2.80 GHz processor and 16 GB RAM.

3.6.1 Piecewise Linear (PL) Approximation Heuristic

Section 3.4.5 describes two alternative solution approaches using Algorithm 1: (i) enumerating over integer-valued fertilizer amounts using the data points provided in Figure 3.3 and optimizing the discrete decisions, and (ii) using the PL approximation to optimize all decisions simultaneously. In this section, we compare those two approaches in terms of computational performance and solution quality. We investigate how increasing L, the number of linear segments, affects the solution quality of the heuristic approach.

Table 3.6 summarizes the computational performance of the alternative solution approaches for corn following corn. The middle columns contain the solutions obtained using different numbers, L, of linear segments. The row labeled "N Rate" indicates the optimal values of t, which is the only management decision variable whose value differs according to the solution approach and value of L. Recall that the PL approximation uses $u(t)$ to generate percent of maximum yield. The enumeration strategy, on the other hand, uses the actual data points instead of $u(t)$ and enumerates over all integer-valued t from 0 to t_{max}, as illustrated in Figure 3.3. Therefore, the same decisions may yield slightly different expected profits when those two strategies are compared. To make a fair profit comparison between those two strategies, after having applied the PL approximation heuristic, we calculate $\rho(t')$ by fixing all the decisions generated from the heuristic in equation (3.12a). Thus, we use the real percent of maximum yield data instead of $u(t)$ to report the profit values for the heuristic in Table 3.6. The piecewise linear approximation heuristic finds a solution within 25 minutes but enumeration over all integer N rates takes more than 13 hours. The profit achieved by implementing the PL approximation heuristic solution is nearly optimal if L is sufficiently large.

Table 3.6: Changing L and its relationship with optimality for corn-corn rotation

	PL Approximation Heuristic								Optimal
	$L=3$	$L=4$	$L=5$	$L=6$	$L=7$	$L=8$	$L=9$	$L=10$	Enum.
N Rate (lbs/acre)	223.87	228.75	231.75	185.25	189.47	191.64	204.09	205.05	205.00
Profit ($/acre)	615.87	615.56	615.04	615.44	616.44	616.43	617.04	617.41	617.41
Optimality Gap (%)	0.25	0.30	0.38	0.32	0.16	0.16	0.06	0.00	-
Comp. (s)	803.16	910.25	964.92	1077.27	1145.43	1287.05	1454.43	1500.30	49539.25

The accuracy of the piecewise linear approximation with L sufficiently large indicates that the stochastic mixed-integer program (7) could be solved to find near-optimal solutions for the true nonlinear relationship between yield and N rate. In the remainder of the paper we enumerate over t using Algorithm 1 to explore the relationship between the N rate and the binary decisions.

3.6.2 Baseline Results

Figure 3.5 presents the optimal solutions and profits for corn following corn (C-C) and corn following soybean (S-C), respectively. For both crop rotations, full summer sidedress is the optimal fertilizer application timing decision, while the yield protection plan with maximum coverage rate at 85% is the best insurance decision when the N rate is set to its optimal value. For the C-C case, Figure 3.6 shows the components of expected profit to explain the nonconvex shape of the profit curve. While increasing t also increases the expected harvest income with diminishing returns, it reduces the expected insurance indemnity at a decreasing rate. However, the indemnity payment flattens out faster than harvest income. As a result, the expected profit initially shows a decreasing trend, after which it continues to increase until the optimal solution is reached.

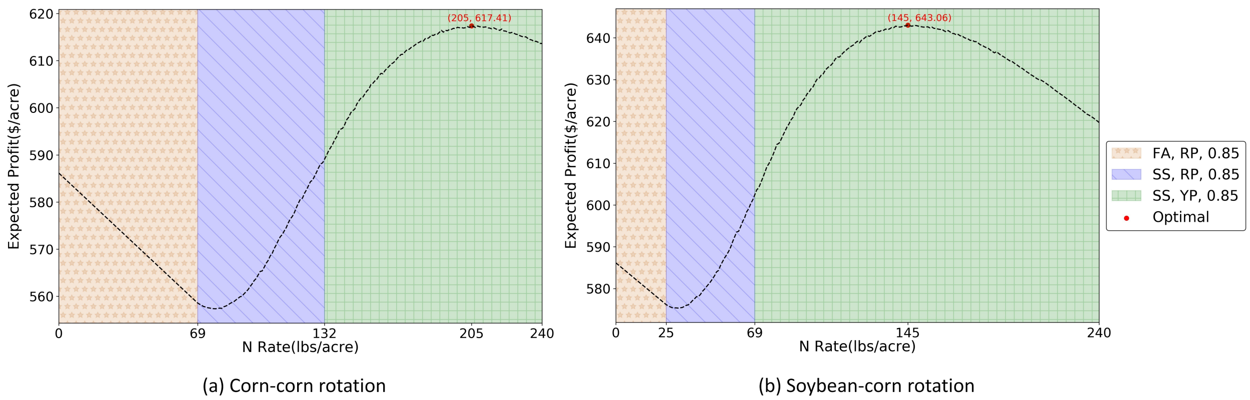


Figure 3.5: Baseline case results. Shaded regions are labeled by N timing decisions (FA = fall application, SS = summer sidedress), type of insurance (RP = revenue protection, YP = yield protection), and insurance coverage rate, f_v

The impact of the fertilizer application rate decision on other farming decisions is also investigated. Fertilizer application rate is a critical farming decision, not only affecting the farmer's profitability but also causing environmental consequences. Environmentalists and social planners ideally would prefer to reduce N application rate as much as possible to lower nitrate-N loss through leaching. Although we investigate the problem from a farmer's point of view, understanding how different N application rates affect the profit and other management decisions is just as important as knowing farmers' optimal solutions. Based on the applied fertilizer rate, we observe three combinations of optimal fertilizer timing and insurance decisions. Recall that fall N application is expected to produce the lowest yield, but it also imparts less risk than the other timing alternatives because the random variables τ_1 and τ_2 have no impact on subsequent decisions or yield. On the other hand, summer sidedress application is expected to result in the highest yield according to previous research, yet is also risky. For very low values of t (below 70 lbs/acre for C-C and or 26 lbs/acre for S-C), fall application is optimal. For any higher N application rate, summer sidedress is the best N timing decision. As illustrated in Figure 3.3, increasing the N application rate also increases the yield. It might be expected that, to overcome the lower yield resulting from low N rates, one would select a higher-yielding timing alternative. However, close examination reveals why low fertilizer rates and fall N application are selected together. When the N rate is low, the model relies on minimizing the harvest yield to maximize the crop insurance indemnity payment. Therefore, the insurance alternative providing the most protection, the revenue protection plan with the highest coverage, is selected. The perverse incentives that exist with low N rates are illustrated in Figure 3.5 by the decrease of profit as t increases for low values of t. Also note that, even if minimizing the harvest yield with low N rate to maximize the insurance indemnity payments were optimal in one year, it would not be viable in the long term because indemnity payments depend on the actual production history of the farm.

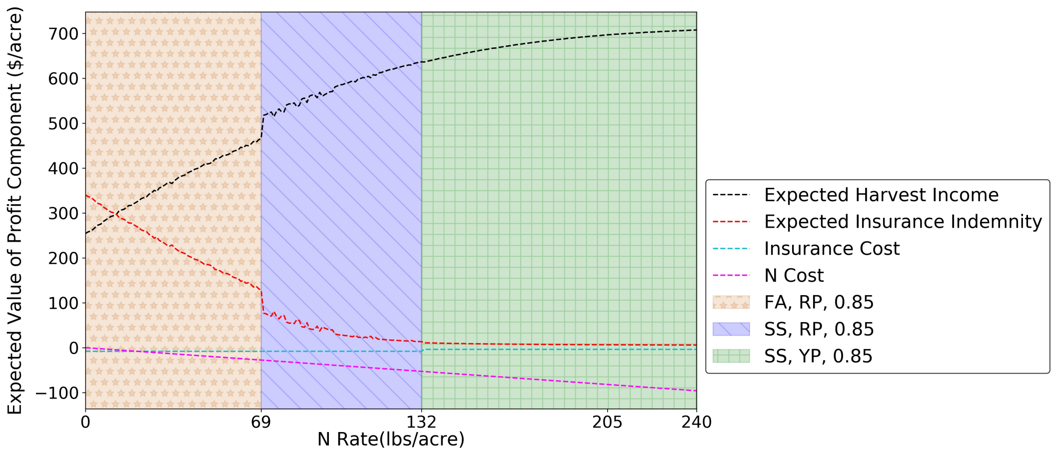


Figure 3.6: Expected value of profit components for corn-corn rotation. Shaded regions are labeled by N timing decisions (FA = fall application, SS = summer sidedress), type of insurance (RP = revenue protection, YP = yield protection), and insurance coverage rate, f_v

When the fertilizer application rate reaches 70 lbs/acre for C-C or 26 lbs/acre for S-C, maximizing the harvest yield and maximizing the profit align. As a result, summer sidedress becomes the best N timing decision. In this intermediate interval (70-132 lbs/acre for C-C or 26-69 lbs/acre for S-C), the revenue protection plan with the highest coverage rate at 85% is still the best crop insurance decision because the applied fertilizer amount is still not high enough to achieve good crop yield. Finally, when the fertilizer application rate exceeds 132 lbs/acre for C-C or 70 lbs/acre for S-C, the yield protection plan with the highest coverage becomes the best insurance decision as yield risk is reduced.

Due to the higher efficiency (greater percentage of maximum yield for a given N rate) of corn following soybean, as illustrated in Figure 3.3, the optimal N application rate is lower for S-C, while the expected profit per acre is higher than for C-C. Likewise, the N rates at which the timing and insurance decisions change are different for S-C and C-C.

The optimal N rate is 205 lbs/acre for C-C and 145 lbs/acre for S-C. However, if we calculate the expected application rates using discrete probability outcomes of τ_2 presented in Table 3.5, we find that the expected N rate actually applied is approximately 180 lbs/acre for C-C and 127 lbs/acre for S-C. That means the optimal solution includes a higher N rate to benefit from the higher yield potential of summer sidedressing decision by compensating for the risk of random variable τ_2. As a further note, when low risk, low yield fall application is forced to be selected, the optimal N rate is 184 lbs/acre for C-C and 130 lbs/acre for S-C.

3.6.3 Alternative Crop Insurance Premiums

Crop premiums can be higher than our baseline rates, depending on the yield trend of the farm and its surrounding county. In this section, we investigate the impact of the alternative, higher insurance premiums shown in Table 3.2. The results are illustrated in Figure 3.7.

Increasing the insurance premiums does not cause any significant change in fertilizer rate or N timing decisions. For S-C, the optimal fertilizer rate and N timing decision with alternative insurance premiums are exactly the same as for the lower baseline insurance premium rates. Similarly, with C-C, we observe only a slight increase in the optimal N application rate compared to baseline premiums. The only significant change occurs in the crop insurance choices. With higher premium rates, the optimal solution foregoes insurance. Even with those high premium rates, the maximum or next highest coverage rate is selected for every fertilizer application rate. If the applied N rate is low, the revenue protection plan is selected with the highest coverage rate. The yield protection plan is selected for higher N application rates with coverage rates at either

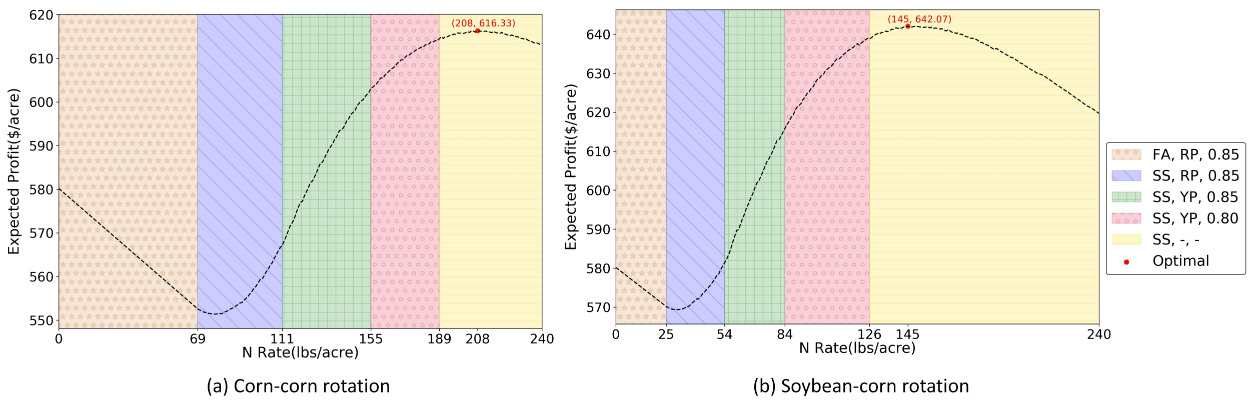


Figure 3.7: Results with higher crop insurance premiums. Shaded regions are labeled by N timing decisions (FA = fall application, SS = summer sidedress), type of insurance (RP = revenue protection, YP = yield protection), and insurance coverage rate, f_v

80% or 85%. If the N application rate is higher than 189 lb/acre for C-C and 126 for S-C, buying an insurance plan is not part of the optimal solution.

3.6.4 Water Quality Implications

Lawlor et al. (2008) estimate the nitrate-N concentration in subsurface drainage based on tests performed in Iowa. According to their study, a N rate application of 205 lbs/acre (the optimal result from C-C in the baseline case) results in a nitrate-N concentration of 20.23 mg/L, while an application of 145 lbs/acre (the optimal result from S-C) corresponds to 12.93 mg/L. According to Lawlor et al. (2008), applying no fertilizer will result in a N concentration of 7 mg/L.

Considering the current Iowa nitrate-N concentration target of 5-6 mg/L based on the 41% reduction goal (Iowa State University et al., 2017), it is highly unlikely to achieve this goal by simply focusing on fertilizer management strategies (i.e., additional nitrogen management, land use and edge-of-field nutrient practices are needed to achieve target reduction goals). In this section, we investigate how much water quality improvement can be achieved by simply focusing on fertilizer management practices. By exploring various N concentration targets achievable as illustrated in Table 3.7, we show the limitations of fertilizer management in improving water quality, and also indicate the incentives needed to achieve those concentration targets when only fertilizer management is considered. Table 3.7 displays the expected profit foregone by the farmer to achieve various N concentration targets. To generate the table, we extracted the fertilizer application rate corresponding to each nitrate-N concentration target, based on the information provided by Lawlor et al. (2008), and solved the optimization model repeatedly with fixed t equal to each fertilizer rate in turn. For example, when corn follows corn the farmer's profit from applying 100 lbs/acre to meet the 10 mg/L target is \$52.14 per acre lower (a 8.4% reduction) than the optimal profit achieved by applying 205 lbs/acre. This represents an opportunity cost that, alternatively, drops to \$12.93/acre for corn following soybean (a 2% reduction). These results also demonstrate the combined financial and environmental advantages of crop rotation. It is important to underline that those incentive rates are generated under two assumptions: (i) farmers are rational and have the single objective of maximizing their short-term profit and (ii) other nutrient reduction practices are not considered. Therefore, the realistic fertilizer-based incentive rates are expected to be lower than what is reported in Table 3.7. Still, we believe the incentive rates reported for alternative N concentration targets provide a valuable insight to policymakers as those values represent the upper envelope of fertilizer-based incentives. In other words, those rates would ensure the cooperation of rational farmers under the current assumptions but true rates may be lower than what are reported.

Another environmental takeaway concerns the use of sidedressing strategies. The common consensus in agronomy suggests that summer sidedress application increases the farm yield and also reduces the N loss, compared to other N timing decisions such as fall or spring applications. Our results also indicate that this fertilizer timing option optimizes the farmer's profit. However, this decision is highly susceptible to weather uncertainty. If the soil moisture is high during the summer, there is a high chance that the farmer will not be able to apply all of the intended fertilizer. This economic risk can be mitigated by increasing the planned N application rate which, if carried out, will increase the N loss. As a result, summer sidedress may not be the best decision from an environmental perspective when all uncertainties are considered.

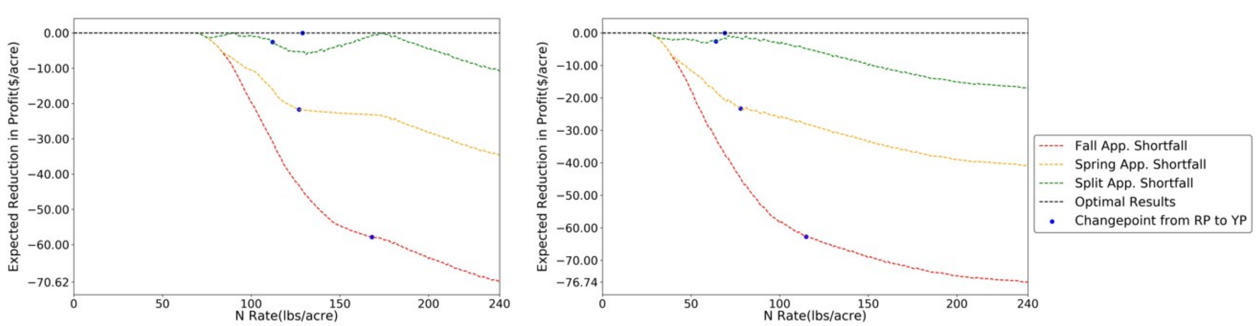
Table 3.7: Farmer's opportunity cost of achieving N concentration targets

Target(mg/L)	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**20**
N Rate to achieve target (lbs/acre)	0	46	78	100	118	133	145	205
Foregone profit for C-C (\$/acre)	31.26	49.66	60.06	52.14	38.58	27.47	18.42	0
Foregone profit for S-C (\$/acre)	56.91	62.04	31.12	12.93	4.77	1.25	0	-

Note that trying to achieve a 7 and 8 mg/L N concentration appears less costly than 9 mg/L for C-C, and likewise 7 mg/L looks less costly than 8 mg/L for S-C. As discussed in section 3.6.2, this nonintuitive result occurs because, for low N application rates, it is optimal to minimize the yield in order to maximize the insurance payout. As a result, we observe a decreasing expected profit curve for low values of t.

3.6.5 Mitigation of N Management Risk by Insurance

Figure 3.8 illustrates how different N application timing decisions affect the expected farm profit. Expected reduction in profit (\$/acre) represents the cost of selecting a different fertilizer timing decision compared to the optimal baseline results provided in Figure 3.5. To generate the plots, we fix x_i to a specific nitrate timing alternative i and enforce its selection in model (3.9). Then, we obtain the expected profit reduction by calculating the difference between newly obtained results and optimal results from Figure 3.5.



(a) Corn-Corn Rotation (b) Soybean-Corn Rotation

Figure 3.8: Comparison of N application timing decisions for the baseline case

The sidedressing strategies, split and complete summer sidedress, are considered as part of precision agriculture. Those strategies aim to apply the N during a period of growth and when it is needed most. The idea is to increase the crop uptake efficiency by timely synchronizing the nutrient availability in the soil, considering crop demand based on its growth stages. Therefore, sidedressing strategies are expected to improve water quality and farm yield compared to other fertilizer application timing decisions as less N leaching due to early fertilizer application is expected. For that reason, split fertilizer application is a risk reducing strategy since it reduces the risk of N loss. The results in Figure 3.8 align with the scientific expectations where both split and summer sidedress applications result in smaller profit reductions in the case study. Interestingly, the expected per-acre profit gap between different N time decisions increases with the N application rate. When the expected yield is very low, resulting from low N application rates, the insurance programs cover the economic deficits. Therefore, the reduction in profit is indistinguishable for different N application time decisions when the N application rate is very low ($<$ 100 bu/acre). In the literature, reducing the N application rate and sidedressing N application timing are considered as two valuable nutrient reduction practices related to N management. However, our results demonstrate that when the N application rates are reduced, timing-related N reduction practices can be redundant for producers concerned only with maximizing their profits because insurance programs also act as a risk-reducing strategy. In other words, risk-reducing conservation practices such as split N application may be redundant when combined with crop insurance policies. This insight demonstrates the importance of including insurance programs in environmental investigations and designing insurance programs so as to not undermine water quality efforts.

