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**A BIOGEOCHEMICAL-ECONOMIC MODEL FOR THE VALUATION OF COVER  
CROPS ECOSYSTEM SERVICES UNDER CLIMATE CHANGE**

BY

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B.Sc. Agriculture, Zamorano University, 2015

THESIS

Submitted to University of New Hampshire  
in Partial Fulfillment of  
the Degree Requirements of

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in  
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## ABSTRACT

THESIS TITLE: A BIOGEOCHEMICAL-ECONOMIC MODEL FOR THE VALUATION OF  
COVER CROPS ECOSYSTEM SERVICES UNDER CLIMATE CHANGE

By

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University of New Hampshire

Cover crop (CC) adoption is a promising conservation practice that provides multiple ecosystem services, such as reduced nitrate pollution and increased soil health. These CC ecosystem services have been demonstrated in the biogeochemistry literature. However, widespread adoption of CC in the Midwestern U.S. is still low, in part because there continues to be a debate about whether adopting CC is privately optimal for farmers and how climate change might affect the private incentives to adopt. Economic analyses of CC adoption are complicated by the difficulty to account for the economic benefits of CC ecosystem services, in a changing climate.

In this thesis, we developed a biogeochemical-economic model that estimates the ecosystem service benefits provided by CC under different climate scenarios on a corn-soybean farm and contrasts them with CC costs over 10 years. We used the DeNitrification-DeComposition (DNDC) model as the ecological production function in the biogeochemical-economic model. DNDC simulated changes in three non-market ecosystem services, namely soil water storage, soil organic matter accumulation, and N retention, with and without cover crops, and linked them to changes in corn yields and nitrogen fertilizer input.

The biogeochemical-economic model simulation results suggest that under most climate scenarios, and except for the case of constant extreme droughts, CC adoption does not generate a sizable difference in farm net present values (NPVs). Under historical Iowa weather (2004-2013), adopting CC reduces a farm's NPV by 4%, relative to no CC adoption. However, if two years of drought occur in the 10 years, the difference in NPVs goes down to 0.5%. The ranking of NPVs is reversed in the most likely scenario where precipitation increases in the spring and decreases in the summer: adopting CC increases a farm's NPV by 1.1%, relative to no CC adoption. This difference increases sizably when the farmer experiences a greater number of drought years. Under frequent extreme droughts, adopting CC increases a farm's NPV by 15%, relative to no CC. This difference is explained by higher corn yields in the CC treatment, where corn yields were 15% higher under frequent extreme droughts. DNDC simulation results show that this yield increase is due to an increase in the following three ecosystem services in the CC system: improved soil water storage, soil organic matter accumulation, and N retention.

Finally, using the certainty equivalent measure, we found that the baseline results for a risk-neutral farmer do not change in the case of a moderately risk-averse farmer.

## CHAPTER I

### INTRODUCTION AND LITERATURE REVIEW

A wide body of research has been conducted to analyze different aspects of climate change. This literature review focuses on the impact of climate change on agricultural production and nitrogen pollution. Additionally, strategies to increase resilience while reducing nitrogen pollution in agroecosystems were explored, including literature on cost-benefit analysis for these strategies. A breadth of scholarship and knowledge about how climate change affects nitrogen pollution, crop production, and management in the Midwestern United States were explored.

#### 1.1 Climate change impacts on agriculture

Agriculture will face enormous challenges over the next century. In addition to the increasing food demand to feed the rapidly growing global population and the need to increase environmental sustainability of agricultural systems, climate change is expected to reduce agricultural productivity (Foley et al., 2011). Higher temperatures and changing precipitation patterns are expected to reduce mean global crop yields and increase year to year variability by 30% (Lobell & Field, 2007). These effects have already been observed. For example, climate change reduced global maize (*Zea mays L.*) yields by 3.8% from 1980 to 2008 (Lobell et al., 2013). Climate projections show that the Midwestern U.S. will experience changes in precipitation patterns including intense but shorter rainfall events, and longer periods of drought (Deser et al., 2012). Climatic impacts on Midwestern agriculture have global implications, as the region produces one-third of the world's maize. Under a high-carbon emissions scenario, maize yields will be reduced by up to 30-40% by the end of the 21<sup>st</sup> century. These projections hold even when

accounting for the ameliorating effect of higher atmospheric CO<sub>2</sub> concentration, which increases carboxylation and transpiration efficiency in some crops (Jin et al., 2017).