Similarly, Figure 3.9 highlights the expected reduction in profit when the purchase of insurance policies is not allowed (i.e., solutions to model (3.9) are forced to not select any insurance plan). N is a limiting nutrient in agriculture because plants cannot utilize atmospheric N directly in its gaseous form. By applying N, agricultural producers ensure the N availability in the soil to maximize yield potential. However, N is susceptible to leaching. Therefore, agricultural producers may tend to apply more N to the soil than necessary to cover the required N uptake by the crops. Figure 3.9 demonstrates that increasing the N application rate acts as a risk-reducing strategy for agricultural producers when crop insurance is taken out of the picture. As the N application rate increases, we observe that the expected benefit of insurance programs is diminishes to negligibility. This finding is important as it suggests that federal crop insurance programs significantly decrease the economic loss arising from the N application reduction. Specifically, in this case study, the expected C-C rotation profit range ($/acre) is [557.3, 617.4] with insurance programs and [322.9, 616.9] without insurance. For S-C rotation, the corresponding ranges are [575.3, 643.1] and [514.4, 642.9], with and without insurance, respectively. It also means that the opportunity cost of achieving N concentration targets shared in Table 3.7 is expected to be higher when the insurance programs are not considered. That is, insurance programs can potentially complement nutrient reduction programs (i.e., they are effective instruments to mitigate the risk of yield loss from reduced N applications).

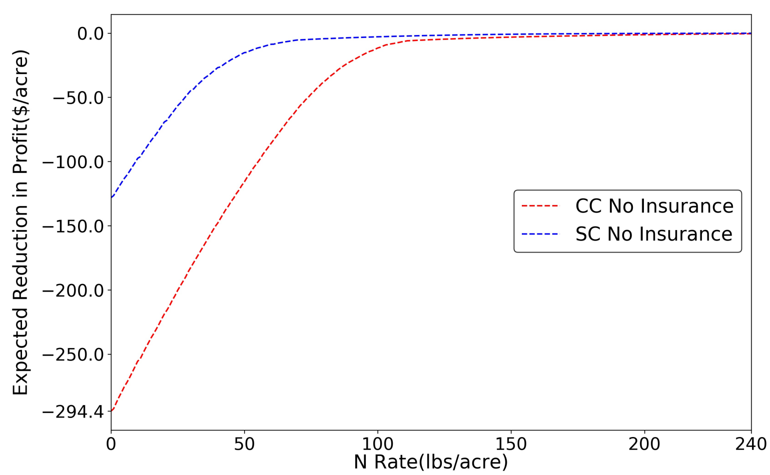


Figure 3.9: Impact of crop insurance programs on farm profitability

Uncertainty and the resulting risk are primary agricultural concerns, and our numerical results indicate that they significantly impact fertilizer rate and timing decisions. Because the purpose of insurance programs is to reduce risk exposure, the insurance purchase options that exist should be considered when studying N management from an environmental perspective. The environmental impact of insurance programs may be inconsistent and circumstantial. Specifically, we observe that crop insurance has a complementary role in reducing the N application rate with a positive environmental impact. However, if the N application rate drops below a certain level, the crop insurance reduces the motivation to use environmentally beneficial N timing strategies. Those inconsistent results demonstrate the complicated interactions between N management and crop insurance programs. The incentive rate estimates in Table 3.7 are generated based on the existing federal insurance program structure and parameters while considering N management decisions only. Updating the structure and parameters of existing crop insurance programs or integrating additional parametric insurance options could reduce the need for financial incentives for adopting environmental best practices. Appropriately designed insurance plans could be vehicles for aligning economic and environmental incentives.

3.7. Conclusion

This paper explores some major annual farming decisions of a corn producer under uncertain growing season precipitation and temperature, harvest price, and soil moisture during critical time windows. We built a two-stage stochastic mixed-integer program for annual farm management decisions to maximize the expected farm profit. Because the two-stage stochastic program is computationally expensive due to its disjunctive and linearization constraints and the predominance of binary variables, we suggested a heuristic solution approach that produces near-optimal solutions.

By examining the farmer's optimal behavior under uncertainty, the case study derives valuable input to policymakers concerned with developing effective policies and promoting nutrient reduction practices to reduce N loss. Previous field experiments in agronomy demonstrate the advantages of spring and sidedress N application compared to fall N application. Sidedressing strategies specifically are expected to lower N loss and increase crop yields and, thus, appear advantageous for both farmers and the environment. Our results, however, indicate that other decisions taken to mitigate farming risks can negate the environmental benefits. Farmers maximizing expected profit would compensate for the additional risks resulting from weather uncertainties if sidedressing is chosen by increasing the planned N application rate. Spring and sidedressing strategies, especially, are more susceptible to the risk of insufficient days suitable for fieldwork, and could paradoxically increase N leaching if the farmer carries out the plan of applying more N to compensate for the yield risk.

To explore financial incentives that policymakers could offer to alter farmers' major annual decisions, we estimate the cost to the farmer, in terms of foregone profit, of achieving potential N reduction targets by fertilizer management alone. The results show that significant incentives are needed under corn-corn rotation for substantial changes in N loss while up to 20% N reduction is achievable under soybean-corn rotation with little impact on profit.

This research explores how crop insurance programs can influence the adoption of environmentally beneficial N management practices. How insurance interacts with other environmental practices constitutes a gap in the literature. If carefully designed, insurance programs have the potential to align economic and environmental incentives. Therefore, expanding the consideration to all available insurance tools and modifying them accordingly to incentivize environmental programs is a promising research direction. Future work could address (i) how insurance programs relate to other best management practices (i.e., use of inhibitors, cover crops, land use changes, etc.) and (ii) how available insurance tools can be used or modified to further incentivize environmentally beneficial practices.

This model has several limitations due to the "reductionist" character of traditional agronomy research (Drinkwater et al., 2016), which informed both the model structure and the case study inputs. The case study performed currently relies on empirical field tests to obtain information about critical outputs, including yield and N loss. These experiments are carefully designed to isolate the impact of one variable, such as fertilizer application rate, on yield. Unfortunately, they are inadequate to investigate all components of an agricultural system and their interactions simultaneously. Simplifying assumptions in our model, such as independence of the effects of management decisions and uncertain factors on yield, are based on the empirical information available but could distort the optimization results. For a decision model to properly reflect the interactions among management decisions and uncertain elements as they unfold over time, more accurate multivariate functional relationships are needed. Numerical agronomic simulation models may help fill this gap and allow for better model fidelity to actual decision processes.

3.8. References

Abendroth, L. J., Woli, K. P., Myers, A. J., and Elmore, R. W. (2017). Yield-based corn planting date recommendation windows for Iowa. *Crop, Forage & Turfgrass Management*, 3(1):1–7.

Adams, W. P. and Sherali, H. D. (1990). Linearization strategies for a class of zero-one mixed integer programming problems. *Operations Research*, 38(2):217–226.

Antón, J., Cattaneo, A., Kimura, S., and Lankoski, J. (2013). Agricultural risk management policies under climate uncertainty. *Global Environmental Change*, 23(6):1726–1736.

Arbuckle Jr, J. G., Morton, L. W., and Hobbs, J. (2015). Understanding farmer perspectives on climate change adaptation and mitigation: The roles of trust in sources of climate information, climate change beliefs, and perceived risk. *Environment and Behavior*, 47(2):205–234.

Archontoulis, S. V., Castellano, M. J., Licht, M. A., Nichols, V., Baum, M., Huber, I., Martinez-Feria, R., Puntel, L., Ordóñez, R. A., Iqbal, J., et al. (2020). Predicting crop yields and soil-plant nitrogen dynamics in the US Corn Belt. *Crop Science*, 60(2):721–738.

Baum, M. E., Licht, M. A., Huber, I., and Archontoulis, S. V. (2020). Impacts of climate change on the optimum planting date of different maize cultivars in the central US Corn Belt. *European Journal of Agronomy*, 119:126101.

Bierman, P. M., Rosen, C. J., Venterea, R. T., and Lamb, J. A. (2012). Survey of nitrogen fertilizer use on corn in Minnesota. *Agricultural Systems*, 109:43–52.

Bloemhof-Ruwaard, J. M. and Hendrix, E. M. (1996). Generalized bilinear programming: An application in farm management. *European Journal of Operational Research*, 90(1):102–114.

Bosch, D. J. and Pease, J. W. (2000). Economic risk and water quality protection in agriculture. *Review of Agricultural Economics*, 22(2):438–463.

Cao, P., Lu, C., and Yu, Z. (2018). Historical nitrogen fertilizer use in agricultural ecosystems of the contiguous united states during 1850–2015: application rate, timing, and fertilizer types. *Earth System Science Data*, 10(2):969–984.

Capitanescu, F., Marvuglia, A., Gutiérrez, T. N., and Benetto, E. (2017). Multi-stage farm management optimization under environmental and crop rotation constraints. *Journal of Cleaner Production*, 147:197–205.

Chlingaryan, A., Sukkarieh, S., and Whelan, B. (2018). Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review. *Computers and Electronics in Agriculture*, 151:61–69.

Claassen, R., Horowitz, J., Duquette, E., and Ueda, K. (2014). *Additionality in U.S. Agricultural Conservation and Regulatory Offset Programs*. ERR-170, U.S. Department of Agriculture, Economic Research Service.

Drinkwater, L. E., Friedman, D., and Buck, L. (2016). *Systems Research for Agriculture: Innovative Solutions to Complex Challenges*. Sustainable Agriculture Research and Education (SARE), Brentwood, MD.

Edwards, W. (2015). Farm machinery selection. http://www.extension.iastate.edu/agdm/crops/html/a3-28.html. (accessed 24 November 2020).

Elmore, R. W. (2012). Progress of corn planting and corn emergence. *Integrated Crop Management News*, 187. https://dr.lib.iastate.edu/handle/20.500.12876/18160.

Elmore, R. W. (2013). Corn planting FAQs. *Integrated Crop Management News*, 66. https://dr.lib.iastate.edu/handle/20.500.12876/19437.

EPA (2017). Northern Gulf of Mexico hypoxic zone. https://www.epa.gov/ms-htf/northern-gulf-mexico-hypoxic-zone. Mississippi River/Gulf of Mexico Hypoxia Task Force.

Geng, R., Yin, P., and Sharpley, A. N. (2019). A coupled model system to optimize the best management practices for nonpoint source pollution control. *Journal of Cleaner Production*, 220:581–592.

Goolsby, D. A., Battaglin, W. A., Aulenbach, B. T., and Hooper, R. P. (2000). Nitrogen flux and sources in the Mississippi River basin. *Science of the Total Environment*, 248(2-3):75–86.

Gramig, B. M., Massey, R., and Do Yun, S. (2017). Nitrogen application decision-making under climate risk in the US Corn Belt. *Climate Risk Management*, 15:82–89.

Greiner, R., Patterson, L., and Miller, O. (2009). Motivations, risk perceptions and adoption of conservation practices by farmers. *Agricultural Systems*, 99(2-3):86–104.

Gupte, A., Ahmed, S., Cheon, M. S., and Dey, S. (2013). Solving mixed integer bilinear problems using MILP formulations. *SIAM Journal on Optimization*, 23(2):721–744.

Hanna, M. (2014). Fieldwork days in Iowa. *Ag Decision Maker Information Files*, 7. https://lib.dr.iastate.edu/pubs_agdm/7.

Hanna, M. (2016). Estimating the field capacity of farm machines. *Ag Decision Maker Information Files*, 8. https://lib.dr.iastate.edu/pubs_agdm/8.

Howley, P., Buckley, C., Donoghue, C. O., and Ryan, M. (2015). Explaining the economic 'irrationality'of farmers' land use behaviour: the role of productivist attitudes and non-pecuniary benefits. *Ecological Economics*, 109:186–193.

Hyytiäinen, K., Niemi, J. K., Koikkalainen, K., Palosuo, T., and Salo, T. (2011). Adaptive optimization of crop production and nitrogen leaching abatement under yield uncertainty. *Agricultural Systems*, 104(8):634–644.

Iowa State University (2020). Iowa soil properties and interpretations database. https://www.extension.iastate.edu/soils/ispaid.

Iowa State University, Iowa Department of Agriculture and Land Stewardship, and Iowa Department of Natural Resources (2017). Iowa nutrient reduction strategy: A science and technology-based framework to assess and reduce nutrients to Iowa waters and the Gulf of Mexico. http://www.nutrientstrategy.iastate.edu/sites/default/files/documents/2017%20INRS%20Complete_Revised%202017_12_11.pdf.

Irwin, S. and Hubbs, T. (2018). How many days does it take to plant the U.S. corn crop? *Farmdoc Daily*, 8(70).

Jekel, C. F. and Venter, G. (2019). pwlf: A python library for fitting 1d continuous piecewise linear functions. https://github.com/cjekel/piecewise_linear_fit_py.

Jones, C. S., Nielsen, J. K., Schilling, K. E., and Weber, L. J. (2018). Iowa stream nitrate and the Gulf of Mexico. *PLOS One*, 13(4):1–17.

Kaini, P., Artita, K., and Nicklow, J. W. (2012). Optimizing structural best management practices using SWAT and genetic algorithm to improve water quality goals. *Water Resources Management*, 26(7):1827–1845.

Kucharik, C. J. (2008). Contribution of planting date trends to increased maize yields in the Central United States. *Agronomy Journal*, 100(2):328–336.

Lawlor, P. A., Helmers, M. J., Baker, J. L., Melvin, S. W., and Lemke, D. W. (2008). Nitrogen application rate effect on nitrate-nitrogen concentration and loss in subsurface drainage for a corn-soybean rotation. *Transactions of the ASABE*, 51(1):83–94.

Li, Q., Hu, G., Jubery, T. Z., and Ganapathysubramanian, B. (2017). A farm-level precision land management framework based on integer programming. *PloS one*, 12(3):e0174680.

Li, Y., Guan, K., Schnitkey, G. D., DeLucia, E., and Peng, B. (2019). Excessive rainfall leads to maize yield loss of a comparable magnitude to extreme drought in the United States. *Global Change Biology*, 25(7):2325–2337.

Liu, J., Men, C., Cabrera, V. E., Uryasev, S., and Fraisse, C. W. (2008). Optimizing crop insurance under climate variability. *Journal of Applied Meteorology and Climatology*, 47(10):2572–2580.

Marra, M., Pannell, D. J., and Ghadim, A. A. (2003). The economics of risk, uncertainty and learning in the adoption of new agricultural technologies: where are we on the learning curve? *Agricultural Systems*, 75(2-3):215–234.

McMinimy, M. (2019). The 2018 Farm Bill (PL 115–334): Summary and side-by-side comparison. https://crsreports.congress.gov/product/pdf/R/R45525. Washington, DC: Congressional Research Service.

Minnesota Pollution Control Agency (2014). The Minnesota nutrient reduction strategy. https://www.pca.state.mn.us/sites/default/files/wq-s1-80.pdf.

Mississippi River/Gulf of Mexico Watershed Nutrient Task Force (2008). Gulf hypoxia action plan 2008: For reducing mitigating, and controlling hypoxia in the northern Gulf of Mexico and improving water quality in the Mississippi River Basin. https://www.epa.gov/ms-htf/hypoxia-task-force-2008-action-plan-and-related-documents. Washington, D.C.

Moghaddam, K. S. and DePuy, G. W. (2011). Farm management optimization using chance constrained programming method. *Computers and Electronics in Agriculture*, 77(2):229–237.

Moschini, G. and Hennessy, D. A. (2001). Uncertainty, risk aversion, and risk management for agricultural producers. *Handbook of Agricultural Economics*, 1:87–153.

Nleya, T., Chungu, C., and Kleinjan, J. (2016). Corn growth and development. In *iGrow Corn: Best Management Practices*, chapter 5. South Dakota State University.

Peña-Haro, S., Pulido-Velazquez, M., and Llopis-Albert, C. (2011). Stochastic hydro-economic modeling for optimal management of agricultural groundwater nitrate pollution under hydraulic conductivity uncertainty. *Environmental Modelling & Software*, 26(8):999–1008.

Pflug, G. C. (2001). Scenario tree generation for multiperiod financial optimization by optimal discretization. *Mathematical Programming*, 89(2):251–271.

Puntel, L. A., Sawyer, J. E., Barker, D. W., Dietzel, R., Poffenbarger, H., Castellano, M. J., Moore, K. J., Thorburn, P., and Archontoulis, S. V. (2016). Modeling long-term corn yield response to nitrogen rate and crop rotation. *Frontiers in Plant Science*, 7:1630.

Randall, G. W. et al. (2008). Nitrogen application timing, forms, and additives. In *Final Report: Gulf Hypoxia and Local Water Quality Concerns Workshop*, pages 73–85, St. Joseph, MI. American Society of Agricultural and Biological Engineers.

Randall, G. W. and Mulla, D. J. (2001). Nitrate nitrogen in surface waters as influenced by climatic conditions and agricultural practices. *Journal of Environmental Quality*, 30(2):337–344.

Rware, H., Kayuki, C., Macharia, M., and Oduor, G. (2016). Fertilizer use optimization approach: An innovation to increase agricultural profitability for African farmers. *African Journal of Agricultural Research*, 11(38):3587–3597.

Sawyer, J., Nafziger, E., Camberato, J., Steinke, K., Kaiser, D., Culman, S., and Laboski, C. (2020). Corn nitrogen rate calculator. http://cnrc.agron.iastate.edu/.

Sawyer, J., Nafziger, E., Randall, G., Bundy, L., Rehm, G., Joern, B., et al. (2006). *Concepts and Rationale for Regional Nitrogen Rate Guidelines for Corn*. Iowa State University Extension, Ames, IA.

Sawyer, J. E. (2019). Springtime precipitation – a tool for estimating nitrogen application need for corn. *Integrated Crop Management News*, page 2563.

Sawyer, J. E., Barker, D. W., and Lundvall, J. P. (2016). Impact of nitrogen application timing on corn production. *Agronomy Conference Proceedings and Presentations*, 61.

Scharf, P. C., Wiebold, W. J., and Lory, J. A. (2002). Corn yield response to nitrogen fertilizer timing and deficiency level. *Agronomy Journal*, 94(3):435–441.

Schnitkey, G. (2019). 2019 crop insurance premiums and the crop insurance decision tool. *Farmdoc Daily*, 9(12).

Sexton, B., Moncrief, J., Rosen, C. J., Gupta, S. C., and Cheng, H. (1996). Optimizing nitrogen and irrigation inputs for corn based on nitrate leaching and yield on a coarse-textured soil. *Journal of Environmental Quality*, 25(5):982–992.

Shahhosseini, M., Hu, G., and Archontoulis, S. (2020). Forecasting corn yield with machine learning ensembles. *Frontiers in Plant Science*, 11:1120.

Shahhosseini, M., Martinez-Feria, R. A., Hu, G., and Archontoulis, S. V. (2019). Maize yield and nitrate loss prediction with machine learning algorithms. *Environmental Research Letters*, 14(12):124026.

Sherali, H. D. and Shetty, C. M. (2012). *Optimization with Disjunctive Constraints*, volume 181. Springer Science & Business Media.