Warmer climates will also increase the frequency of extreme weather events, resulting in increased agricultural variability (Trenberth et al., 2014). Greater frequency of severe rainfall and intense periods of drought are likely to increase yield variability by altering soil moisture dynamics (Mishra et al., 2010). Projections show that precipitation will increase during winter and spring, resulting in excessive soil moisture early in the season (Tomasek et al., 2017; Urban et al., 2012). During summer, rising temperatures combined with increased evapotranspiration will decrease soil moisture, leading to increased onset of drought (Trenberth et al., 2014; Zipper et al., 2016). Both extremes (too much water or too little water) can wreak havoc in crop production systems. Excessive soil moisture can damage crops directly and indirectly, with different magnitudes over the growing season (Urban et al., 2015). Direct effects depend on the crop growth stage and the risk associated with each stage. For example, excessive soil moisture during the juvenile stage can directly increase the risk of seedling diseases. Indirect effects depend on crop management activities and seasonal risks (Urban et al., 2015; Lobell et al., 2014; Mishra et al., 2010). For example, a delay in spring planting because of saturated fields can push the reproductive stage into the late summer, when drought risk is expected to increase (Tomasek et al., 2017).

Since 2000, drought and excess moisture have increased the risk of crop failure and yield variability (Lobell et al., 2014). Severe rainfall can cause flood conditions, which add costs if affected areas need to be replanted. At worst, flooding can result in total crop loss if the farmer is unable to plant. In 1993, flooding damage near the Mississippi River resulted in more than 11 million acres of crop losses and cost \$3 billion in damages (Rosenzweig & Tubiello, 2007). At the other extreme, short-term drought can cause substantial yield losses, and prolonged drought



may cause total crop failure (Zipper et al., 2016). For example, the drought of 2012 caused agricultural losses of \$30 billion, where nearly two-thirds of the U.S was affected by drought (Rippey, 2015). Faced with this possibility, farmers may opt to plant shorter-season varieties with lower grain yield potential. It can also spur the growth of weeds, insects, and damaging pathogens (Walthall et al., 2012). Further, extreme weather can affect yield in ways not typically captured in modeling studies. For example, current models do not account for climate impacts such as flooding, anaerobic soil conditions, and catastrophic erosion (Hunter, 2018). Because of the enhanced crop production challenges due to climate change, there is a clear need for new and more comprehensive strategies to maintain high and stable yields in the face of climate change.

#### *Climate change adaptation in agriculture*

Agricultural systems are human-dominated ecosystems that are vulnerable to climate change. This vulnerability depends on both the biophysical effects of climate and the response taken by humans to moderate these effects (Walthall et al., 2012). To reduce agricultural vulnerability, effective adaptation strategies are needed. Adaptation is the process of adjustment to present or future climate and its effects, which reduce vulnerability and capitalize on beneficial opportunities (Smit & Skinner, 2002). Four agricultural adaptation strategies have been identified: 1) technological advances, 2) farm production practices, 3) farm financial management, and 4) government programs and insurance.

Technological advances can substantially reduce the negative effects of climate change (Cassman et al., 2010). Historically, technology has played an important role in reducing some of the agricultural risks related to weather variability (Smithers & Blay-Palmer, 2001). However, these risks are not limited to the effect of average weather conditions on plant growth. It also

includes the effect of extreme weather events and yield response to pathogen pressure. To close the 30% production gap, yield improvements will have to keep pace with a rapidly changing climate (Edmeades et al., 2004). Until today, technological advances alone have not offset the risk associated with weather variability.

Modifying production practices can increase resilience, however, only a few farmers are willing to adopt them (Roesch-Mcnally et al., 2017). Some of these changes increase crop diversity, alter planting dates, increase pesticide and fertilizer use, plant different crop varieties, and reduce tillage. For example, diverse crop rotation can increase the average maize yield over time and reduce yield losses under drought years (Bowles et al., 2020). Another example is to increase the use of soil conservation practices such as eliminating tillage, this can improve soil water storage during punitive drought years. Because these practices require farmers to change their status quo, only a small group has made changes to reduce risk exposure (Harvey et al., 2014; Mase et al., 2017). Further, some of these adaptation practices are expensive and require technical knowledge.

Governments have multiple mechanisms to reduce risk from agricultural production. One way is to promote farm-level adaptation strategies by providing technical and financial support that allows farmers to adopt new strategies that otherwise they wouldn't have adopted. Another way to reduce income uncertainty from annual production is to allow farmers to remove sensitive lands from production in exchange for annual payment (Lohmann & Van der Hamsvoort, 1997). The government can also provide financial management support by subsidizing crop insurance, reducing the risk of catastrophic financial losses due to poor yields and/or revenue.

In future climate scenarios, farmers will face ecological-economic trade-offs when adopting climate-resilient strategies. Emerging insights from soil and agricultural systems show

that ecological, system-based approaches can enhance agroecosystem resilience to extreme weather events.

## **1.2 Agriculture, climate change and nitrogen pollution**

Nitrogen (N) pollution is among the most critical environmental problems stemming from agriculture. Agricultural production has doubled the amount of N added to terrestrial ecosystems compared to natural sources (anthropogenic 120 Tg N yr<sup>-1</sup> and natural 63 Tg N yr<sup>-1</sup>), mainly through the use of synthetic fertilizers and the management of biological fixation (Fowler et al., 2013). This widespread anthropogenic alteration of the global N cycle comes with both benefits and costs. Nitrogen has substantially increased crop production needed to meet the food, fuel, and fiber needs of the growing population. However, the excess of N is also associated with the pollution of surface and groundwater, loss of wild habitat, soil acidification, stratospheric ozone depletion, and increased greenhouse gas emissions (Rabalais et al., 2001; Swinton et al., 2007; Robertson & Vitousek, 2009; Zhang et al., 2015).

Future climate is expected to magnify the trade-offs between crop production and N pollution (Deser et al., 2012; Sinha et al., 2017). Extensive evidence suggests that N cycling is highly dependent on precipitation and soil moisture (Austin et al., 2004; Bowles et al., 2018). Projections show that the Midwestern U.S will experience changes in precipitation patterns with more intense but shorter rainfall events and longer periods of drought (Deser et al., 2012). The Midwestern Corn Belt is known for its high agricultural productivity and as a global leader in the production of corn and soybean. However, this high productivity has come at a cost; for example, it is estimated that 65% of the total N delivered to the Gulf of Mexico each year comes from the upper Mississippi River Basin, primarily from the Corn Belt agricultural fields (Rabalais et al.,

2001; Robertson & Saad, 2013). Given future climate projections, the total N loaded to the Gulf of Mexico is expected to increase by 19%, and offsetting this increment would require a 33% reduction in N inputs (Sinha et al., 2017). In the context of climate change, achieving this reduction requires a deep understanding of the agronomic, environmental, and economic trade-offs between crop production and N pollution in all its forms.

Additional to the damages caused by eutrophication in the Gulf of Mexico, N pollution can cause other forms of N-related damages. For example, the effects of N pollution can cause a reduction in air quality ( $\text{NO}_x$ ,  $\text{NH}_3$ ,  $\text{NH}_4\text{NO}_3$ ), and can contribute to greenhouse gas emissions ( $\text{N}_2\text{O}$ ) (Robertson & Vitousek, 2009; Vitousek et al., 2009). Further, reactive forms of N can have multiple transformations and can have a cascade effect over space and time (Robertson & Vitousek, 2009). A recent study shows that the magnitude of the damage depends on the location, vulnerability, and preferences of the populations affected by N (Keeler et al., 2016). The quantification of these damages remains a big challenge because the N cycle is messy, complex, and dynamic (Keeler et al., 2016).

#### *U.S. Agro-environmental policy approach to N pollution*

For the last decade, the U.S policy approach to environmental issues has been slow and ineffective (Dowd et al., 2008). The current policy heavily favors crop production by providing crop insurance and subsidy payments for commodity crops. These programs have minimal environmental requirements, which fail to target nutrient loss, air quality, GHG emissions, and other environmental damages. Moreover, many environmental regulations currently exempt agricultural activities. For example, the Clean Water Act does not require agricultural producers to apply for a National Pollution Discharge Elimination System permit nor regulates farming

activities (Adler, 1994), mainly because implementing this policy would require sums of money larger than the budgets of local regulatory agencies (Dowd et al., 2008). Instead, the policy approach is to provide funding for voluntary programs.

In order to maintain crop yields while minimizing N pollution, the USDA promotes the voluntary adoption of conservation practices (Dowd et al., 2008). The Environmental Quality Incentives Program (EQIP) and the Cost Share Program (CSP) provides cost-share and technical assistance to encourage farmers to adopt conservation practices on productive land, both edge-of-field and in-field (Reimer & Prokopy, 2014). Edge-of-field practices usually require farmers to make a long-term commitment and reduce the area of farmland to implement physical structures and/or perennial vegetation (Roley et al., 2016). Edge-of-field practices are designed to capture or treat sediments and nutrients runoff (Mahl et al., 2015). In contrast, in-field practices require a short-term commitment by integrating conservation into daily management decisions (Hansen et al., 2012). In-field practices can minimize erosion or nutrient transport without sacrificing farmland. One important in-field conservation practice is the adoption of cover crops.