Singh, A. (2012). An overview of the optimization modelling applications. *Journal of Hydrology*, 466:167–182.

Srivastava, P., Hamlett, J., Robillard, P., and Day, R. L. (2002). Watershed optimization of best management practices using AnnAGNPS and a genetic algorithm. *Water Resources Research*, 38(3).

Stockle, C. O., Martin, S. A., and Campbell, G. S. (1994). Cropsyst, a cropping systems simulation model: water/nitrogen budgets and crop yield. *Agricultural Systems*, 46(3):335–359.

Thorburn, P., Biggs, J., McMillan, L., Webster, T., Palmer, J., and Everingham, Y. (2020). Innovative economic levers: a system for underwriting risk of practice change in cane-farming. Technical report, National Environmental Science Program. Reef and Rainforest Research Centre Limited, Cairns (67pp.).

Turner, R. E. and Rabalais, N. N. (2004). Suspended sediment, C, N, P, and Si yields from the Mississippi River basin. *Hydrobiologia*, 511(1-3):79–89.

USDA (2020). World agricultural supply and demand estimates. https://www.usda.gov/oce/commodity/wasde.

USDA and NASS (2020). Crop production. https://www.nass.usda.gov/Publications/Todays_Reports/reports/crop0920.pdf.

Xu, H., Twine, T. E., and Girvetz, E. (2016). Climate change and maize yield in Iowa. *PLOS One*, 11(5):e0156083.

Yamoah, C., Walters, D., Shapiro, C., Francis, C., and Hayes, M. (2000). Standardized precipitation index and nitrogen rate effects on crop yields and risk distribution in maize. *Agriculture, Ecosystems & Environment*, 80(1-2):113–120.

Yong, T., Chen, P., Dong, Q., Du, Q., Yang, F., Wang, X., Liu, W., and Yang, W. (2018). Optimized nitrogen application methods to improve nitrogen use efficiency and nodule nitrogen fixation in a maize-soybean relay intercropping system. *Journal of Integrative Agriculture*, 17(3):664–676.

CHAPTER 4. OPTIMAL UTILIZATION OF FARM FINANCIAL PROGRAMS WITH IMPACTS ON NUTRIENT USE

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4.1. Abstract

Crop yield, which depends on weather conditions, and the market-driven fluctuating crop prices are major uncertainties that affect farm revenue. Because nitrogen (N) and other nutrients are needed to increase the yield, farmers apply fertilizer to the soil to compensate for its nutrient deficiencies. However, losses of N to the ecosystem cause severe ecological problems. In the US, federal crop insurance and income support programs are the primary financial instruments available to mitigate farmers' financial risk. In addition to providing financial security for farmers, these programs also affect fertilizer management decisions and, thus, may have unanticipated environmental consequences. We build a two-stage stochastic program, including CVaR as a risk measure, to optimize utilization of the risk-mitigating instruments (RMIs) as well as the fertilizer application rate under a range of risk preferences. In a case study of US Midwest corn production, we investigate how much financial safety the RMIs provide to farmers and their impact on nutrient use. The results demonstrate that the RMIs eliminate most of the risk to producers resulting from yield and price uncertainty by significantly tightening their profit range. Contingent income support programs are demonstrated to be more effective than the direct support payments they replaced in recent legislation. Furthermore, the optimal utilization of RMIs significantly reduces the optimal fertilizer application rate, especially for highly risk-averse producers, with financial and environmental benefits.

4.2. Introduction

Uncertainty and risk are prominent features of agricultural production. Hardaker et al. (2004) define uncertainty as imperfect knowledge and risk as exposure to uncertain unfavorable economic consequences. Commonly, risk incorporates both objective and subjective components; e.g., an objective loss function and subjective risk preference (Rockafellar, 2007; Hansson, 2010). Agricultural risks arise due to uncertain weather conditions, such as temperature and precipitation, that affect farm yield, or imperfect and changing market conditions that affect crop prices (Menapace et al., 2013). Farm management decisions, including the fertilizer application rate, may cause different economic and environmental consequences when combined with these uncertainties. In the US, federal crop insurance (FCI) and income support programs (ISP) are the primary financial instruments available to mitigate the risk. These programs target yield and/or price uncertainty and reduce the probability of low profit in the event of a low yield and/or price outcome. However, finding the optimal combination of management and financial risk-mitigating instrument decisions to mitigate their financial risk is a complicated task for producers.

Nitrogen (N) is a key nutrient needed in agricultural production. However, plants cannot take in N directly from the air and must absorb it from the soil instead. If the soil lacks enough N to match the required plant uptake, the farm's yield and the farmer's revenue will suffer. Farmers apply fertilizer to the soil to compensate for its nutrient deficiencies. However, not all N in the soil is used by plants. Instead, a significant portion is lost to the atmosphere through denitrification and volatilization and to the hydrosphere through runoff and leaching (Martínez-Dalmau et al., 2021). According to Billen et al. (2013), approximately half of the N fertilizer applied is lost to the ecosystem. The excess chemical N input causes serious environmental problems including aquatic dead zones, depletion of the ozone layer, and increased greenhouse gas emissions (Erisman et al., 2013). Insurance products have the potential to alter fertilizer management decisions by modifying the economic risk (Thorburn et al., 2020).

Historically, the US government has provided financial assistance to farmers through several programs defined in legislation known as the Farm Bill. These programs are revised periodically as a reaction to agricultural market outcomes in prior years. As a result, their shape has evolved over time. In the 2014 Farm Bill, farmer concerns about uncertainty and the resulting risk were explicitly acknowledged in the legislation, and direct income support payments were converted to contingent payments taking the form of crop insurance subsidies. In this study, the abbreviation ISP exclusively denotes contingent income support payments. Under the 2014 Farm Bill, the US Department of Agriculture (USDA) characterized FCI and ISP as a "safety net" for agricultural producers. These financial instruments induce both economic and environmental impacts. First, those programs are designed and expected to provide some financial security for agricultural producers and ideally keep the agriculture sector financially sustainable. Hence, it is important to explore how much financial protection they provide and whether the newly designed ISP is financially more beneficial than the old direct support payments. Second, both FCI and ISP have the potential to alter farm management decisions and indirectly affect the resulting environmental consequences. However, the consequences of these changes have not been investigated well. The risk attitude of the producers is another critical factor to include. Since those programs are designed to mitigate the agricultural risks, farmers' utilization of FCI and ISP may differ greatly based on their risk preferences. Accordingly, the resulting financial and environmental impacts may vary among producers along with their optimal insurance and management decisions.

Since the 2014 Farm Bill was enacted, agricultural economists have investigated the effectiveness of the risk-mitigating instruments (RMIs) it included and tried to assess whether those programs, either solely or in combination, really provide financial security (Plastina and Hart, 2018; Boehlje and Langemeier, 2016; Schnitkey and Zulauf, 2016; Barnaby and Russell, 2016). The previous research used either historical observations or point estimates of uncertain elements. By neglecting yield and price uncertainty, these studies could not capture the impact of risk on producers' optimal decisions according to their risk preferences. Instead, they were limited to analyzing the outcomes of past decisions or conducting "what-if" explorations of currently available decisions.

To best of our knowledge, Liu et al. (2008) and Emirhüseyinoğlu and Ryan (2022) describe the only optimization studies that have explored the use of RMIs. Liu et al. (2008) build a mathematical program to investigate the FCI decisions of a peanut farm in Florida under weather uncertainty to minimize the expected farm loss using a CVaR constraint. Emirhüseyinoğlu and Ryan (2022) also construct a stochastic program and investigate major annual farm-level decisions of a Midwest farmer, including FCI purchase. In this paper, we provide a more comprehensive financial risk model considering all risk-mitigating instruments (except one option introduced in 2021) currently available to agricultural producers in the US. In particular, we include more detail on FCI and additionally consider ISP with its supplemental coverage option (SCO) to build a more comprehensive model that can help policymakers and researchers understand financial and environmental impacts of those tools.

Thorburn et al. (2020) also acknowledge that insurance programs can significantly impact fertilizer application. The study acknowledges that applying N fertilizer in excess of crop needs is a rational response by farmers to minimize the risk of crop growth (low yield). Focusing on sugarcane farms in Australia, it investigates how insurance programs can be designed to mitigate the risk of yield loss from reduced N applications. The goal is to generate a fertilizer-based parametric insurance tool that does not depend on public funding and effectively improves water quality by reducing fertilizer application rates. Due to the lack of empirical data to provide a robust assessment, the study uses APSIM, an agricultural systems simulation tool, to explore the interaction between weather-related uncertainties and fertilizer application rate. The results reveal what magnitude of fertilizer reductions N insurance might facilitate. It is shown that, if parametric insurance is widely adopted, substantial reductions in inorganic N discharged to streams can be achieved. However, considerable effort to build understanding and trust in the suggested N insurance instrument amongst farmers is needed. In this paper, unlike Thorburn et al. (2020), we do not attempt to design a new insurance product for corn. However, we investigate currently available financial support programs provided in the Farm Bill to explore their impacts on fertilizer application. By doing so, we help identify how effective the RMIs are in reducing fertilizer application and clarify whether a similar insurance product is needed in the US Midwest. In the agronomy literature, numerous studies look for optimal N application rates (Rware et al., 2016; Sexton et al., 1996; Yong et al., 2018). However, those studies rely on previous empirical tests to identify the best alternative among the limited number of experiments instead of finding mathematical optimality according to a model. Researchers commonly use popular crop simulation tools to estimate several outputs, including yield and N loss, and couple those simulation models with genetic algorithms to select management practices that maximize profit and improve water quality (Kaini et al., 2012; Srivastava et al., 2002; Geng et al., 2019).

Our focus on corn is motivated by the fact that the US Midwest is one of the most intense agricultural production areas in the world and consistently affects the global economy. According to the recent report titled "The World Agricultural Supply and Demand Estimates" (USDA, 2022e), around 16% of total grain and 32% of total corn production in the world originated from the US in 2021. The state of Iowa meets around 17% of the total corn production in the US as the most prominent supplier (USDA, National Agricultural Statistics Service, 2022). In this paper, we build a comprehensive insurance model from farmers' perspective considering the RMIs currently available to US farmers and their interaction with the N application rate. We assume the producers are rational with a single objective to maximize the farm profit and investigate the optimal selection of insurance policies under fluctuating market prices and uncertain weather conditions that affect crop yields. We generate discrete probabilistic scenarios for harvest yields and market prices where the yield depends on random weather variables. The scenarios are used in a novel two-stage stochastic program, including CVaR as a risk measure, to find optimal RMI choices and fertilizer application rates under a range of risk preferences. We design our computational tests based on county-level data with the goal to generate valuable financial and environmental insights for policymakers. To the best of our knowledge, this is the first study to build a comprehensive optimization model including both FCI and ISP along with fertilizer management, considering the uncertainties that Midwest corn farmers face. While the case study represents corn production in Iowa, the model can be parameterized for other regions.

Furthermore, this type of model and implemented solution strategy can apply to various crops in jurisdictions with different types of RMIs.

The key findings in this paper are summarized as follows:

- We demonstrate that optimal use of RMIs can eliminate most of the risk resulting from yield and price uncertainties.
- In terms of CVaR of profit, ISP is financially more beneficial than the old direct support payments for most producers (some exceptions are observed for highly risk-averse producers).
- Previous empirical studies indicate that risk aversion is negatively correlated with the adoption of environmentally beneficial practices (Prokopy et al., 2019). When RMIs are excluded from the model, the optimal N application rate follows this pattern. However, our numerical results show that the inclusion of RMIs reverses this effect; namely, the optimal N rate is slightly lower for more risk-averse producers.
- Optimal use of RMIs significantly lowers the magnitude of the incentives needed to reduce fertilizer use.

The rest of the paper is organized as follows. In Section 4.3, we provide a detailed explanation of RMIs. Section 4.4 includes a detailed problem description and a two-stage stochastic formulation. In Section 4.5, we specify the parameters used in the computational study and in Section 4.6, we present the numerical results. Finally, we share the concluding remarks in Section 4.7.

4.3. Financial Risk-Mitigating Instruments for US Crops

FCI is managed by USDA Risk Management Agency (RMA) in partnership with private crop insurance providers. Producers have the option to purchase the policy they want by paying its premium to receive an indemnity payment if the selected policy covers the financial loss. The federal government subsidizes a portion of the crop insurance premiums, which helps make it cost-effective for farmers. Premium rates and insurance terms are commonly established by RMA and the costs are the same regardless of the private insurance agency. Yield Protection (YP) and Revenue Protection plans (RP) are the most popular insurance alternatives. YP provides a production based guarantee and protects against yield loss that may arise due to weather uncertainty. RP is more extensive protection than YP, involving a higher premium, and provides a revenue guarantee by additionally taking crop price uncertainty into account.

For income support, direct payment programs were the primary tools in the 1990s and early 2000s. Under the 2014 Farm Bill, farmer concerns about uncertainty and the resulting risk were acknowledged in the legislation, and deterministic direct support payments were repealed and converted to contingent payments taking the form of insurance subsidies. The most recent 2018 Farm Bill allows agricultural producers to select one of three programs: Price Loss Coverage (PLC), Agriculture Risk Coverage-County (ARC-CO), or Agriculture Risk Coverage-Individual (ARC-IC). PLC offers price protection. Payments are triggered when the price of a covered commodity falls below a pre-determined reference price. ARC policies follow a similar logic as RP, and payment is triggered if the actual crop income drops below a specified guarantee. ARC/CO uses county trend-adjusted yields while ARC/IC uses the farm's actual yields to specify the threshold. Unlike the federal crop insurance, the enrollment for government income support programs is free. The producers can purchase any FCI policy on top of the election of one of the ISPs.

Additionally, if the farmers enroll in PLC, they can choose to buy the Supplemental Coverage Option (SCO). SCO is a crop insurance option that provides additional coverage for a portion of the farmer's underlying FCI policy deductible. It must be purchased as an endorsement to the YP or RP policy (see section 4.3.3 for more detail). A summary of RMIs considered in this paper is provided in Figure 4.1.

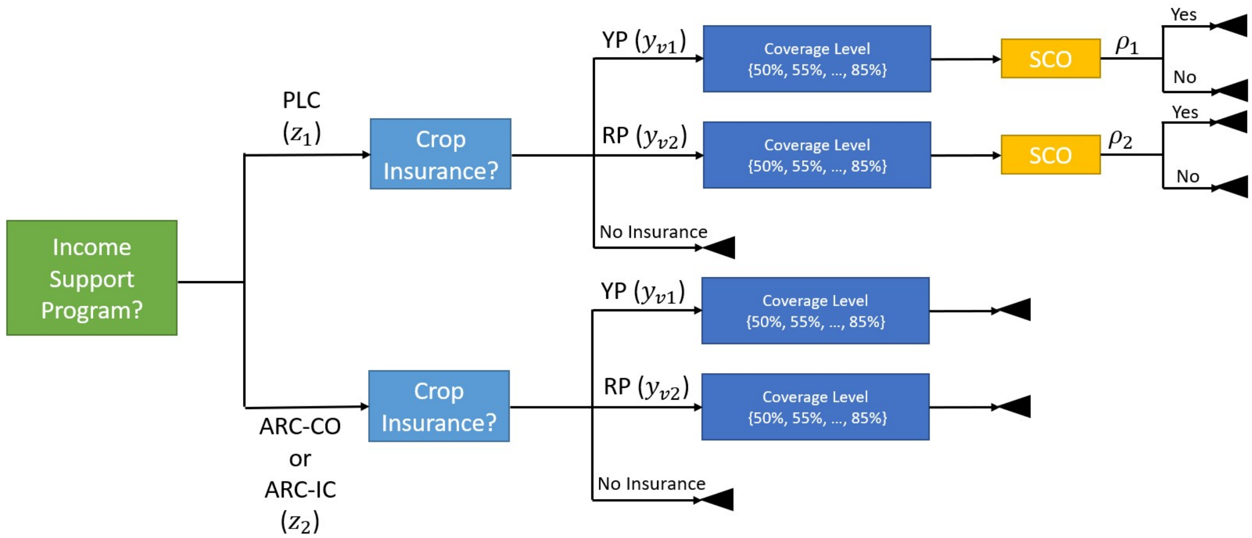


Figure 4.1: Decision tree for utilization of Federal Crop Insurance and Income Support Programs (symbols in parenthesis represent the decision variable notation)

4.3.1 Federal Crop Insurance

In this study, we consider the two most popular FCI plans: YP and RP. Each alternative has several options in the set $\mathcal{V} = \{1, 2, ..., 8\}$ corresponding to coverage levels $\{50\%, 55\%, ..., 85\%\}$, respectively. The premia that agricultural producers have to pay for each combination of insurance plan and coverage rate depend on several factors, including the location, historical yield information, the yield trend, and the size of the farm (acres). Just before the start of planting season in spring, March 15 is the deadline for all FCI purchases for corn in the US.

4.3.1.1 Yield Protection Plan

The YP plan offers a production based guarantee by insuring the producers against a yield loss. The indemnity payment of this option, denoted by σ_1, is calculated as follows:

$$\sigma_1 = \max\Big(r'_d(\mu f_v - A), \quad 0\Big), \tag{4.1}$$

where r'_d is the projected corn price, f_v is the coverage percentage, μ is the actual production history (APH) for the farm, and A is the uncertain yield realized at harvest.

The parameter r'_d is the monthly volume-weighted average of the December Chicago Board of Trade (CBOT) futures contract price during the month of February, and it is publicly announced by the RMA before the March 15 deadline. The parameter μ is calculated as trend-adjusted historical mean yield, as detailed in Section 4.5.

4.3.1.2 Revenue Protection Plan

The RP plan offers a revenue guarantee and insures the producers against both yield loss and harvest price uncertainty. The indemnity payment of this plan, denoted by σ_2, is calculated as:

$$\sigma_2 = \max\Big(r'_d\mu f_v - R_d A, \quad R_d(\mu f_v - A), \quad 0\Big), \tag{4.2}$$

where R_d is the harvest price. The random variable R_d represents the volume-weighted monthly average of daily December CBOT futures contract price during the month of October, and it is uncertain to farmers at the time of FCI purchases.

4.3.2 Income Support Programs

The 2018 Farm Bill allows agricultural producers the opportunity to select one of three policies: PLC, ARC-CO, or ARC-IC. As with FCI, the ISP election deadline is March 15.

4.3.2.1 Price Loss Coverage (PLC)

PLC is a program initially authorized by the 2014 Farm Bill, and continued in the 2018 Farm Bill for the 2018 through 2023 crop years. It provides price loss coverage for eligible crops when the actual price is lower than the reference price. It does not cover revenue (price $\times$ yield) losses.

A PLC payment, denoted by β_1, is calculated as:

$$\beta_1 = \zeta \max\Big[(r_1 \text{ - } R_m), 0\Big] a_{plc}, \tag{4.3}$$

where the parameter ζ is a constant factor and the parameter r_1 refers to the pre-announced reference price. The parameter a_{plc} is the PLC farm yield and represents historical yield at a specific location. The details of ζ, r_1, and a_{plc} calculation are discussed in Section 4.5.

The random variable R_m represents the uncertain crop price of the upcoming marketing year. Unlike FCI, ISP uses the sales-weighted crop marketing year average (MYA) to determine the policy payments. For corn, the marketing year starts in September and ends in August of the following year. The final MYA price of the previous corn marketing year is usually announced during September or October. Monthly agricultural price reports, including the monthly prices and sales weights, are published by USDA (2022a). An insurance timeline including both FCI and ISP is illustrated in Figure 4.2. For example, for the 2019 crop year, farmers elected their ISP option before the start of planting season on March 15, 2019. With the start of the harvesting season on September 1, the crop marketing year for 2019 began and continued until the end of the harvesting season of the following crop year, August 31, 2020. Finally, after the final MYA price is announced, the ISP payments were made to producers in October, 2020. Note that R_m is the only random variable unknown to the agricultural producers when calculating β_1. Historical data representing all the parameters for both ARC and PLC programs are published by USDA (2022b).