### **1.3 Cover crops: an innovative agroecosystem solution**

Cover crops may play an important role in adapting agriculture to climate change while also reducing N pollution. In annual cropping systems, cover crops increase plant diversity and replace bare fallows where the soil is left without living plants. Cover crops can reduce nutrient leaching by taking nitrogen (N) that otherwise would be lost in the environment (Carpenter-Boggs et al., 2010; Tonitto et al., 2006). Other benefits of cover crops include mitigation of weed, insects, and pathogens pressure, and increased soil health (Schipanski et al., 2014; Kaspar et al., 2011; Mcdaniel et al., 2014). Further, shoots and roots inputs of cover crops residues can be efficiently

transformed into soil organic matter (SOM) (Austin et al., 2017). Increased SOM leads to greater stability of soil aggregates, nutrient retention, water availability, and boosts root association with beneficial microbes (Six et al., 2000; Tiemann et al., 2015; Basche et al., 2016a; Bowles et al., 2017).

Employing cover crops can help buffer yields against increased weather variability by improving soil water dynamics (Williams et al., 2016). Cover crops can enhance soil water storage and can reduce the risk of flooding during spring, allowing farmers to plant on time (Tomasek et al., 2017). Cover crops can increase available water for plants by improving infiltration rate and storage capacity in the short term by slowing overland water flow and in the long term by increasing macro-porosity, aggregation, and field capacity (Basche et al., 2016a; Blanco-Canqui et al., 2015). Cover crop residues can act as mulch and substantially reduce evaporation from the soil surface (Wang et al. 2018). In a long-term experiment, rye cover crop increased soil water availability by 21% (Basche et al., 2016a; Wang et al., 2018). Further, survey evidence also suggests that cover crops may provide adaptation strategies: farmers reported 10- 15% higher yields in cover-cropped fields of maize and soybean in Midwest states affected by drought 2012 (NRDC, 2015). Additionally, cover crops can reduce evaporative and transpiration losses if they disrupt weed life cycles (Baraibar et al., 2018). While these benefits are promising, the continued provision of ecosystem services provided by cover crops can be limited by several factors.

Cover crops ecosystem services vary by cropping systems, management practices, and climate. For example, a global meta-analysis showed that the effects of cover crops on SOM accumulation strongly differ depending on cover crop species, fertilization rates, mean annual temperature, and soil carbon stock (Austin et al., in review). Another study showed that N released from cover crops residue is highly influenced by climatic conditions, residue C:N ratio, and

management practices (Jahanzad et al., 2016). Additionally, reducing N leaching depends on cover crops establishment, species, and biomass production (Cates et al., 2018; Finney et al., 2016; Tonitto et al., 2006). Other studies have shown that the effects of cover crops on soil C, water retention, and nutrient status are heavily influenced by N fertilization rates (Snapp & Surapur, 2018). Since cover crops ecosystem services vary across climate, management practices, and region, cash crop response to cover crops varies significantly.

Accumulating research indicated that cover crops have positive (legume) or at least non-negative (non-legume) effects on cash crops yields (Marcillo & Miguez, 2017; Snapp & Surapur, 2018; Austin et al., in review; Seifert, Azzari, & Lobell, 2019). Legume cover crops, commonly clover and vetch, can fix atmospheric N<sub>2</sub>, contributing to additional N and reducing fertilizer application (Blanco-Canqui et al., 2015). Legume residues have similar C:N ratios (25:1) compared to soil microbes (5:12), hence can increase soil C by promoting microbial efficiency and SOM formation (Kirkby et al., 2016; USDA, 2011). Yield increases due to greater residue quality and N production of legume cover crops have been well documented (Marcillo & Miguez, 2017; Tonitto et al., 2006). On the other hand, yield response to non-legume cover crops is less understood. Non-legume cover crops are good at scavenging N and have the potential to contribute additional N to subsequent crops (Krueger et al., 2011). However, N release from non-legume cover crops is usually not synchronized with cash crop peak demand (Jahanzad et al., 2016). Further, the dynamic nature of soil N pools makes it difficult to predict synchrony between soil N mineralization and crop N demand. Timing of N immobilization is important in crop production, as the synchrony of N release relative to plant demand N has consequences for yield and N fertilizer efficiency (Snapp & Surapur, 2018; White et al., 2017). Non-legume cover crops, such as cereal rye, oats, and wheat, have higher C:N ratios (37:1) than soil microbes, therefore,

microbial efficiency might be reduced, and SOM formation lowered (Austin et al., in review). Despite these limitations, research showing that non-legume cover crops provide soil benefits is accumulating.