4.3.2.2 Agricultural Risk Coverage (ARC-CO and ARC-IC)

ARC is another income support program authorized by the 2014 Farm Bill and reauthorized by the 2018 Farm Bill. It provides revenue loss payments based on both yield and price combined. ARC-CO is calculated using the county yields while ARC-IC uses the farm yield. In this study, instead of using individual farm data, we use the generalized county information. Therefore, we also simplify ARC-IC and ARC-CO to be the same, and refer to it simply as ARC.

An ARC payment, denoted by β_2, is calculated using the following expression:

$$\beta_2 = \min\Big[\zeta \max\big(0.86 r_1 a_{arc} - R_m A, 0\big), \quad 0.1 r_1 a_{arc}\Big], \tag{4.4}$$

where the random variable A represents the uncertain crop yield and we assume it to be the same for both FCI and ISP. The parameter a_{arc} refers to the benchmark yield and it is calculated as previous five year Olympic average of the Farm Service Agency (FSA) county yield. The fixed parameter values are announced before producers finalize their policy decisions and can be accessed at USDA (2022b).

4.3.3 Supplemental Coverage Option (SCO)

SCO is a county-level crop insurance option that provides additional coverage for qualified farmers. This additional coverage is available only to producers who elect PLC as their base income support program and also purchase one of the FCI alternatives (YP or RP).

For example, if a farmer elects PLC and purchases RP with coverage level of f_v, the purchased RP policy covers only a certain portion, f_v, of the expected farm revenue. SCO can be purchased by the farmer to obtain an additional county-level coverage of the gap from f_v to 86% (if $f_v = 70\%$, then SCO raises the coverage from 70% of expected farm revenue to 86% of the expected county level revenue). Therefore, the RP-SCO combination provides two types of coverage: (i) a farm-level coverage coming from RP of the proportion f_v of the crop value, and (ii) an additional $0.86 - f_v$ county-level RP coverage between f_v and 86%. In summary, an agricultural producer who purchases SCO will always end up at 86% coverage regardless of the initial RP or YP coverage level (f_v) selection. The only difference is, the extra $0.86 - f_v$ coverage rate will be a county level protection instead of a farm-level protection. Purchasing SCO is cheaper than buying RP or YP at the same coverage rate because the federal government pays a higher percentage of the SCO premium.

The SCO policy begins to pay when county average revenue falls below 86% of its expected level. The full amount of the SCO coverage is paid out if the county average revenue drops below the coverage level, f_v, of the farmer's underlying policy. SCO payments are determined only by county average revenue or yield and are not affected by whether the farmer receives a payment from the underlying RP or YP policy. Thus, it is possible to experience an individual loss but not receive an SCO payment, or experience an individual gain and yet receive an SCO payment. A simple example demonstrating how the SCO program works is given in the Appendix.

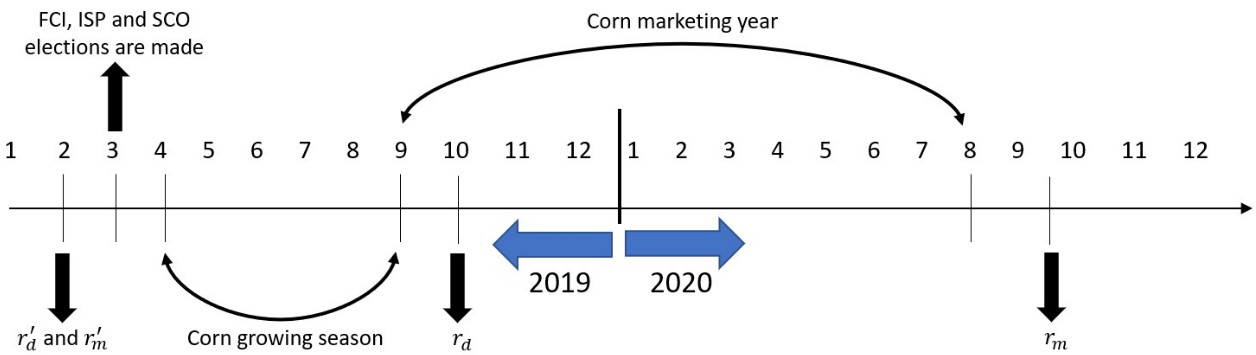


Figure 4.2: Federal Insurance and Income Support timeline for 2019 corn crop year. Numbers indicate the months.

4.4. Model Definition

In this paper, we consider the ISP adoption, FCI purchase, and N application rate decisions of an agricultural producer under price and yield uncertainty. We formulate a two-stage stochastic mixed-integer program with the objective of maximizing CVaR of farm profit.

4.4.1 Uncertainties in Crop Production

Farm revenue primarily depends on uncertain crop yield, A, and market-driven fluctuating crop prices. The crop yield can be considered as a complicated function of many interrelated components including management decisions and environmental conditions during a crop year. In literature, agro-simulation tools and machine learning models are commonly used to estimate crop yield (Archontoulis et al., 2020; Sharma et al., 2020; van Klompenburg et al., 2020; Shahhosseini et al., 2021). However, most of the financial and management-related decisions farmers have to make each year are taken before the growing season begins. All RMIs related decisions considered in this study have to be finalized before March 15 of each crop year (where the corn growing season can start as early as April in Iowa while we define a corn crop year from

September to August). As a result, even though the yield estimation studies can potentially be helpful tools for any agricultural decision-making process, the majority of weather-related features that are required as an input to use those tools are random variables. Therefore, it is impossible to estimate the crop yield accurately until the realization of weather uncertainties, including temperature and precipitation that affect farm yield, are observed. In this paper, we use the notation ω to represent the vector of random weather variables that affect the corn harvest yield, and denote the uncertain county yield by $A(\omega)$.

The random variables R_d (necessary to calculate FCI indemnity payments, see section 4.3.1) and R_m (used for ISP calculations, see section 4.3.2) are the uncertain crop prices needed to build an insurance-based risk model. In addition to insurance related calculations, we assume that farmers sell the harvested yield at the harvest price of R_d (i.e., we assume that FCI harvest price and farmer's actual selling price are same).

Assuming we have a finite number of realizations for each of the random variables, we define the scenario set $\mathcal{S} = \{1, ..., S\}$ that consists of scenarios s, each of which represents a particular combination of realizations. Scenario s occurs with probability p^s. As a result, we rewrite $A(\omega), R_d$, and R_m as A^s, r_d^s, and r_m^s respectively.

Many of the elements of ω needed to predict $A(\omega)$ are unknown to producers before the growing season, which limits the usability of yield estimation studies for decision-makers. Acknowledging this gap, Emirhüseyinoğlu et al. (2022) propose a crop yield scenario generation procedure that incorporates the uncertainties in both the growing season weather and the machine learning prediction error. In this paper, we follow the same procedure to generate discrete vectors including yield and market price fluctuations. Further information about the implemented scenario generation procedure and details of how A^s, r_d^s, and r_m^s are generated is discussed in Section 4.5.

4.4.2 The Impact of N Application Rate on Yield

The online Corn Nitrogen Rate Calculator tool provides reliable information showing the impact of N rate on yield based on research trials (Sawyer et al., 2020). The tool generates data points for the percent of maximum yield given different N application rates for six Midwestern states (Illinois, Iowa, Michigan, Minnesota, Ohio, and Wisconsin). Generated data points for Iowa, with integer-valued N application rates between 0 and 240 lbs/acre, are illustrated in Figure 4.4. The tool currently does not elaborate on how precipitation affects the relationship between N rate and yield. Previous experiments demonstrate the need for a higher N rate under wet conditions to acquire the yield percentage provided in Figure 4.4, yet current research is not reliable enough to indicate how much additional N would be needed (Sawyer, 2019). To preserve the linearity of the optimization model, we generate piecewise linear functions to approximate the data points displayed in Figure 4.4. We denote the percent of maximum yield by $u(t)$ for a given fertilizer application rate t and the uncertain maximum county yield as $A(\omega)$. Although t and ω interact to influence yield, we treat their impacts on yield as mutually independent because the information relevant to each is drawn from different sources. Thus, the yield that results from the decision t and uncertain weather ω is modeled as $u(t)A(\omega)$.

4.4.3 Risk-Neutral Two-stage Stochastic Program

Emirhüseyinoğlu and Ryan (2022) formulated a stochastic program to investigate major annual farm-level decisions, including purchase of a FCI policy. In this study, we include more detail on FCI and additionally consider ISP with its SCO. We extend the farmer's model provided by Emirhüseyinoğlu and Ryan (2022) as model (4.5).

We define the binary decision variables, y_{v1} and y_{v2}, for YP and RP, respectively, to indicate which coverage level, $v \in \mathcal{V}$, is selected by the farmer. Similarly, the binary decision variables, z_1 and z_2, are introduced for adopting PLC and ARC, respectively, while binary decision variables ρ_1 and ρ_2 represent whether a SCO is purchased or not. Figure 4.3 depicts the decisions and recourse actions at each stage. For simplicity, we also use the notation X to refer to the

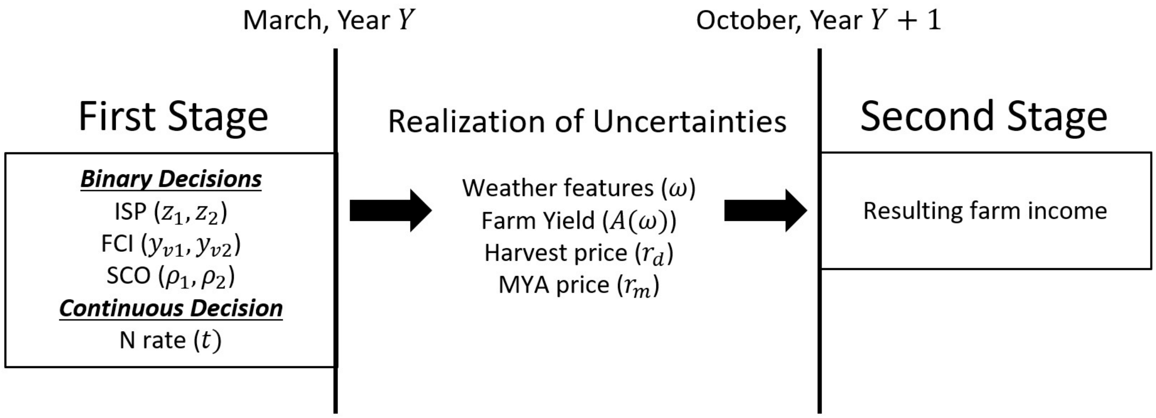


Figure 4.3: Stage representation of stochastic program

combination of all insurance decisions (i.e., $X = \{y_{v1}, y_{v2}, z_1, z_2, \rho_1, \rho_2\}$). A detailed nomenclature for the insurance model is provided in Table 4.1. Using those decision variables and assumptions, we build the following two-stage stochastic program:

$$\max_{X,t,\sigma_1^s,\sigma_2^s,Q^s} (\$/\text{acre}) \qquad \sum_{s\in\mathcal{S}} p^s \pi^s(X,t) \tag{4.5a}$$

s.t.

$$\pi^s(X,t) = -\sum_{v\in\mathcal{V}} \Big(c_{v1}y_{v1} + c_{v2}y_{v2} + e_{v1}\rho_1 + e_{v2}\rho_2\Big) - gt + \Big(r_d^s A^s + \sigma_1^s + \sigma_2^s + \beta_1^s z_1 + \beta_2^s z_2\Big) \qquad \forall s \in \mathcal{S} \tag{4.5b}$$

$$0 \le t \le t_{max} \tag{4.5c}$$

$$\sigma_1^s \le r_d'\mu \sum_v \Big(f_v y_{v1} + d_v\rho_1\Big) - r_d' A^s u(t) + Mq_1^s \qquad \forall s \in \mathcal{S} \tag{4.5d}$$

$$\sigma_1^s \le M(1 - q_1^s) \qquad \forall s \in \mathcal{S} \tag{4.5e}$$

$$\sigma_2^s \le r_d'\mu \sum_v \Big(f_v y_{v2} + d_v\rho_2\Big) - r_d^s A^s u(t) + Mq_2^s \qquad \forall s \in \mathcal{S} \tag{4.5f}$$

$$\sigma_2^s \le r_d^s\mu \sum_v \Big(f_v y_{v2} + d_v\rho_2\Big) - r_d^s A^s u(t) + Mq_3^s \qquad \forall s \in \mathcal{S} \tag{4.5g}$$

$$\sigma_2^s \le Mq_4^s \qquad \forall s \in \mathcal{S} \tag{4.5h}$$

$$q_2^s + q_3^s + q_4^s = 2 \qquad \forall s \in \mathcal{S} \tag{4.5i}$$

$$z_1 + \sum_v y_{v1} - 2\rho_1 \geq 0 \tag{4.5j}$$

$$z_1 + \sum_v y_{v2} - 2\rho_2 \geq 0 \tag{4.5k}$$

$$z_1 + z_2 \leq 1 \tag{4.5l}$$

$$\sum_v \Big(y_{v1} + y_{v2} \Big) \leq 1 \tag{4.5m}$$

$$y_{v1}, y_{v2} \in \{0, 1\} \qquad \forall v \in \mathcal{V} \tag{4.5n}$$

$$z_1, z_2, \rho_1, \rho_2 \in \{0, 1\} \tag{4.5o}$$

$$\sigma_1^s, \sigma_2^s \geq 0 \qquad \forall s \in \mathcal{S} \tag{4.5p}$$

$$q_1^s, q_2^s, q_3^s, q_4^s \in \{0, 1\} \qquad \forall s \in \mathcal{S} \tag{4.5q}$$

The objective is to maximize the expected net income and the notation $\pi^s(X, t)$ indicates the net income under scenario s. The first set of terms in $\pi^s(X, t)$ represent the cost of the insurance alternatives. The second group of terms are the sales revenue, expected indemnity payments for the yield and revenue protection plan, and income support payments for PLC and ARC, in order. Finally, the term gt is the fertilizer application cost.

Equation (4.5c) indicates the lower and upper bound for the fertilizer application rate decision. The disjunctive variables, σ_1^s and σ_1^s, represent the indemnity payments from YP and RP, respectively, by also considering their possible SCO combinations. Specifically, disjunctive constraints, (4.5d)-(4.5e), are used to compute σ_1^s in each scenario s, while constraints (4.5f)-(4.5i) are used to compute σ_2^s by using a big-M reformulation. The base logic of the disjunctive constraints are explained in detail in Emirhüseyinoğlu and Ryan (2022). We use Q^s to refer to the set of second stage disjunctive variables (i.e., $Q^s = \{q_1^s, q_2^s, q_3^s, q_4^s\} \quad \forall s \in \mathcal{S}$). The constraint (4.5j) ensures that SCO-YP combination is possible only if both PLC and YP are selected together. Similarly, constraint (4.5k) makes sure SCO-RP combination is possible only if both PLC and RP are selected together. Constraints (4.5l) and (4.5m) allow the purchase/election of a single FCI and ISP plan, respectively. The remaining constraints are the sign and binary restrictions on the decision variables.

Table 4.1: Nomenclature for the insurance model

Sets	
$\mathcal{S}$	Set of all future scenarios ($\{1, \ldots, S\}$) – indexed by s
$\mathcal{V}$	Set of FCI coverage alternatives ($\{1, \ldots, V\}$) – indexed by v
$\mathcal{L}$	Number of piecewise functions generated based on yield and N Rate relation
Decision Variables	
y_{v1} and y_{v2}	Binary variables representing FCI programs and their coverage level selection
	Specifically, $y_{v1} \rightarrow$ YP and $y_{v2} \rightarrow$ RP
	Equal to 1 if a coverage level v is chosen, otherwise equal to 0
σ_1^s and σ_2^s	Indemnity paid based on the combination of FCI and SCO decisions
$Q = \{q_1^s, q_2^s, q_3^s, q_4^s\}$	Disjunctive variables used for big-M reformulation
z_1 and z_2	Binary variables representing the selection of income support programs
	Specifically, $z_1 \rightarrow$ PLC and $z_2 \rightarrow$ ARC
	Equal to 1 if the respective policy is selected, otherwise equal to 0
ρ_1 and ρ_2	Binary variables representing the selection of YP-SCO and RP-SCO combinations
	Equal to 1 if the respective policy combination is selected, otherwise equal to 0
t	N application rate (lbs/acre)
u	Impact of N application rate to yield (percent of maximum yield)
X	Represent all RMI decisions
$\pi^s(X, t)$	Net income under scenario s
Parameters	
g	Cost of N application (\$/lbs)
p^s	Probability of scenario s
c_{v1}	Insurance premium cost for yield protection plan for coverage option v (\$/acre)
c_{v2}	Insurance premium cost for revenue protection plan for coverage option v (\$/acre)
r'_d	Projected corn price used during FCI calculations (\$/bu)
r'_m	February corn market price announced by USDA (\$/bu)
μ	Expected county yield (bu/acre)
f_v	Coverage rate for coverage option v
M	A sufficiently large number
e_{v1} and e_{v2}	Extra premium costs of selecting YP-SCO and RP-SCO combinations (\$/acre)
β_1^s and β_2^s	PLC and ARC payments under scenario s (\$/acre)
d_v	Additional coverage rate attained by purchasing SCO for coverage level v
t_{max}	The maximum application rate allowed with respect to Figure 4.4 (lbs)
a_l, b_l	Constants of piecewise linear function l generated with respect to Figure 4.4
Random Variables	
A	Maximum crop yield (bu/acre)
R_d	Harvest price (\$/bu)
R_m	Weighted MYA price (\$/bu)

4.4.4 CVaR Reformulation

The risk-neutral formulation, (4.5a), represents producer indifference to risk. Solutions to risk-neutral models may be unsatisfactory if the decision-makers have low risk tolerance. To represent risk aversion, risk models and measures that have been widely studied in the literature include utility functions, value-at-risk (VaR), conditional value-at-risk (CVaR), mean-risk models, and stochastic dominance relations. No approach to modeling risk is universally accepted; for example, while the utility functions can be difficult to elicit, stochastic dominance relations are challenging to satisfy.

CVaR, introduced by Rockafellar and Uryasev (2000), is a risk measure that is frequently incorporated into optimization models because it is coherent (Artzner et al., 1999; Shapiro et al., 2021) and computationally tractable. It is based on the VaR, which represents the worst-case threshold defined by a chosen α quantile. CVaR is the expected loss beyond the VaR breakpoint (Noyan and Rudolf, 2013)).

For a gain random variable π with a cumulative distribution function (CDF) denoted by F_π, VaR is defined as:

$$\mathrm{VaR}_\alpha(\pi) = \inf\{\eta : F_\pi(\eta) \geq \alpha\} \tag{4.6}$$

and CVaR is defined as:

$$\mathrm{CVaR}_\alpha(\pi) = \sup\Big\{\eta - \frac{1}{\alpha}\mathbb{E}\big([\eta - \pi]_+\big)\Big\}. \tag{4.7}$$

Note that CVaR captures a wide range of risk preferences including risk-neutral (represented by $\alpha = 1$), and pessimistic worst case (for sufficiently small values of α) (Noyan and Rudolf, 2013). That is, the selected α value represents the decision maker's risk preference.

Suppose that π is a discrete random variable with realizations $\pi^1, ..., \pi^S$ that occur with respective probabilities $p^1, ..., p^S$. Then, equation (4.7) is equivalently formulated as a linear program:

$$\mathrm{Max}\Big\{\eta - \frac{1}{\alpha}\sum_{s\in\mathcal{S}} p^s w^s : w^s \geq \eta - \pi^s \;\; \forall s \in \mathcal{S}, \;\; w^s \in \mathbb{R}, \;\; \eta \in \mathbb{R}\Big\} \tag{4.8}$$

The representation in (4.8) allows CVaR to be incorporated easily in an optimization model. This measure is also related to other ways of modeling risk preferences. Among these, stochastic dominance concerns the point-wise comparison of performance outcomes of alternative decisions (Müller and Stoyan, 2002; Dentcheva and Ruszczynski, 2003; Noyan, 2012). To investigate first order stochastic dominance (FSD), CDFs are compared directly. Specifically, for gain random variables, π_1 dominates π_2 in the first order if

$$F_{\pi_1}(\eta) \geq F_{\pi_2}(\eta) \quad \forall \eta \in \mathbb{R} \tag{4.9}$$

FSD is rarely observed because the performance outcomes are compared at every point.

Second order stochastic dominance (SSD) is implied by FSD but is easier to satisfy. It is defined as

$$F_{\pi_1}^{(2)}(\eta) \leq F_{\pi_2}^{(2)}(\eta) \quad \forall \eta \in \mathbb{R}, \tag{4.10}$$

where $F_{\pi}^{(2)}(\eta) = \int_{-\infty}^{\eta} F_{\pi}(\xi) d\xi$. Ogryczak and Ruszczynski (2002) shows that SSD is equivalent to

$$\mathrm{CVaR}_{\alpha}(\pi_1) \geq \mathrm{CVaR}_{\alpha}(\pi_2) \quad \forall \alpha \in (0, 1] \tag{4.11}$$

Both FSD and SSD are related to expected utility. Dentcheva and Ruszczynski (2003) demonstrate that if π_1 stochastically dominates π_2 in the first order, then $\mathbb{E}\big(u(\pi_1)\big) \geq \mathbb{E}\big(u(\pi_2)\big)$ for all nondecreasing utility functions. Likewise, if π_1 stochastically dominates π_2 in the second order, then $\mathbb{E}\big(u(\pi_1)\big) \geq \mathbb{E}\big(u(\pi_2)\big)$ for all nondecreasing concave utility functions (Ogryczak and Ruszczynski, 2002), which reflect risk aversion. Thus, establishing stochastic dominance can eliminate the need to elicit the utility function. In turn, establishing CVaR preference, $\mathrm{CVaR}_{\alpha}(\pi_1) \geq \mathrm{CVaR}_{\alpha}(\pi_2)$ for every value of α, can be a tractable way to identify SSD of π_1 over π_2.

In summary, we use CVaR as the risk measure to find the optimal crop insurance choices and fertilizer application rates under a range of risk preferences without specifying utility functions. However, we observe that some of the case study results discussed in Section 4.6 identify decisions that produce SSD profit. Accordingly, model (4.12) represents the CVaR reformulation of model (4.5) and allows us to optimize under various producer risk preferences.

$$\max_{X,t,\sigma_1^s,\sigma_2^s,Q^s,\omega^s,\eta} (\$/\text{acre}) \quad \eta - \frac{1}{\alpha}\sum_{s\in\mathcal{S}} p^s w^s \tag{4.12a}$$

s.t.

$$(4.5b) - (4.5q) \tag{4.12b}$$

$$w^s \geq \eta - \pi^s(X,t) \quad \forall s \in \mathcal{S} \tag{4.12c}$$

$$w^s \geq 0 \qquad \forall s \in \mathcal{S} \tag{4.12d}$$

$$\eta \in R \tag{4.12e}$$

For each discrete scenario s, we use the net income $\pi^s(X,t)$ as defined in (4.5b) under scenario s as the performance function to construct the CVaR formulation. Constraint (4.12b) is directly taken from model (4.5) and still needed to calculate $\pi^s(X,t)$.

4.4.5 Shortened Binary Formulation and Solution Procedure

Emirhüseyinoğlu and Ryan (2022) observed that the existence of disjunctive variables and the predominance of binary variables made a simpler version of model (4.5) computationally expensive to solve. To reduce the complexity, they used a decomposition-based solution approach by separating the fertilizer rate decision, t, from all other decisions. In this paper, the CVaR reformulation further increases the problem complexity. Therefore, this study also uses the same decomposition-based solution procedure which is described in Algorithm 2.

Fixing the decision variable t to a value t' allows us to pre-calculate the values of decision variables σ_1^s and σ_2^s from equations (4.1) and (4.2) and convert them into parameters denoted by

σ_{v1}^s and σ_{v2}^s as follows:

$$\sigma_{v1}^s = \max\Big(r_d'(\mu f_v - A^s u(t')), \quad 0\Big) \qquad \forall s \in \mathcal{S} \tag{4.13}$$

$$\sigma_{v2}^s = \max\Big(r_d' \mu f_v - r_d^s A^s u(t'), \quad r_d^s(\mu f_v - A^s u(t')), \quad 0\Big) \quad \forall s \in \mathcal{S} \tag{4.14}$$

We also additionally introduce new parameters γ_{v1}^s and γ_{v2}^s representing the additional indemnity income resulting from YP-SCO and RP-SCO combinations respectively. As a result, we build the following shortened formulation of model (4.5) under the assumption that the decision variable t is now fixed to a value t'.

$$\max_{X} (\$/\text{acre}) \qquad \sum_{s\in\mathcal{S}} p^s \pi^s(X, t') \tag{4.15a}$$

s.t.

$$\pi^s(X,t') = -\sum_{v\in\mathcal{V}} \Big(c_{v1}y_{v1} + c_{v2}y_{v2} + e_{v1}\rho_{v1} + e_{v2}\rho_{v2}\Big) - gt'$$

$$+ \sum_{v\in\mathcal{V}} \Big(\sigma_{v1}^s y_{v1} + \sigma_{v2}^s y_{v2} + \gamma_{v1}^s \rho_{v1} + \gamma_{v2}^s \rho_{v2}\Big) + \beta_1^s z_1 + \beta_2^s z_2 \qquad \forall s \in \mathcal{S} \tag{4.15b}$$

$$z_1 + y_{v1} - 2\rho_{v1} \geq 0 \qquad \forall v \in \mathcal{V} \tag{4.15c}$$

$$z_1 + y_{v2} - 2\rho_{v2} \geq 0 \qquad \forall v \in \mathcal{V} \tag{4.15d}$$

$$\sum_{v} \Big(y_{v1} + y_{v2}\Big) \leq 1 \tag{4.15e}$$

$$z_1 + z_2 \leq 1 \tag{4.15f}$$

$$y_{v1}, y_{v2}, \rho_{v1}, \rho_{v2} \in \{0, 1\} \qquad \forall v \in \mathcal{V} \tag{4.15g}$$

$$z_1, z_2 \in \{0, 1\} \tag{4.15h}$$

Accordingly, we update the model (4.12) as follows:

$$\max_{X} (\$/\text{acre}) \qquad \eta - \frac{1}{\alpha} \sum_{s\in\mathcal{S}} p^s w^s \tag{4.16a}$$

s.t.

$$(4.15b) - (4.15h) \tag{4.16b}$$

$$w^s \geq \eta - \pi^s(X, t') \quad \forall s \in \mathcal{S} \tag{4.16c}$$

$$w^s \geq 0 \quad \forall s \in \mathcal{S} \tag{4.16d}$$

$$\eta \in R \tag{4.16e}$$

Algorithm 2 Fertilizer rate decomposition

1: Initiate BestResult = 0
2: **for** t'=0, $t' \leq t_{max}$, $t' = t'_{next}$, $t'_{next} \in T'_{cand}$ **do**
3: Solve model (4.16) using t'
4: **if** NewResult > BestResult **then**
5: BestResult = NewResult and $t^* = t'$
6: **end if**
7: **end for**

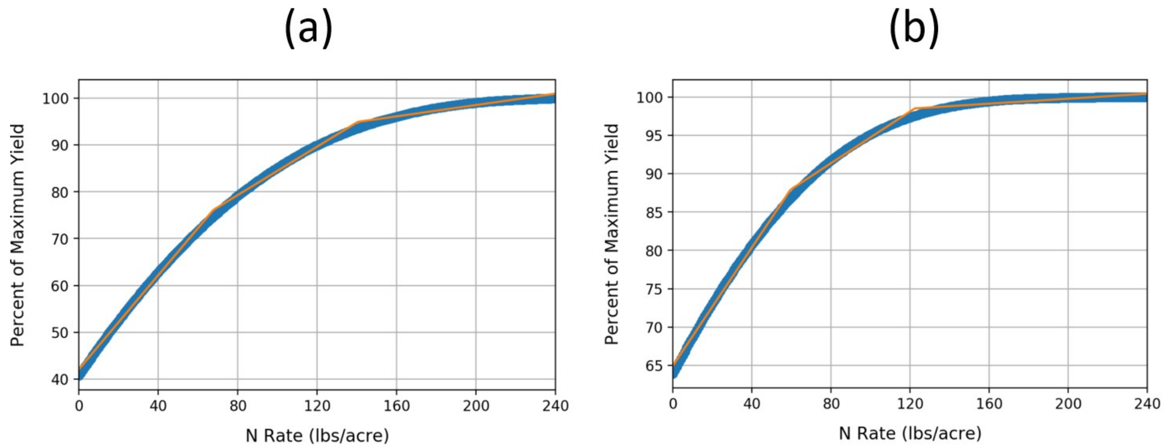
4.5. Computational Study

We use the 2019 corn crop year to investigate the impact of RMIs on producer profits and fertilizer use. Three counties in Iowa are selected as the test cases. Story has average yield productivity among Iowa counties while Taylor has one of the lowest and Sioux has one of the highest yields over the past decade. In this section, we briefly discuss how the dataset is generated.

Historical county-level corn yields (bu/acre) are collected from annual survey statistics provided by USDA, National Agricultural Statistics Service (2021) for years 1980-2018. Additionally, daily meteorological data for precipitation (mm), minimum and maximum temperature (degree Celsius), shortwave radiation (W/m^2) is gathered and aggregated using Daymet(Thornton et al., 2020) between the years of 1980 and 2018.

4.5.1 N Rate - Yield Relationship

The impact of the N application rate on yield is reflected in our model based on data points illustrated in Figure 4.4. All the tests are performed for both corn following corn (C-C) and corn following soybean (S-C) rotations, respectively. The N application cost, g, is assumed to be \$0.4/lb (Emirhüseyinoğlu and Ryan, 2022).



$$u(t) = \begin{cases} 0.50t + 42.09, & 0 \le t < 67.64 \\ 0.26t + 58.61, & 67.64 \le t < 140.39 \\ 0.06t + 86.46, & 140.39 \le t \le 223.87 \\ 100.00, & 223.87 \le t \le 240.00 \end{cases} \qquad u(t) = \begin{cases} 0.39t + 64.97, & 0 \le t < 59.47 \\ 0.17t + 77.89, & 59.47 \le t < 122.33 \\ 0.02t + 96.52, & 122.33 \le t \le 212.95 \\ 100.00, & 212.95 \le t \le 240.00 \end{cases}$$

Figure 4.4: Impact of N rate on yield as discrete points and piecewise linear approximation with $L = 3$. (a) Corn-corn rotation (b) Soybean-corn rotation (Sawyer et al., 2020)

4.5.2 FCI Parameters

There are two alternatives for producers to determine the value of parameter μ. The first is to use the historical crop yield average of the farm directly (a production history for a minimum of four years and a maximum of 10 years have been required for the last 12 years). However, historically, mean corn yield per unit area has trended upward due to improved farm management strategies and crop genetics (Shahhosseini et al., 2020). Therefore, the mean historical production may not represent the correct yield potential. As a result, trend-adjusted APH yields have been used as the second alternative since 2012 (Plastina and Edwards, 2014; USDA, 2021). In this study, we assume producers use trend-adjusted yields and elect Enterprise units to form their FCI policies. Table 4.2 demonstrates how trend-adjusted yields are calculated for FCI policies based on production history and trend-adjustment factors. We use the past 10 year county yield data to represent the producer's production history. County-level trend-adjustment factors are publicly announced each year by RMA. The value of this annual change was 2.12 bu/acre for Story County in 2019. The final trend-adjusted yield value from Table 4.2 is used as the parameter μ in FCI calculations. Accordingly, FCI premia are estimated using the USDA (2022c) online tool.

Table 4.2: Trend-adjusted yield calculation for crop year 2019, Story County, Iowa

Year	**Historical Yield (bu/acre)**	**Trend-Adj. (bu/acre)** Adj. Factor × (2019-Year)	**Trend-Adj. Yield (bu/acre)** Hist. Yield + Trend Adj.
2009	174.70	21.20	195.90
2010	163.90	19.08	182.98
2011	163.20	16.96	180.16
2012	157.60	14.84	172.44
2013	137.20	12.72	149.92
2014	169.90	10.60	180.50
2015	188.00	8.48	196.48
2016	211.90	6.36	218.26
2017	200.30	4.24	204.54
2018	192.30	2.12	194.42
Average	**175.90**		$\mu =$**187.56**

4.5.3 ISP Parameters

According to the 2018 Farm Bill, a_{plc} from equation (4.3) is calculated as the simple mean of crop yield during 2013-2017 multiplied by a commodity based detrending factor which is equal to 90% for corn times another 90%. Alternatively, farmers can replace their actual historical yield for a given year (if the yield loss is high) with the pre-quote yield rates (also referred to as substitute yields), equal to 75% of county yield (that is, the average of 75% of county yield during 2013-2017 is a lower bound for a_{plc}, and farmers can increase that value by using their actual yield information during the same years.

To estimate a_{plc}, we assume farmers use the actual production history instead of using pre-quote yields provided at USDA (2022b). According to the 2018 Farm Bill, the parameter a_{plc} should be estimated using yield information between 2013 and 2017. Accordingly, to represent the actual production data, we use the average of annual county yields from 2013-2017 provided by NASS (USDA, 2022d), multiplied by 90% × 90%.

The constant factor ζ from equations (4.3) and (4.4) is approximately equal to 0.79. ISP payments are made on 85% of base acres. Furthermore, a budget sequestration of 6.8% is also included. Accordingly, ζ represents those reductions and calculated as $85\%(1 - 6.8\%)$. The parameter r_1 from equations (4.3) and (4.4) is the pre-announced reference price, calculated as $r_1 = \min[\max(0.85r_2, \quad r_3), \quad 1.15r_3]$. The parameter r_2 refers to the Olympic average of price of the previous five marketing years. To calculate the Olympic average, the highest and lowest observations are eliminated and the arithmetic mean of remaining observations is calculated. The parameter r_3 represents statutory reference price. It is a fixed rate and currently equal to \$3.7/bushel. An upper limit called capacity, which restricts the reference price, is equal to 115% of the statutory reference price. Overall, r_1 is equal to r_3 under the 2018 Farm Bill for marketing years 2019-2022. The rest of 2019 ISP data, including a_{arc}, and r_1, is collected from USDA (2022b).

4.5.4 Scenario Generation Procedure

Historical market corn prices have fluctuated over the years. For instance, in 2004, the realized value of R_d was as low as \$1.93 while in 2012, its value reached a peak of \$7.5. Therefore, using the annual historical data directly to generate the discrete scenarios for R_d and R_m may not be accurate. It is essential to underline that even if the farmers cannot know the exact values of those random variables, they have some partial knowledge. Recall that the projected corn price r'_d announced by RMA is the average of the CBOT futures contract price during February, while R_d is the average of the CBOT futures contract price during the following October. Therefore, even though the producers do not know r_d; they know r'_d. Similarly, R_m is the weighted MYA average announced by USDA (see Section 4.3.2.2). Agricultural producers must finalize the ISP decisions in March, while the marketing year starts the following September. Thus, it is impossible to know the following marketing year prices. The latest piece of information the producers can obtain is the February market price midway through the previous marketing year. Consequently, assuming the producers make use of the latest available price information before taking the insurance decisions, we define random variables R_d and R_m as follows:

$$R_d = r'_d + \Delta R_d \tag{4.17}$$

$$R_m = r'_m + \Delta R_m, \tag{4.18}$$

where we define r'_m as the February market price of the previous crop year announced by USDA while the random variables ΔR_d and ΔR_m represent the changes (or market deviations). In other words, we use the historical market data to generate Δr^s_d and Δr^s_m and eventually obtain r^s_d and r^s_m.

We gather the historical data for r_d and r_m from 1980-2018 and r'_d and r'_m from 1980-2019. Accordingly, we generate historical deviation data from 1980-2018 for random variables Δr_d and Δr_m so that we can use that information to generate discrete market price deviation scenarios for 2019. All market price information is adjusted for inflation to 2019 values.

A brief summary of the adopted yield scenario generation procedure is as follows (we refer the reader to Emirhüseyinoğlu et al. (2022) for a comprehensive description of each step):

1. The 20 most important weather predictors, considering minimum and maximum air temperature in degrees C, total precipitation in mm/day, and average shortwave radiation in W/m^2, are identified using the feature selection procedure provided by Shahhosseini et al. (2020).

2. The machine learning strategy introduced by Shahhosseini et al. (2020) is used to generate the yield prediction function $A(\omega)$. Shahhosseini et al. (2020) consider several base prediction models, including linear regression, Least Absolute Shrinkage and Selection Operator (LASSO), random forest, extreme gradient boosting (XGBoost), and LightGBM, and propose an optimized weighted ensemble model that outperforms each base model by finding the optimal weights combining those models. The study uses soil and weather

(temperature, precipitation, and shortwave radiation) data at different granularity levels (weekly, monthly and quarterly) to generate county-level annual corn yield predictions for US Corn Belt States and achieves an RRMSE value of around 9%.

3. A nonparametric approximation strategy, known as moment matching (Høyland and Wallace, 2001) is implemented to generate discrete weather scenarios for the identified weather features ω and the market deviations ΔR_d and ΔR_m with statistical properties that match the estimates from historical data. A nonlinear program is formulated to minimize the distance between the statistical properties (four marginal moments and covariance matrix) of generated probabilisitic outcomes and the specified values. The total number of scenarios, $|S_1|$, is set according to a degrees-of-freedom calculation to avoid under- or over-fitting.

4. The prediction error distribution of $A(\omega)$ is investigated and additional scenario outcomes, $|S_2|$, are generated to capture the additional uncertainty arising from the prediction error.

5. For $s \in \mathcal{S}$, A^s, r_d^s, and r_m^s are formed as independent combinations of S_1 and S_2. The cardinality of the final set of scenarios is $|S| = |S_1| \times |S_2|$.

Note that Shahhosseini et al. (2020) ranks the most critical corn yield predictors based on the feature importance rates and finds no soil data among top 20 features, emphasizing the significance of weather features for county-level predictions. In line with our goal to inform policymakers, we ignore the location-based soil information to generate high-level yield information for our analysis. The top weather features identified for predicting the 2019 crop year county-level yield prediction are listed in Table 4.3. Those weather features compose the random variable vector ω and are used to generate $A(\omega)$.

Overall, we generate 42 (14×3) discrete scenarios for A^s, r_d^s, and r_m^s, using random variables $\omega, \Delta r_d$, and Δr_m by following the scenario generation procedure discussed in Emirhüseyinoğlu et al. (2022).