Because of the documented benefits, and the cost-share programs, cover crops acreage has doubled nationally from 2012 to 2017 (SARE-CTIC, 2016). In Iowa, cover crops acres have increased beyond cost-shared programs (Rundquist & Carlson, 2017). The most widely grown cover crop in Iowa is cereal rye (*Secale cereale L.*) because of its N scavenging capacity and adaptability to the soils and climates in the region. However, recent satellite imagery reported that only 2.6% (591,880 acres) of Iowa cropland incorporated cover crops into corn-soybean rotations in 2015 (Rundquist & Carlson, 2017). Although this study accounted for failures in match imagery such as late cover crop emergence or early termination, the adoption rate of cover crops continued to be low. Nationally, only 3.2% of the total cropland production in the U.S was planted with cover crops (Basche & Roesch-McNally, 2017). These estimates are similar to Iowa, where farmers planted 760,000 acres (3.3% of corn-soybean cropland) of cover crops during 2017 (ILF 2019). This small increment in cover crop adoption doesn't come as a surprise, because multiple constraints inhibited adoption (Survey, 2018).

#### **1.4 Costs of cover crop adoption**

Obstacles to cover crop adoption include farmers' status-quo and economic constraints (Roley et al., 2016; Snapp et al., 2006). Status quo refers to the behavioral barrier to adopt cover crops, as this practice require farmers to alter their seasonal management practices in a system with an already short management window for planting and harvesting cash crops (Roesch-McNally et al., 2018). This short management window increases uncertainty regarding opportunity costs, e.g.



delayed operation for sowing and planting the cash crop. The need to alter seasonal management practices can discourage adoption. Additionally, farmers have consistently expressed that the economic returns on cash crop production are low given the high cost of inputs (e.g. seeds, fertilizer, chemicals), hence the additional costs of cover crops may be too high for producers (Dunn et al., 2016; Roesch-Mcnally et al., 2018; Plastina et al., 2018). Here we have identified five main cost categories of cover crops:

Seed cost, which depends on local seed source supply and demand, therefore, varies regionally and year to year (Roley et al., 2016). In a regions where conventional farming (i.e. corn-soybean rotation followed by bare fallow during winter) governs, the lack of knowledge and infrastructure to produce small grains is a major barrier in the supply chain of cover crops seeds.

Previous work by Longbucco & Porter, (2019) identified the major barriers in the value chain of cover crop seeds. The value chain starts from seed producers, seed dealers, and agricultural retailers until it reaches the farmers and landowners (Longbucco & Porter, 2019). Cover crop seed producers face a lack of specialized agronomy, equipment, storage facilities, and technical knowledge (Longbucco & Porter, 2019). Seed dealers' challenges are lack of understanding of seed rules and regulations, lack of secondary markets for leftover seeds, and limited capacity to forecast supply and demand. Until today, there is no entity that provides information about cover crop seeds rules and regulations such as quality, shipping regulations, and protected varieties (Longbucco & Porter, 2019). Retailers cannot forecast demand because farmers treat cover crops as extraneous during crop year planning. Retailers forecast demand through pre-payment, but farmers do not include cover crops in this process (Longbucco & Porter, 2019). These barriers have a big impact on the direct costs of cover crop adoption, as farmers tend to buy seed when the price is high (Longbucco & Porter, 2019). Helping farmers to make decisions early in

the season and pre-pay for cover crops seed while supply is high have the potential to considerably reduce the direct cost of seeds (Longbucco & Porter, 2019).

Planting costs consist of the labor, material, and fuel costs of planting through either aerial, broadcast, inter-seeding, or drilling methods (Roley et al., 2016). Most farmers use drilling to plant cover crops, however, farmers that face shorter planting windows tend to aerially seed cover crops into soybeans and cornstalks (Survey, 2018). Additionally, farmers have consistently expressed the challenge to plant and establish cover crops following cash crops in wet springs (Plastina et al., 2018). Low temperatures and excessive soil moisture during fall can result in poor cover crop establishment. For example, the probability of favorable conditions for establishing and growing cereal rye cover crops in Minnesota was 25% based on historical weather data of 41 years (Strock et al., 2004).

Termination costs include the labor, material, and fuel costs of either herbicide applications, crimping, cutting, rolling, or tillage (Roley et al., 2016). Most farmers terminate cover crops using herbicides (Survey, 2018). However, the amount of herbicide varies among farmers and depends on weather conditions (Arbuckle & Roesch-McNally, 2015; Plastina et al., 2018). The perceived risk of cereal rye becoming a weed during cash crop growth can lead farmers to increase herbicide spraying rates (Plastina et al., 2018). Additionally, high precipitation and low temperatures during spring can limit the efficiency of the herbicide used to terminate cover crops and therefore delay cash crop planting (Arbuckle & Roesch-McNally, 2015). Unsuccessful termination of cover crops can be perceived as high risk with negative impacts on cash crops yield.

Additional costs are associated with the changes in cropping system management and can be group in three categories (e.g. hiring extra labor, purchasing new equipment, increasing cash crop input use) (Roley et al., 2016).

The *first* category of additional costs is related to changes in labor. Hiring extra labor consist of custom hire planting and harvesting cash crop. Some farmers reported to custom hire planting and harvesting cash crops so that they can focus on planting and terminating the cover crops (Plastina et al., 2018). Other farmers reported to increase labor hours to assess cover crop growth in order to prevent unexpected circumstances or monitoring weather around planting and termination (Plastina et al., 2018). For example, it is important to avoid cold weather during herbicide application to properly terminate cover crop.

The *second* category of additional costs relates to buying machinery to manage cover crop residues. Cover crop residues can interfere with the contact between seed and soil bed leading farmers to adjust or buy new equipment. For example, some farmers have reported buying new attachments for soybean planters because of cover crop residues (Plastina et al., 2018). Others have bought tractors or drills for cover crop planting.

The *third* category of additional costs consists of increased cash crop inputs such as fertilization, seeding, and herbicide rates due to the perceived unintended consequences of cover crops (Plastina et al., 2018). Farmers reported using higher cash crop seeding rates because cover crop residues reduce soil temperatures. Further, N immobilization due to cover crops is a big concern for most farmers (Arbuckle & Roesch-McNally, 2015). For example, farmers have reported applying extra N because of the perceived risk of cover crops tiding up N.

Opportunity costs are those associated with forgone cash crop yields (Roley et al., 2016). Farmers who perceive higher levels of uncertainty associated with climatic conditions and cover crops are less likely to use them. For example, if the farmer perceives that cover crops will cause water stress to the subsequent cash crop during a dry year, then the farmer will not adopt cover crops. Additionally, low water availability after cover crop use is a major concern for farmers, as

this can also have unintended consequences of cash crop yield reduction (Arbuckle & Roesch-McNally, 2015). The uncertainty of the effect of cover crops in cash crop yields is a major obstacle to cover crop adoption, therefore it is important to provide farmers with a better understanding of the costs and uncertainty associated with cover crop use.

These additional costs of cover crops conflict with the thin profit margins that farmers are facing due to the high input costs and low commodity prices. Farmers need information about cover crop benefits, in order to decide whether it's worth incurring these additional costs.

### **1.5 Cost-benefit analysis of cover crop adoption**

Most economic analyses of cover crops have resulted in negative net returns, which depended on the time frame of the analysis (Plastina et al., 2018; Roth et al., 2018; Pratt et al., 2014). These negative returns are explained by whether cover crop benefits are considered in the short or long-term. For example, Plastina et al. (2018) accounted for the short-term benefits of payments received through cost-share programs and changes in cash crop yields. On average, cover crop adoption resulted in a *negative* net return of \$56 ha<sup>-1</sup> (Plastina et al., 2018). Roth et al. (2018) also quantified the short-term benefits of cover crops but included some ecosystem services, such as the reduction of N leaching, N credit provided by cover crop residues, and reductions in soil erosion. These short-term benefits were not enough to recover the annual cost of adopting cover crops, resulting in a *negative* net return of \$93 ha<sup>-1</sup> (Roth et al., 2018). Other studies evaluated the long-term benefits of cover crops, including increased SOM and reduced compaction. Including these long-term benefits resulted in a *positive* net return of \$22 ha<sup>-1</sup> (Pratt et al., 2014). These studies highlight the need to combine the short-term and long-term benefits provided by cover crops regarding reduced N leaching, N credits, and increased SOM.