Table 4.3: Weather features included (ω) (m: month, Q: Quarter)

Minimum Temperature	m-June m-July m-September m-October Q1:Q3
Maximum Temperature	m-August m-September m-October Q2 Q3
Precipitation	m-July m-August Q1:Q3 Q3
Shortwave Radiation	m-June m-July Q2

4.6. Results and Discussion

In this section, we summarize the results of our computational runs by discussing in order: (i) how the RMIs affect the optimal N applications rates and what are the overall financial benefits for the producers; (ii) a brief comparison of the optimal results with historical ISP elections; (iii) the comparison between the current contingent ISP payments and former direct support payments; (iv) the financial incentives needed to reduce N application rates, and how the RMIs affect those incentives.

The proposed models are formulated in Python using Gurobi 9.5 as the optimization engine on a machine with Intel Core i7-7700HQ @ 2.80 GHz processor and 16 GB RAM.

4.6.1 Combined Impact of RMIs

In this section, we investigate how the RMIs affect the optimal N rate decisions and producer income for different risk preferences. Figure 4.5 illustrates how different N rates affect the expected farm profit with and without RMIs for S-C and C-C crop rotations, respectively. The expected profits and corresponding optimal points are generated for a risk-neutral producer. The shaded area represents the additional gain and financial safety acquired thanks to the RMIs. The results are somewhat surprising, as the highest expected profit is realized when the N rate is 0. We observe a decreasing expected profit trend at decreasing rates between [0, 79] for S-C ([0, 130] for C-C). Beyond 79 lbs/acre, the expected profit increases again, reaching the local optimum at 120 lbs/acre. Similar results are also observed for C-C rotation. In this case study, the expected per acre profit is higher if the farmer intentionally tries to minimize the farm yield by applying less fertilizer to the soil and maximizing the insurance income. This strategy is profitable in the short run thanks to the combination of FCI and ISP. For N rate less than or equal to 79 lbs/acre, the optimal RMI selections are ARC and RP, with an 85% coverage rate. Recall that both ARC and RP cover a potential yield loss. On the other hand, for any N rate over 79 lbs/acre for S-C and 130 lbs/acre for C-C, maximizing the harvest yield and maximizing the profit align. As a result, we observe that the combination of RP with a 60% coverage rate, PLC, and SCO is the best RMI alternative in this second N rate interval.

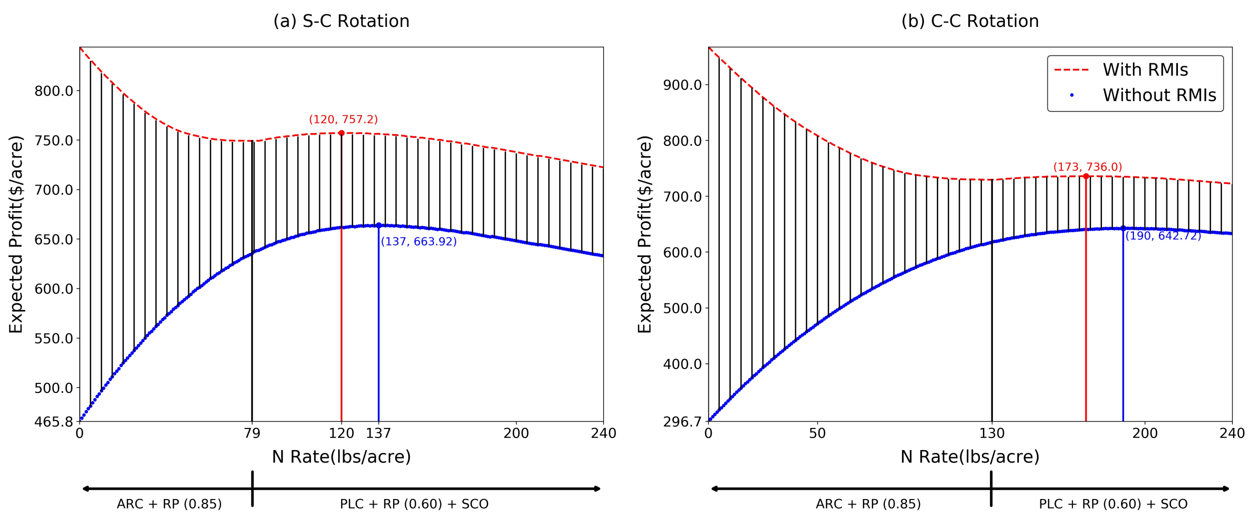


Figure 4.5: Preliminary results for a risk-neutral **Story County** producer (“With RMIs”: All RMIs are available, “Without RMIs”: No RMI selection is allowed)

However, suggesting that a farmer deliberately minimize the yield in a single year to maximize the income is not realistic or sustainable. First, reducing the yield will negatively affect the expected FCI income for the future as the indemnity payments depend on the actual production history of the farm (see section 4.3.1). Second, expecting all the producers to follow the optimal decisions would effectively eliminate the agriculture sector and make ISP unsustainable. Therefore, minimizing the N rate and harvest yield is not a viable option in the long term.

To eliminate this myopic strategy, we modify the production guarantee of FCI and ISP. Recall that FCI yield production guarantee program depends on μ and f_v where the parameter μ represents the trend-adjusted production history over a maximum of 10 years and f_v is the coverage rate. In Table 4.2, we demonstrate the calculation of μ for a specific example. Based on that calculation, and denoting the trend-adjusted historical county yield in year y by A'_y, the APH for use in FCI purchase for crop year Y is computed as $\mu_Y = \frac{1}{10}\sum\limits_{y=Y-10}^{Y-1} A'_y$. However, instead of considering only the current year's RMI payments, we force consideration of RMI payments in future years by using the expected actual production history of the next 10 years and update the calculation of μ as follows:

$$\mu = \tfrac{1}{10}\sum_{y=Y}^{Y+9} \mu_y \tag{4.19}$$

where, for $y \geq Y$, we assume that $A'_y = \sum_s p^s A^s u(t)$; i.e., the expected yield scenario will occur and the N rate will be the same as the decision taken for year Y. This modification converts the former parameter μ to a decision variable that forms nonlinear expressions in model (4.12). However, model (4.16) remains linear with the APH estimated for each scenario in equations (4.13) and (4.14). In effect, equation (4.19) penalizes the producers if they deliberately try to minimize the yield because low yields reduce the value of μ and the resulting FCI production guarantee.

Note that if a producer elects ARC-CO, a_{arc} will not be affected by the individual N rate decisions. However, because we provide our analysis on the county level and ISP programs are not sustainable if the farmers intentionally reduce the yield, we also modify the a_{arc} and a_{plc} correspondingly to depend on the current year's N rate decision.

Figure 4.6 illustrates the updated results of a risk-neutral producer for S-C and C-C rotations, respectively. We now observe that the local optimum in the second interval shown in Figure 4.5 is the new global optimum. The optimal decisions for different risk preferences are summarized in Table 4.4. Recall that $\alpha = 1$ represents the risk neutral case, and smaller α values represent more risk aversion. The tables also highlight the optimal N rate decisions when the RMIs are not considered to interpret better how the insurance programs affect the producer's risk and N rate decisions. Specifically, we preclude any insurance policy selection by fixing the binary FCI and ISP decisions, y_{v1}, y_{v2}, z_1, and z_2, to 0 when solving model (4.16).

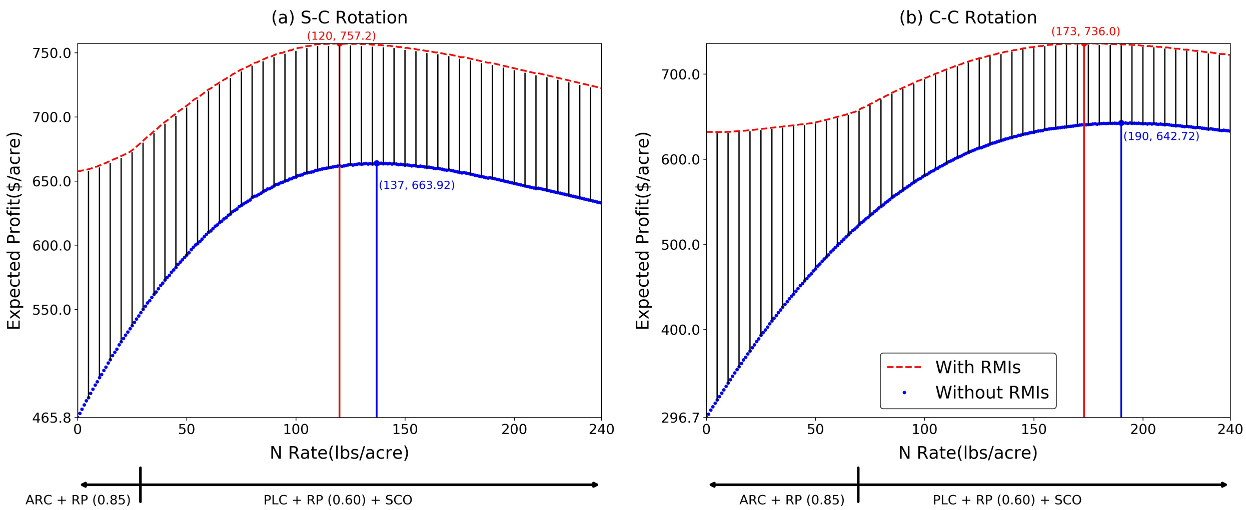


Figure 4.6: Impact of RMIs on expected farm profit for risk neutral Story County producer ("With RMIs": All RMIs are available, "Without RMIs": No RMI selection is allowed)

The results show that RMIs drastically affect the optimal fertilizer application rates. Specifically, for the risk-neutral producers, the optimal N rate reduces from 137 to 120 lbs/acre for S-C rotation and from 190 to 173 lbs/acre for C-C rotation. Moreover, as shown in Table 4.4, the optimal N rate tends to increase without RMIs as the producer becomes more risk-averse (i.e., as the parameter α decreases). Note that this increase might be an underestimation due to the limitation discussed in Section 4.4.2. However, unexpectedly, we observe the N rate decreasing with risk aversion when RMIs are included. In the literature, applying N fertilizer in excess of crop needs is considered a rational response by self-oriented risk-averse farmers trying to minimize the crop risk and maximize profitability (Rajsic and Weersink, 2008; Greiner et al., 2009; Prokopy

Table 4.4: Optimal N rate and insurance decisions for different risk preferences, and **Story County** (FCI results are labelled by the type of insurance and coverage rate; "With RMIs": All RMIs are available, "W/oRMIs": No RMI selection is allowed; "α": Risk preference)

α	**SC Rotation**					**CC Rotation**				
	W/oRMIs	**With RMIs**				**W/oRMIs**	**With RMIs**			
	N Rate	N Rate	ISP	FCI	SCO	N Rate	N Rate	ISP	FCI	SCO
0.01	151	104	PLC	RP, 0.60	Yes	204	151	PLC	RP, 0.60	Yes
0.05	151	104	PLC	RP, 0.60	Yes	204	151	PLC	RP, 0.60	Yes
0.1	149	104	PLC	RP, 0.60	Yes	202	151	PLC	RP, 0.60	Yes
0.2	146	110	PLC	RP, 0.60	Yes	199	163	PLC	RP, 0.60	Yes
0.3	146	110	PLC	RP, 0.60	Yes	199	163	PLC	RP, 0.60	Yes
0.4	143	110	PLC	RP, 0.60	Yes	197	163	PLC	RP, 0.60	Yes
0.5	143	110	PLC	RP, 0.60	Yes	197	163	PLC	RP, 0.60	Yes
0.6	143	110	PLC	RP, 0.60	Yes	197	163	PLC	RP, 0.60	Yes
0.7	139	110	PLC	RP, 0.60	Yes	193	163	PLC	RP, 0.60	Yes
0.8	139	110	PLC	RP, 0.60	Yes	193	163	PLC	RP, 0.60	Yes
0.9	137	111	PLC	RP, 0.60	Yes	190	164	PLC	RP, 0.60	Yes
1	137	120	PLC	RP, 0.60	Yes	190	173	PLC	RP, 0.60	Yes

et al., 2019; Thorburn et al., 2020). Yet, the results demonstrate that RMIs completely alter the direction of this trend and potentially bring unanticipated environmental benefits.

Another critical point is that the optimal RMI decisions are the same for all risk preferences. In other words, the insurance package corresponding to RP purchase with 0.6 coverage rate, PLC, and SCO election dominates all the other RMI decision alternatives in the SSD sense. Thus, based on the discussion in Section 4.4.4, the selected insurance package is the best alternative for producers with any nondecreasing concave utility function. Figure 4.7 shows the CDF of optimal profit for different risk preferences. The optimal objective values for various risk preferences are very similar. The combined impact of RMIs eliminates most of the risk from the problem causing the optimal decision sets for different risk preferences to be almost identical. The results of further tests where we explore the isolated impacts of RMIs and compare ARC and PLC in detail are described in the Appendix.

The results presented above are for Story County. To explore the reliability of our analysis, Taylor and Sioux counties of Iowa are also investigated. We summarize the optimal decisions for these high- and low-yield counties in Tables 4.5 and 4.6, respectively, while Figures 4.8 and 4.9 illustrate the expected profit for risk-neutral decision-makers. The relationship between N rate

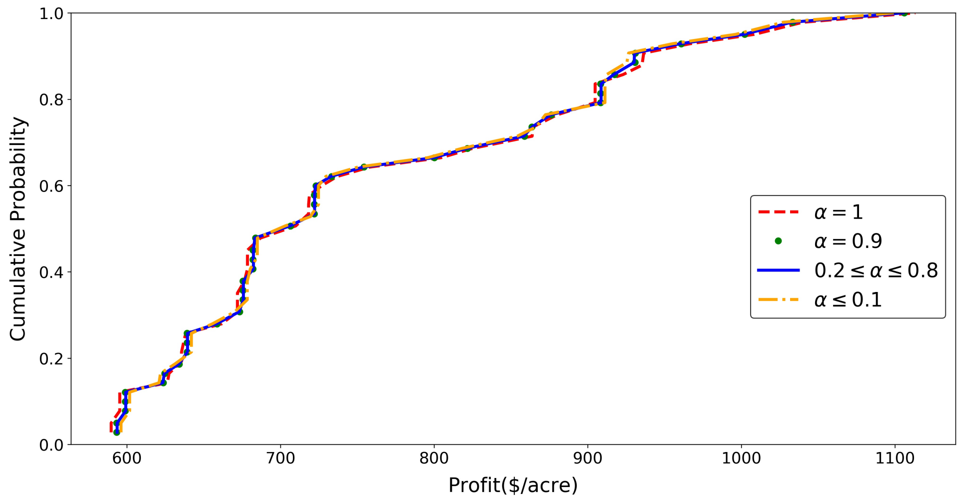


Figure 4.7: Probability distribution of the optimal profit function for different risk takers (Story County)

and risk preference for all three counties align. Likewise, the RMI decisions remain dominant for all risk preferences. The only difference is the optimal insurance package selections. Specifically, for Taylor County the optimal insurance package for S-C rotation corresponds to the combination of RP purchase with a coverage rate of 0.5, PLC and SCO elections while the optimal package for C-C rotation includes RP purchase with a coverage rate of 0.85 and ARC election. Likewise, the optimal insurance package for Sioux County for both rotations corresponds to the combination of RP purchase with a coverage rate of 0.5, PLC and SCO elections.

4.6.2 Optimal Results vs Actual Selections

USDA (2022b) provides detailed information about actual ISP enrollments since 2019. Table 4.7 summarizes the actual ISP enrollment distribution for corn in percentages from the last three years. According to the data, PLC enrollments were dominant both in the US and Iowa in 2019 and 2020, while ARC enrollments increased significantly in 2021 (total corn enrollment is slightly above 95M and 15M acres in the US and Iowa, respectively). Plastina and Hart (2021) explores the historical PLC and ARC-CO data to project/estimate the yearly average $/bu payments of each policy for Iowa. Table 4.8 summarizes the most recent estimations.

Table 4.5: Optimal insurance decisions for different risk preferences, **Taylor County** (FCI results are labelled by the type of insurance and coverage rate)

Risk Preference (α)	**S-C Rotation**				**C-C Rotation**			
	N Rate	FCI	ISP	SCO	N Rate	FCI	ISP	SCO
0.01	101	RP, 0.50	PLC	Yes	137	RP, 0.85	ARC	No
0.05	101	RP, 0.50	PLC	Yes	137	RP, 0.85	ARC	No
0.1	104	RP, 0.50	PLC	Yes	137	RP, 0.85	ARC	No
0.2	104	RP, 0.50	PLC	Yes	137	RP, 0.85	ARC	No
0.3	104	RP, 0.50	PLC	Yes	137	RP, 0.85	ARC	No
0.4	104	RP, 0.50	PLC	Yes	137	RP, 0.85	ARC	No
0.5	104	RP, 0.50	PLC	Yes	145	RP, 0.85	ARC	No
0.6	104	RP, 0.50	PLC	Yes	151	RP, 0.85	ARC	No
0.7	105	RP, 0.50	PLC	Yes	155	RP, 0.85	ARC	No
0.8	109	RP, 0.50	PLC	Yes	157	RP, 0.85	ARC	No
0.9	109	RP, 0.50	PLC	Yes	157	RP, 0.85	ARC	No
1	109	RP, 0.50	PLC	Yes	158	RP, 0.85	ARC	No

Table 4.6: Optimal insurance decisions for different risk preferences, **Sioux County** (FCI results are labelled by the type of insurance and coverage rate)

Risk Preference (α)	**S-C Rotation**				**C-C Rotation**			
	N Rate	FCI	ISP	SCO	N Rate	FCI	ISP	SCO
0.01	104	RP, 0.50	PLC	Yes	151	RP, 0.50	PLC	Yes
0.05	104	RP, 0.50	PLC	Yes	151	RP, 0.50	PLC	Yes
0.1	104	RP, 0.50	PLC	Yes	151	RP, 0.50	PLC	Yes
0.2	104	RP, 0.50	PLC	Yes	155	RP, 0.50	PLC	Yes
0.3	109	RP, 0.50	PLC	Yes	155	RP, 0.50	PLC	Yes
0.4	120	RP, 0.50	PLC	Yes	173	RP, 0.50	PLC	Yes
0.5	125	RP, 0.50	PLC	Yes	178	RP, 0.50	PLC	Yes
0.6	120	RP, 0.50	PLC	Yes	173	RP, 0.50	PLC	Yes
0.7	125	RP, 0.50	PLC	Yes	178	RP, 0.50	PLC	Yes
0.8	129	RP, 0.50	PLC	Yes	182	RP, 0.50	PLC	Yes
0.9	129	RP, 0.50	PLC	Yes	182	RP, 0.50	PLC	Yes
1	132	RP, 0.50	PLC	Yes	185	RP, 0.50	PLC	Yes