In support of long-term economic analyses, qualitative analyses of cover crops confirm that the perceived long-term benefits incentivize adoption and continued use. Using data from the national survey on cover crops, Dunn et al., 2016 found that despite the negative net returns from cover crops, many farmers continue to expand their cover cropped land even without the use of cost-share funding. In a focus group discussion of the cost-benefit analysis of cover crops, farmers expressed that the long-term benefits of improving soil health and reduced erosion were undervalued in these analyses (Basche & Roesch-McNally, 2017). Further, in-depth interviews with farmers highlighted that the motivation to adopt cover crops is driven by the long-term sustainability of the farm operation given the emerging challenges of weather variability (Roesch-McNally et al., 2018). Therefore, in order to make informed cover crop adoption decisions, farmers need to know the trade-offs between short-term production goals and long-term goals of building soil health and increased resilience (Roesch-McNally et al., 2018).

While several studies have focused on the short-term and long-term benefits of cover crops, fewer studies have estimated the net returns of cover crops (Pratt et al., 2014; Plastina et al., 2018). For example, Pratt et al. (2014) evaluated the potential trade-off between cover crops and an additional 4.01 metric ton ha<sup>-1</sup> corn stover removal. Corn stover is defined as the above-ground biomass left in the field after corn grain harvest. This biomass is usually linked to SOM and removing it causes a decline in soil health. However, if farmers use cover crops to offset the reduction of SOM and sell the corn stover as a forage, a cost-benefit analysis suggests that net benefits could range between \$158 and \$249 ha<sup>-1</sup>, assuming a farm-gate price of \$88 metric ton<sup>-1</sup> (Pratt et al., 2014). In another example, Plastina et al. (2018) used partial budgets based on survey data and found that farmers that use cover crops for livestock grazing and forage have a positive net return of \$21 and \$36 ha<sup>-1</sup> (Plastina et al., 2018). These analyses suggest that cover crops have

the potential to provide enough additional income to cover any additional cover crop costs, resulting in positive net returns. Both analyses included the cost-share program payments and highlighted the critical role of these programs on supporting farmers who wish to use this practice.

Cost-share programs facilitate cover crop adoption by alleviating financial hurdles while not covering all the private costs. The implementation of cover crops results in a private cost to farmers, often resulting in negative returns. At the same time, the use of cover crops produces a significant public benefit by reducing N pollution. For this reason, cover crop adoption is eligible for cost-share funds from the United States Department of Agriculture (USDA). Previous economic analyses focused on the additionality of cost-share programs: Plastina et al. (2018) found that farmers who received cost-share payments planted 18% more of their land with cover crops compared to farmers that did not receive cost share. Other studies have focused on the USDA program cost-effectiveness in terms of cost per kilogram of N removed (Roley et al., 2016). Compared to other conservation practices, cover crops had the highest cost and lowest N removal (Roley et al., 2016). From the USDA perspective, the cost of N removal through cover crops was \$4.6 kg N<sup>-1</sup> higher than wetlands and two-stage ditches conservation practices (Roley et al., 2016).

Cover crops provide public benefits by improving soil health. Healthy soils increase biodiversity, prevent erosion, improve water quality, reduce flood risk, sequester carbon, and reduce pest and disease outbreaks (Amundson et al., 2015; Stevens, 2015). Most of these benefits are not exclusively captured by farmers who adopt cover crops and are considered to be positive externalities enjoyed by society at large (Amundson et al., 2015; Stevens, 2015). However, soil health is difficult to incorporate into existing economic and policy frameworks, mainly because soil health is hard to measure (Stevens, 2015). Even natural scientists have different approaches to soil health. Soil health is defined as a holistic system that incorporates chemical, biological, and

physical characteristics (Kibblewhite et al., 2008.). Chemical soil characteristics affected by management include nutrient availability, redox potential, and pH; physical characteristics include aggregate stability, soil compaction, and water storage; and biological characteristics are SOM, mineralizable N, and microbial activity. These characteristics are dynamic and interact with each other. Cover crops particularly influence soil water storage, mineralizable N, and SOM.

In ecosystem-based strategies, ‘non-marketed’ ecosystem services might be a major driver for cost-effectiveness. Because cover crops benefits are ‘non-marketed’, their benefits are not considered in most cost-benefit analyses. For example, the excessive loss of soil health is related to the failure to measure explicitly the values of ecological regulatory functions such as climate regulation, water regulation, and nutrient regulation. Consequently, these benefits have been largely ignored or underpriced in agricultural policy decisions. This is mostly due to methodological challenges in non-market valuation methods.