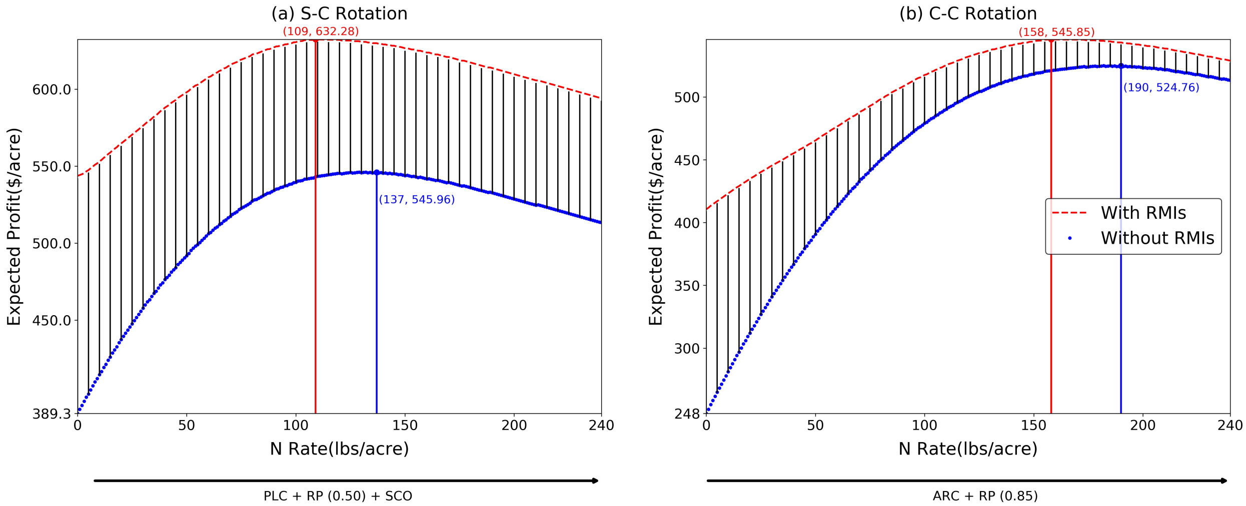


Figure 4.8: Impact of RMIs on expected farm profit for risk neutral Taylor County producer ("With RMIs: All RMIs are available, "Without RMIs": No RMI selection is allowed)

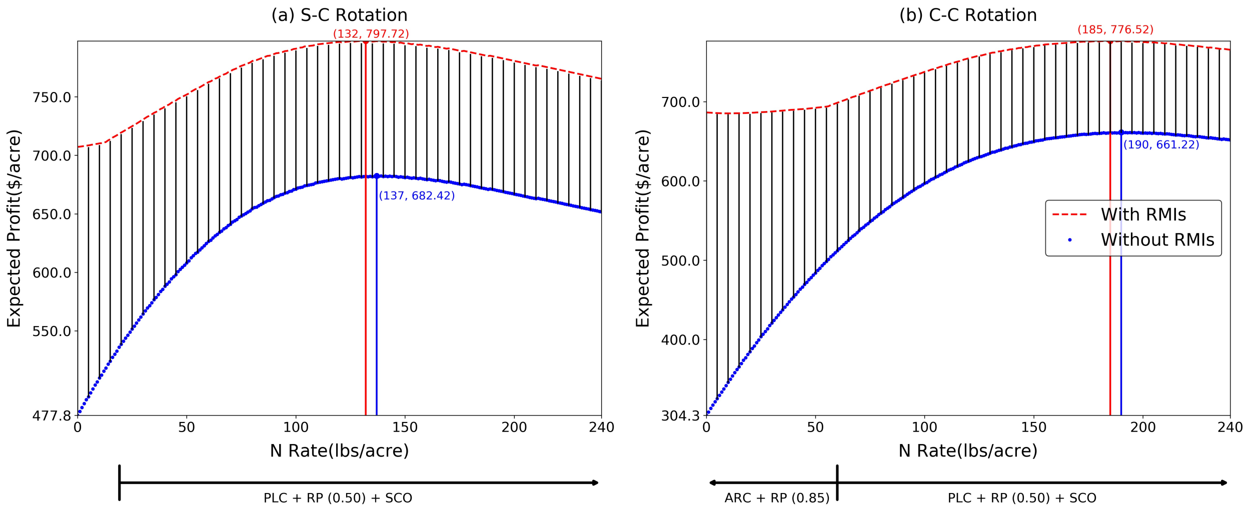


Figure 4.9: Impact of RMIs on expected farm profit for risk neutral Sioux County producer ("With RMIs: All RMIs are available, "Without RMIs": No RMI selection is allowed)

It appears that Iowa farmers tend to elect the highest paying program based on the most recent memory and the payment rates from the last couple of years. After high ARC payments in 2014 and 2015, majority of the producers elected ARC in 2016 and 2017. Similarly, following the low ARC payments, farmers majorly select PLC as their main enrollment plan since 2020. Apparently, the sudden crop price increase in 2020 due to the Covid-19 pandemic and resulting a payment rate of \$0, caused most farmers to switch back to ARC in 2021.

Table 4.7: ISP enrollment rates in the US

Program	**US**			**Iowa**		
	2019	2020	2021	2019	2020	2021
PLC	75.6%	75.3%	51.4%	88.9%	90.4%	34.8%
ARC-CO	18.5%	18.8%	47.2%	6.7%	7.3%	64.6%
ARC-IC	5.9%	5.8%	1.4%	4.4%	2.3%	0.6%

Table 4.8: Historical ISP payment rates in Iowa (per bushel)

Program	2015	2016	2017	2018	2019	2020
PLC	\$10.39	\$39.27	\$39.27	\$10.39	\$16.17	\$0
ARC-CO	\$33.85	\$12.60	\$1.80	\$0.88	\$1.56	\$5.84

4.6.3 Direct Payments vs ARC and PLC Programs

Before the introduction of ARC and PLC with the 2014 Farm Bill, grower support was in the form of direct payments, which transferred to agricultural producers regardless of the agricultural economy. After the commodity programs were modified to ARC and PLC as RMIs, economists compared both systems in recent years (Boehlje and Langemeier, 2016; Schnitkey and Zulauf, 2016; Plastina and Hart, 2018). Their major questions were how much security (or "safety net") those programs provide and whether the new system with the probability of payment less than 1 is more beneficial for the agricultural producers than the certainty of direct payments. Figure 4.10 shows the results of replacing the ISP programs with the direct payment system used in 2008-2012 (Direct Payment = 83.3% $\times$ μ $\times$ \$0.28). Specifically, we removed all ISP decisions from model (4.16) by fixing the binary ISP decisions, z_1 and z_2, to 0 and solving model (4.16), and added the fixed direct payments instead. The results demonstrate that even if the currently ongoing ISP payment probability is less than 1, the objective values are higher than under certain direct payments.

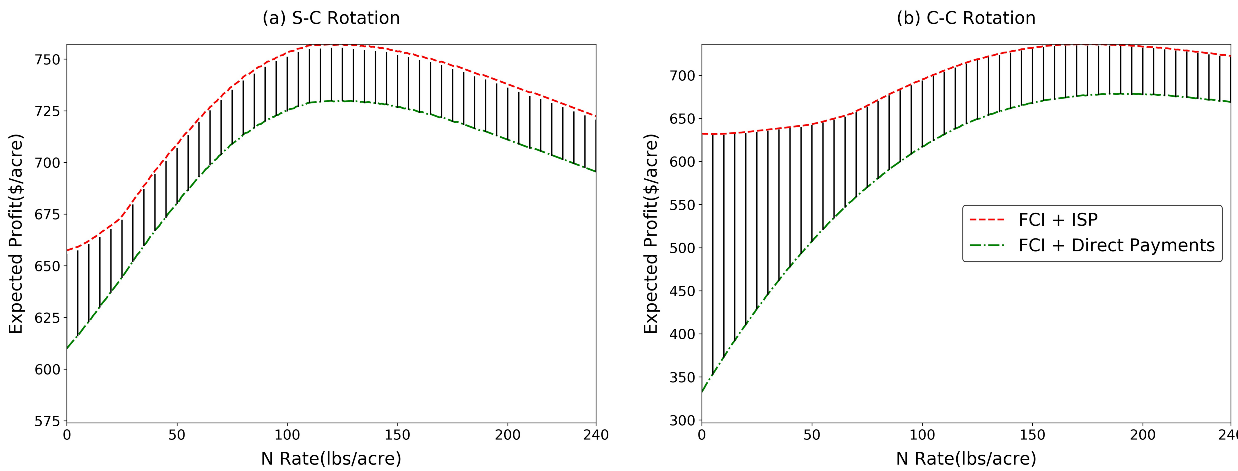


Figure 4.10: Comparing ISP to Direct Payments (Story County, risk-neutral producer)

Table 4.9 compares ISP with direct payments for different risk preferences. The values in each column indicate the per acre return of replacing direct payments with ISP generated based on the optimal results of the stochastic program. While positive values represent a positive income, negative values represent a loss. Specifically, in the first set of columns, we provide a direct comparison by assuming the farmer does not purchase any FCI policy. In the second set of columns, we allow FCI purchases to provide a more practical comparison. Overall, the results demonstrate that individually ISP is much more advantageous than direct payments, especially for risk-averse decision makers. However, when FCI purchases are also allowed, the combined impact shows that ISP actually performs worse than direct payments for decision-makers with very high risk aversion (as a result of the FCI purchase, the tail of the profit distribution corresponds to a different set of scenarios for yield and price). The expected payment from ISP is always larger than the direct payment would have been, whether or not the producer decides to purchase FCI. However, because ISP is contingent and does not guarantee payment, highly risk-averse producers who are protected by an FCI policy may not find it preferable over direct support payments.

Table 4.9: Optimal profit under ISP less optimal profit under direct support payments (Story County)

Risk Preference (α)	FCI not available ($/acre)		FCI available ($/acre)	
	S-C	C-C	S-C	C-C
0.01	215.11	208.61	-25.84	-25.86
0.05	213.40	212.93	-25.81	-25.83
0.1	175.89	175.77	-23.02	-23.05
0.2	104.29	104.28	-10.07	-10.68
0.3	76.27	76.26	3.52	2.90
0.4	62.67	62.66	16.94	16.33
0.5	53.05	53.04	25.79	25. 36
0.6	42.81	42.81	28.13	28.02
0.7	34.36	34.36	31.79	31.15
0.8	32.81	34.81	38.28	37.11
0.9	27.80	27.80	34.21	32.50
1	21.42	21.41	27.31	25.31

4.6.4 Financial Implications of Reducing N Rate

So far, we have demonstrated how the RMIs drastically change the optimal N application rates. In this section, we highlight the financial loss that would result from forcing a reduction of N rates. In Tables 4.10 and 4.11, several arbitrary N rate targets are selected, and per-acre CVaR penalties of achieving those targets for each risk preference are summarized. To generate the per-acre costs for each risk preference, we first resolve the optimization model (4.16) with t fixed to the specific N rate target). Then, we calculate the objective value difference between applying the N rate targets and the optimal N rates from Figure 4.4 for each respective risk preference. All the results provided are generated under the assumption that farmers are rational and have the single objective of maximizing profit. We consider two different settings, (i) including and (ii) excluding the insurance programs.

The CVaR penalty for any risk preference is much smaller when insurance programs are included as part of the decision-making. Those losses could also be interpreted as potential incentives needed for producers to adopt different N rate targets. In Table 4.4, (-) denotes that no financial incentive is necessary to achieve the N rate target of 120 lbs/acre for α values between 0.01 and 0.9. That is because the optimal N rate is already less than 120 lbs/acre for those risk preferences. Note that for a risk-neutral producer ($\alpha = 1$), the optimal N rate for S-C rotation is exactly 120 lbs/acre (see Table 4.4).

Table 4.10: Per acre CVaR costs **($/acre)** of reducing fertilizer application rate (Story County, **S-C** rotation, "WRMI": All RMIs are available, "W/oRMI": No RMI selection is allowed)

Risk Preference (α)	**N application rate targets (lbs/acre)**							
	120		**100**		**80**		**60**	
	WRMI	W/oRMI	WRMI	W/oRMI	WRMI	W/oRMI	WRMI	W/oRMI
0.01	-	1.80	0.21	3.20	2.17	9.01	8.65	18.44
0.05	-	2.01	0.21	3.55	2.17	10.01	8.68	20.49
0.1	-	1.30	0.21	3.77	2.17	13.26	10.80	25.57
0.2	-	0.30	1.62	3.64	7.96	12.35	20.05	24.93
0.3	-	0.27	1.86	5.75	8.73	12.89	21.17	32.20
0.4	-	0.28	1.75	5.77	8.71	14.72	22.49	31.98
0.5	-	0.49	1.78	6.58	8.44	16.29	21.48	34.80
0.6	-	0.69	1.77	7.43	8.88	17.94	23.02	37.77
0.7	-	0.96	2.51	8.34	11.05	19.68	26.50	40.86
0.8	-	1.24	2.65	9.31	12.30	21.51	29.77	44.13
0.9	-	1.65	2.99	10.57	12.71	23.87	30.62	48.29
1	0.00	2.21	4.31	12.14	15.86	26.77	35.87	53.36

Table 4.11: Per acre CVaR costs **($/acre)** of reducing fertilizer application rate (Story County, **C-C** rotation, "WRMI": All RMIs are available, "W/oRMI": No RMI selection is allowed)

Risk Preference (α)	**N application rate targets (lbs/acre)**							
	120		**100**		**80**		**60**	
	WRMI	W/oRMI	WRMI	W/oRMI	WRMI	W/oRMI	WRMI	W/oRMI
0.01	2.99	4.53	9.48	12.43	19.88	24.01	34.22	40.80
0.05	2.99	4.57	9.50	12.49	19.91	24.73	34.24	41.27
0.1	3.25	7.44	11.94	17.83	22.35	33.18	37.02	53.52
0.2	11.02	13.62	20.97	28.21	32.23	48.91	47.16	75.74
0.3	11.61	16.97	23.56	33.69	41.12	57.10	53.50	87.21
0.4	11.68	19.33	25.47	37.48	44.91	62.71	59.33	95.03
0.5	11.30	21.35	24.21	40.69	43.12	67.44	56.75	101.60
0.6	12.06	23.48	25.75	44.09	44.54	72.44	56.23	108.55
0.7	14.85	25.68	29.58	47.57	48.85	77.55	61.38	115.62
0.8	16.84	28.03	33.68	51.27	55.13	82.97	70.24	123.14
0.9	17.22	31.03	34.89	55.98	57.73	89.95	76.46	132.64
1	21.31	34.69	40.81	61.68	64.70	98.14	86.29	144.08

Overall, RMIs have side benefits for the environment by reducing the optimal N application rates. Financial incentives needed to reduce N application rates are significantly smaller with those programs. Furthermore, the results demonstrate that the incentives developed for risk-neutral producers should suffice for risk-averse producers as well.

4.7. Conclusion

This paper investigates the available RMIs for corn production in the US and their interaction with fertilizer application rate to understand their financial and environmental impacts. The uncertain crop price and harvest yield, dependent on random weather features, are represented by discrete probabilistic yield and price scenarios at the county level. We build a two-stage stochastic program, including CVaR as a risk measure, to find optimal RMI utilization choices and fertilizer application rates under a range of risk preferences. We assume that the corn producers are rational decision-makers with a single motive of maximizing farm profits.

The case study results show that each RMI has unique impacts on farmers' profitability and N application rate when they are investigated independently (the optimal decisions also differ depending on the risk preference of the decision-maker). However, when combined, they eliminate most of the risk resulting from yield and price uncertainties. Specifically, we observe second-order stochastic dominance for selected decisions, as the optimal FCI and ISP decisions are the same for all levels of risk aversion. In addition, even though there is no dominant N rate decision, the optimal N rate does not vary much with risk preference.

Overall, the RMIs significantly alter financial and environmental outcomes. These programs have additional environmental benefits on top of their financial benefits by reducing the optimal N application rates. Specifically, we find that the optimal N rate is lower for all risk preferences when RMI use is optimized. Also, although without RMIs, the optimal N rate increases considerably with risk aversion, we find that RMIs cause an opposite effect. Specifically, the optimal N rate for more risk-averse producers is slightly lower.

From a social planner's perspective, the financial impact of reducing the N application rates is significantly less for all risk preferences with currently available RMIs compared to the no-RMI case. That is, financial tools significantly reduce the incentives needed to reduce fertilizer use, no matter the level of risk aversion.

The case study results show that contingent payments under the 2018 Farm Bill can provide more financial security than the former direct payments for all but the highest levels of risk aversion.

By exploring the the interaction between optimal N application rate and selection of RMI options, this research reveals the environmental side benefits of the existing RMIs. By incorporating risk considerations in models that jointly optimize farm management and financial decisions, future research could inform the design of insurance programs for greater environmental benefit.

4.8. References

Archontoulis, S. V., Castellano, M. J., Licht, M. A., Nichols, V., Baum, M., Huber, I., Martinez-Feria, R., Puntel, L., Ordóñez, R. A., Iqbal, J., et al. (2020). Predicting crop yields and soil-plant nitrogen dynamics in the US Corn Belt. *Crop Science*, 60(2):721–738.

Artzner, P., Delbaen, F., Eber, J.-M., and Heath, D. (1999). Coherent measures of risk. *Mathematical Finance*, 9(3):203–228.

Barnaby, G. and Russell, L. A. (2016). Crop insurance will be at the center of the 2019 Farm Bill Debate. *Choices*, 31(316-2016-7834).

Billen, G., Garnier, J., and Lassaletta, L. (2013). The nitrogen cascade from agricultural soils to the sea: modelling nitrogen transfers at regional watershed and global scales. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 368(1621):20130123.

Boehlje, M. and Langemeier, M. (2016). The farm safety net: The good and not so good. *farmdoc daily*, 6(81).

Dentcheva, D. and Ruszczynski, A. (2003). Optimization with stochastic dominance constraints. *SIAM Journal on Optimization*, 14(2):548–566.

Emirhüseyinoğlu, G. and Ryan, S. M. (2022). Farm management optimization under uncertainty with impacts on water quality and economic risk. *IISE Transactions*, pages 1–18.

Emirhüseyinoğlu, G., Ryan, S. M., Hu, G., and Shahhosseini, M. (2022). Scenario generation for decision-making using machine learning prediction models: A case study for crop yield in Midwest. Technical report, Iowa State University.

Erisman, J. W., Galloway, J. N., Seitzinger, S., Bleeker, A., Dise, N. B., Petrescu, A. R., Leach, A. M., and de Vries, W. (2013). Consequences of human modification of the global nitrogen cycle. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 368(1621):20130116.

Geng, R., Yin, P., and Sharpley, A. N. (2019). A coupled model system to optimize the best management practices for nonpoint source pollution control. *Journal of Cleaner Production*, 220:581–592.

Greiner, R., Patterson, L., and Miller, O. (2009). Motivations, risk perceptions and adoption of conservation practices by farmers. *Agricultural Systems*, 99(2-3):86–104.

Hansson, S. O. (2010). Risk: objective or subjective, facts or values. *Journal of Risk Research*, 13(2):231–238.

Hardaker, J. B., Richardson, J. W., Lien, G., and Schumann, K. D. (2004). Stochastic efficiency analysis with risk aversion bounds: a simplified approach. *Australian Journal of Agricultural and Resource Economics*, 48(2):253–270.

Høyland, K. and Wallace, S. W. (2001). Generating scenario trees for multistage decision problems. *Management Science*, 47(2):295–307.

Kaini, P., Artita, K., and Nicklow, J. W. (2012). Optimizing structural best management practices using SWAT and genetic algorithm to improve water quality goals. *Water Resources Management*, 26(7):1827–1845.

Liu, J., Men, C., Cabrera, V. E., Uryasev, S., and Fraisse, C. W. (2008). Optimizing crop insurance under climate variability. *Journal of Applied Meteorology and Climatology*, 47(10):2572–2580.

Martínez-Dalmau, J., Berbel, J., and Ordóñez-Fernández, R. (2021). Nitrogen fertilization. A review of the risks associated with the inefficiency of its use and policy responses. *Sustainability*, 13(10):5625.

Menapace, L., Colson, G., and Raffaelli, R. (2013). Risk aversion, subjective beliefs, and farmer risk management strategies. *American Journal of Agricultural Economics*, 95(2):384–389.

Müller, A. and Stoyan, D. (2002). *Comparison Methods for Stochastic Models and Risks*, volume 389. Wiley.

Noyan, N. (2012). Risk-averse two-stage stochastic programming with an application to disaster management. *Computers & Operations Research*, 39(3):541–559.

Noyan, N. and Rudolf, G. (2013). Optimization with multivariate conditional value-at-risk constraints. *Operations Research*, 61(4):990–1013.

Ogryczak, W. and Ruszczynski, A. (2002). Dual stochastic dominance and related mean-risk models. *SIAM Journal on Optimization*, 13(1):60–78.

Plastina, A. and Edwards, W. (2014). Trend-adjusted actual production history (APH). *Ag Decision Maker*, A1-56. https://www.extension.iastate.edu/agdm/crops/pdf/a1-56.pdf, (accessed: 2022-02-14).

Plastina, A. and Hart, C. (2018). Is ARC-CO acting as a safety net program? Evidence from Iowa. *Choices*, 33(1):1–10.

Plastina, A. and Hart, C. (2021). ARC/PLC payments per base acre in Iowa. https://www.card.iastate.edu/tools/farm-bill/arc-plc/, (accessed: 2021-12-16).

Prokopy, L. S., Floress, K., Arbuckle, J. G., Church, S. P., Eanes, F. R., Gao, Y., Gramig, B. M., Ranjan, P., and Singh, A. S. (2019). Adoption of agricultural conservation practices in the United States: Evidence from 35 years of quantitative literature. *Journal of Soil and Water Conservation*, 74(5):520–534.

Rajsic, P. and Weersink, A. (2008). Do farmers waste fertilizer? A comparison of ex post optimal nitrogen rates and ex ante recommendations by model, site and year. *Agricultural Systems*, 97(1-2):56–67.

Rockafellar, R. T. (2007). Coherent approaches to risk in optimization under uncertainty. In *OR Tools and Applications: Glimpses of Future Technologies*, pages 38–61. Informs.

Rockafellar, R. T. and Uryasev, S. (2000). Optimization of conditional value-at-risk. *The Journal of Risk*, 2:21–42.

Rware, H., Kayuki, C., Macharia, M., and Oduor, G. (2016). Fertilizer use optimization approach: An innovation to increase agricultural profitability for African farmers. *African Journal of Agricultural Research*, 11(38):3587–3597.

Sawyer, J., Nafziger, E., Camberato, J., Steinke, K., Kaiser, D., Culman, S., and Laboski, C. (2020). Corn nitrogen rate calculator. http://cnrc.agron.iastate.edu/. Accessed: 2020-06-15.

Sawyer, J. E. (2019). Springtime precipitation – A tool for estimating nitrogen application need for corn. *Integrated Crop Management News*, page 2563.

Schnitkey, G. and Zulauf, C. (2016). The farm safety net for field crops. *Choices*, 31(316-2016-7846).

Sexton, B., Moncrief, J., Rosen, C. J., Gupta, S. C., and Cheng, H. (1996). Optimizing nitrogen and irrigation inputs for corn based on nitrate leaching and yield on a coarse-textured soil. *Journal of Environmental Quality*, 25(5):982–992.

Shahhosseini, M., Hu, G., and Archontoulis, S. (2020). Forecasting corn yield with machine learning ensembles. *Frontiers in Plant Science*, 11:1120.

Shahhosseini, M., Hu, G., Huber, I., and Archontoulis, S. V. (2021). Coupling machine learning and crop modeling improves crop yield prediction in the US Corn Belt. *Scientific Reports*, 11(1):1–15.

Shapiro, A., Dentcheva, D., and Ruszczynski, A. (2021). *Lectures on Stochastic Programming: Modeling and Theory*. SIAM.

Sharma, R., Kamble, S. S., Gunasekaran, A., Kumar, V., and Kumar, A. (2020). A systematic literature review on machine learning applications for sustainable agriculture supply chain performance. *Computers & Operations Research*, 119:104926.

Srivastava, P., Hamlett, J., Robillard, P., and Day, R. L. (2002). Watershed optimization of best management practices using AnnAGNPS and a genetic algorithm. *Water Resources Research*, 38(3):3–1.

Thorburn, P., Biggs, J., McMillan, L., Webster, T., Palmer, J., and Everingham, Y. (2020). Innovative economic levers: a system for underwriting risk of practice change in cane-farming. Technical report, National Environmental Science Program. Reef and Rainforest Research Centre Limited, Cairns (67pp.).

Thornton, M., Shrestha, R., Wei, Y., Thornton, P., Kao, S., and Wilson, B. (2020). Daymet: Daily surface weather data on a 1-km grid for North America, version 4. https://doi.org/10.3334/ORNLDAAC/1840. Accessed: 2021-06-15.

USDA (2021). Trend-adjusted actual production history standards handbook. https://www.rma.usda.gov/-/media/RMA/Handbooks/Privately-Developed-Products---20000/Trend-Adjustment/2021-20220-1-Trend-Adjusted-APH-Standards.ashx, (accessed: 2022-02-14).

USDA (2022a). Agricultural prices. https://usda.library.cornell.edu/concern/publications/c821gj76b?locale=en&page=2#release-items, (accessed: 2022-02-14).

USDA (2022b). ARC/PLC program data. https://www.fsa.usda.gov/programs-and-services/arcplc_program/arcplc-program-data/, (accessed: 2022-02-14).

USDA (2022c). Cost estimator: Personalized estimate. https://ewebapp.rma.usda.gov/apps/CostEstimator/Estimates/DetailedEstimate.aspx, (accessed: 2022-02-14).

USDA (2022d). Quick stats. https://quickstats.nass.usda.gov/, (accessed: 2022-02-14).

USDA (2022e). World agricultural supply and demand estimates. https://https://www.usda.gov/oce/commodity/wasde. Accessed: 2022-05-29.

USDA, National Agricultural Statistics Service (2021). Survey statistics. https://quickstats.nass.usda.gov/. Accessed: 2021-07-01.

USDA, National Agricultural Statistics Service (2022). Survey statistics. https://quickstats.nass.usda.gov/. Accessed: 2022-05-29.

van Klompenburg, T., Kassahun, A., and Catal, C. (2020). Crop yield prediction using machine learning: A systematic literature review. *Computers and Electronics in Agriculture*, 177:105709.

Yong, T., Chen, P., Dong, Q., Du, Q., Yang, F., Wang, X., Liu, W., and Yang, W. (2018). Optimized nitrogen application methods to improve nitrogen use efficiency and nodule nitrogen fixation in a maize-soybean relay intercropping system. *Journal of Integrative Agriculture*, 17(3):664–676.

Appendix

SCO Example

In this section, we illustrate how a YP-SCO combination works to provide a better understanding of SCO structure. We provide two general examples where we calculate YP-SCO insurance indemnity payments using the values provided in Table 4.12.

Table 4.12: YP-SCO Example 1

Description	Notation	Example 1 Value	Example 2 Value
Expected Yield	μ	100 bu/acre	100 bu/acre
Actual County Yield	A_c	70 bu/acre	82 bu/acre
Actual Farm Yield	A	70 bu/acre	70 bu/acre
Selected YP coverage rate	f_v	0.75	0.75

Example 1 represents the example where the realized farm yield, A, after harvesting season, is equal to realized county yield. Since selected coverage level for YP is equal to 0.75 in this example, one can calculate YP indemnity payment, σ_1, as $\max\Big(\mu f_v r_0 - r_0 A, \quad 0\Big)$. Using the values provided in Table 4.12, $\sigma_1 = 5r_0$.

SCO election by the farmer generates an additional county-level coverage of the amount from f_v to 86%. In other words, in this example, there will be an additional $0.86 - f_v$ county-level coverage, which is equal to 11%. Therefore, since we assume A and A_c are equal to each other in this example, SCO pays to the farmer an additional amount $11r_0$, where the total indemnity payment reaches to $16r_0$.

Example 2 represents an example where the realized farm yield, A, after harvesting season, is different than the realized county yield A_c. In this example, since actual farm yield A is still equal to 70 bu/acre and f_v is 0.75, YP indemnity payment is same as Example 1 where it is equal to $5r_0$. However, SCO is a county-level protection unlike federal crop insurance. Therefore, in Example 2, SCO election generates to the farmer an additional income equal to $4r_0$, which makes the total indemnity payment $9r_0$.

Therefore, the total indemnity payment of YP-SCO combination is $\sigma_1 + \gamma_1$, where $\sigma_1 = \max\Big(\mu f_v r_0 - r_0 A, \quad 0\Big)$, and γ_1 denotes the additional SCO payment and calculated as follows:

$$\gamma_1 = \begin{cases} r_0(0.86\mu - A_c), & \text{if } f_v\mu \le A_c < 0.86\mu \\ r_0(0.86 - f_v)\mu, & \text{if } A_c < f_v\mu \\ 0, & \text{if } A_c \ge 0.86\mu \end{cases}$$

ARC and PLC Comparison

In this section, we specifically focus on ISP to understand how each policy individually affects farm profits. For that purpose, we do not allow FCI purchases by excluding them from the decision-making. Table 4.13 provides the optimal N rate and ISP decisions under different risk-preferences when FCI selections are not allowed. We observe that the ARC structure is a better alternative than PLC for decision-makers with a high risk-aversion (particularly if α is below 0.5). This is expected since the probability of low yield scenarios that generate insurance incomes (yield goes below the production guarantee) is less likely to occur (especially considering the annual increasing yield trend) than the always volatile market scenarios. However, those low-yield scenarios are much more punishing than market volatility. Compared to the no-RMI results, ARC selection tends to reduce the optimal N rate application financially, while the PLC program does not cause any significant changes. Note that when α value is very small, the optimal N rate goes to 0. Low α values correspond to significantly undesirable weather and market scenarios where the producer aims to minimize the yield and maximize the ISP income (which is not realistic in real life). We can assume that it is a similar situation where the farmer knows there will be a flood and prefers not to spend any money on fertilizer by simply aiming for insurance money.

Figure 4.11 illustrates the cumulative profit distribution for different risk preferences, while Figure 4.12 highlight the expected profit under different N application rates for a risk neutral decision-maker. FCI results are also provided for a basic comparison with ISP. Overall, it seems like PLC provides the highest financial contribution when the optimal N rate is applied. However, for different N rates the expected profit variance of PLC is much higher. On the other hand, FCI expected profit looks most stable under different N rates.

Table 4.13: ISP Comparison (Story County, FCI is not allowed)

Risk Preference (α)	**S-C Rotation**		**C-C Rotation**	
	Optimal N Rate (lbs/acre)	ISP Policy	Optimal N Rate (lbs/acre)	ISP Policy
0.01	0	ARC	0	ARC
0.05	134	ARC	0	ARC
0.1	130	ARC	184	ARC
0.2	129	ARC	184	ARC
0.3	126	ARC	181	ARC
0.4	126	ARC	179	ARC
0.5	128	ARC	179	ARC
0.6	142	PLC	197	PLC
0.7	139	PLC	193	PLC
0.8	139	PLC	193	PLC
0.9	137	PLC	190	PLC
1	137	PLC	190	PLC

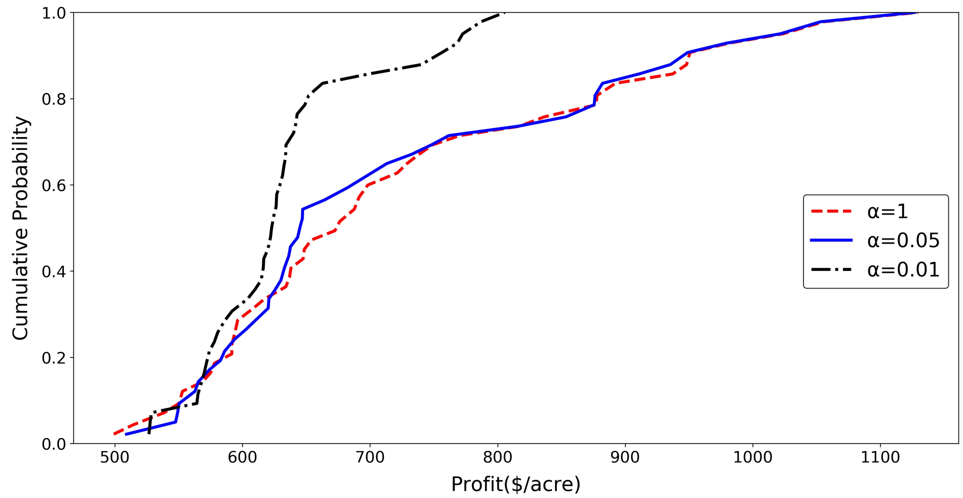


Figure 4.11: ISP comparison: distribution of profit from making optimal decisions under different risk preferences (Story County, S-C rotation, FCI is not allowed)

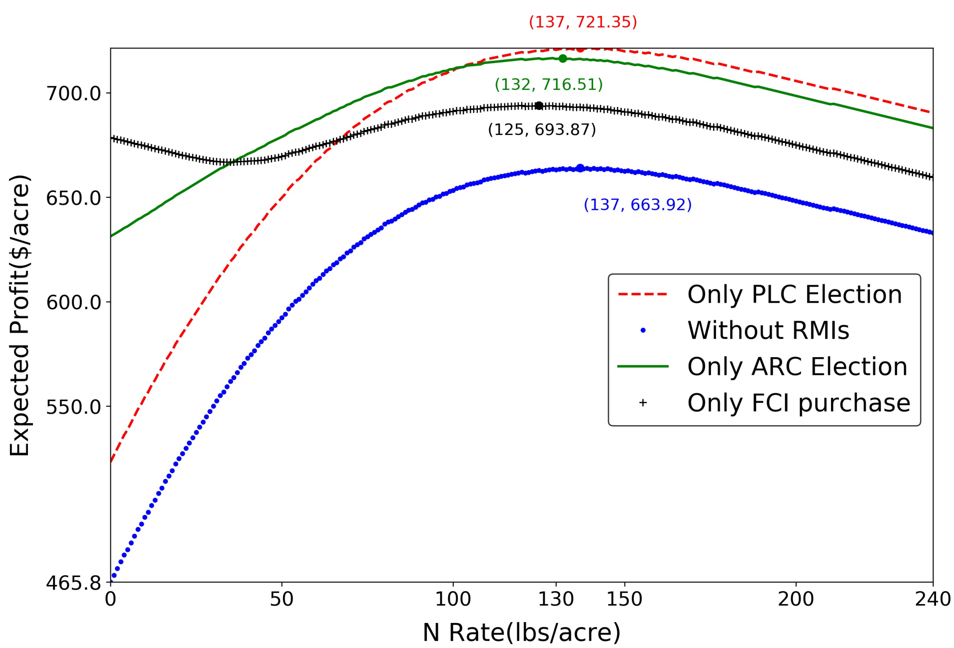


Figure 4.12: ISP comparison: risk-neutral results for Story County and S-C rotation. ("Without RMIs": No RMI selection is allowed)

CHAPTER 5. GENERAL CONCLUSION

Uncertainty is inherent in agricultural production. Farm yield is the output of many interrelated components, including farm management decisions and random weather features. Accordingly, market-driven prices and farm yield are the major uncertainties affecting farm income. Agricultural producers have to complete key management decisions before the realization of uncertainties is observed. For that reason, uncertainty is commonly considered the biggest challenge in agriculture. In this dissertation, we address the uncertainty in agricultural decision-making by building stochastic programs to find optimal decisions under uncertainty. Stochastic programs explicitly include the uncertainty in parameter values by exploiting the fact that the probability distributions of uncertain parameters can be estimated. Since decision-makers cannot know the particular realizations of random variables in advance before making important decisions, stochastic programs are built on the assumption that the decision-maker can anticipate possible outcomes along with their particular probabilities. The general aim is to understand the optimal farming decisions and incentives that would align farmer profit motive with environmental goals.

The first paper (Chapter 2) focuses on a benevolent policy maker who decides optimal land-use decisions to maximize the agricultural profits in a watershed and achieve the nutrient loss reduction targets. We treat nutrient reduction targets as constraints and formulate the problem with a single objective to facilitate optimization under uncertainty. Overall, this chapter considers the whole watershed area as a single entity by prioritizing the total prosperity instead of individual benefits for farmers. Specifically, a multi-stage stochastic mixed-integer program is built for land use decisions to maximize agricultural profits of a watershed while meeting target reductions in nitrate-N and P levels under uncertain precipitation rates. The major contributions in this paper include:

- A novel multistage land use optimization model is built.
- The value of developing and solving a stochastic formulation of land use optimization model is demonstrated.
- A chance-constraint formulation incorporates flexibility in meeting nutrient reduction targets and finds more profitable ways to achieve similar level of nutrient reduction amounts on watershed level than the recourse formulation does.
- Although the financial burden to ensure cooperation under socially optimal strategies is high, substantial reduction in nutrient loss is possible on watershed level.

The second paper (Chapter 3) shifts the research focus from the watershed to the farm level. In this paper, we explore the uncertainty in corn production from a farmer's viewpoint by investigating major annual farm-level decisions, including planting time, fertilizer application rate and timing, and federal crop insurance purchase, to maximize the expected farm profit. A two-stage stochastic program for optimal annual management decisions is proposed. The case study is designed to represent the state of Iowa, but the model can be parameterized for any state in Midwest. The key contributions in this paper are:

- A novel two-stage stochastic mixed-integer program for a Midwestern farmer is built.
- A decomposition-based solution strategy is suggested to reduce the computational complexity resulting from the predominance of binary variables and complicated constraints.
- The numerical results confirm that current N reduction targets for Iowa cannot be achieved by focusing only on N management practices.
- The numerical results indicate that the crop rotation improves the farmer's expected profit and reduces the necessary incentive rates to improve water quality.
- We demonstrate that fertilizer management and insurance policy selection decisions are highly interrelated.

- Results indicate that N is a risk-reducing factor, in that the additional risk associated with a nutrient reduction practice may be mitigated by applying more fertilizer to the soil.

- Farmers compensate for the additional risks associated with nutrient reduction strategies by increasing the planned nitrate application rate. Spring and sidedressing strategies, especially, are more susceptible to the risk of insufficient days suitable for fieldwork, and could paradoxically increase N leaching if the farmer carries out the plan of applying more N to compensate for the yield risk.

Finally, the last paper (Chapter 4) intensifies the research focus on the interaction between fertilizer application and financial risk-mitigating instruments (RMIs). Insurance-related preliminary discussions and findings from Chapter 3 are further expanded in Chapter 4 by building a comprehensive financial risk model considering all RMIs available to the US producers. Major contributions in this paper are:

- A novel two-stage stochastic program, including CVaR as risk measure, is built to find the optimal RMI choices and fertilizer application rates under a range of risk preferences.

- RMIs eliminate most of the risk resulting from yield and price uncertainties and contingent income support payments in the form of insurance subsidies are financially more beneficial for agricultural producers than the old direct support payments.

- We observe second-order stochastic dominance for RMI decisions, which eliminates the need to elicit utility functions.

- Thanks to RMIs, the optimal N rate is slightly lower for more risk-averse producers.

- RMIs significantly reduce the incentives needed to reduce fertilizer for all risk preferences

- Environmental side benefits of the existing RMIs are revealed.

In this dissertation, we demonstrate that simply relying on individual data from historical observations or using point estimates of uncertain elements can cause misleading results.

Specifically, stochastic programming models concerning Midwest Agriculture are limited, and this dissertation study shows the benefits of using stochastic programs to understand optimal decisions under uncertainty. The impact and importance of insurance programs in agricultural decision making is another key takeaway of this dissertation. Uncertainty and risk are prominent features of agricultural production, and insurance programs modify the economic risk. Therefore, insurance subsidies have the potential to alter any management decisions. We believe incorporating insurance programs into financial and environmental investigations exploring farmer behavior will provide more reliable and practical results.