## **1.6 Ecosystem service valuation**

Economic valuation of ecosystem services (ES) is typically done using stated preferences and production function methods (Barbier, 2007). Stated preference methods involve surveying individuals who benefit from (or produce) an ecosystem service and analyze the responses to estimate individual total and marginal willingness to pay (or accept payment) for hypothetical changes in the service. This method must meet two conditions, (1) the information to describe the change in a natural ecosystem must be available in terms of services that people care about; and (2) the change in the natural ecosystem must be explained in the survey instrument in a manner that people will understand and not reject the valuation scenario (Barbier, 2007). Because the stated preference method relies on explanations of hypothetical changes in ecosystem provision in survey

instruments, the individual's response is likely to yield inaccurate measures of their willingness to pay for ecological services (Barbier, 2007). The production function (PF) approach is preferred in the context of ES because does not rely on survey-based scenario descriptions (Barbier, 2007).

The production function approach consists of measuring the aggregate willingness to pay for ES by estimating their value using a production function of a marketed output where the ES is considered as an input (Barbier, 2007). In other words, the PF approach depends on scientific knowledge and the existence of ecological functions that link changes in ES to changes in economic outputs (Barbier, 2007). Barbier (2007) describes it as follows: "if changes in the regulatory and habitat functions of ES affect the marketed production activities of an economy, then the effects of these changes will be transmitted to individuals through the price system via changes in the cost and prices of final goods and services" and any resulting improvement due to enhanced ES that results in lower costs and prices and increased quantities of marketed goods, can lead to market surplus (Barbier, 2007). The market surplus provides a measure of the willingness to pay for the improved quality or increase quantity of an ES.

The PF approach requires modelling the production of the ES and estimating its value as an environmental input (Barbier, 2007). A major limitation of the PF approach is that it requires a decisive characterization of the relevant ecological production functions. Without it, ecosystem service provision cannot be incorporated into resource decision-making (Daily & Matson, 2008). For example, Atallah et al. (2018) used this method to value the ES of pest control provided by shade trees by linking shade level to temperature reduction and reduced pest infestation. In another study, Wu and Atallah (2019) valued the losses of pollination ES by linking yield reductions due to herbicide effects on bee's pollination level.



In the case of cover crops, there are no simple mathematical functions that can link cover crop adoption to changes in soil characteristics and ES that are inputs in crop production. Soil physical, chemical, and biological characteristics are complex and dynamic. The nitrogen and carbon cycle are just two examples of complex dynamics systems affecting soils. To value the ES provided by soils we need to use biogeochemical models that capture the soil response to cover crops. The DeNitrification-DeComposition model (DNDC; described in Chapter 2) can be used as the production function that incorporates soil organic matter, soil water storage, and N retention.

Using the PF approach, the value of ES provided by cover crops to the farmer and to society can be quantified in economic terms. The PF in this case is the DNDC model which relates cover crop planting to changes in SOM, soil water storage, and N retention. By incorporating the DNDC simulation model in a cost-benefit analysis, cover crop planting can be linked to changes in SOM, water storage, and N retention, which in turn are linked to changes in the yields of marketed goods (e.g. cash crop yields) and quantities of inputs (e.g., N fertilizer rate).

### **1.7 Valuation of risk reduction benefits of non-marketed ecosystem services**

Many of the non-market benefits provided by increased SOM, water storage, and N retention might affect the fluctuation of yields, rather than yield averages only. Increased weather variability with higher probability of extreme weather events (e.g. drought) is likely to increase crop production variability, putting farmers at a financial risk. Therefore, in addition to assessing the average effect of cover crops on yields and profits, it is important to evaluate the effect of cover crops on the economic risk for farmers, defined as year-to-year variation of profits, through the regulating effect of the ecosystem services such as soil water storage, N retention, and SOM accumulation.

While most ecological-economic models assume that farmers are risk neutral, analyses that seek to assess the benefits of cover crops under climate change should consider the effect of risk aversion on a farmer's valuation of ES benefits. Analyses of the economic risk of agricultural production is typically done using survey-based econometric models or simulation models. Survey-based econometric models are used to provide an empirical estimate of the effect of marketed or non-marketed inputs (e.g. agrobiodiversity) on production risk (e.g. measured through the variance and/or skewness of yields), using cross sectional or longitudinal grower surveys (Di Falco & Chavas, 2006, 2009). On the other hand, simulation models are used to mechanistically simulate the effect of changes in inputs on the distributions of yields and profit. Then, financial risk assessment measurements are used to rank distributions based on some measure of risk (Abadie et al., 2016; Gloy & Baker, 2001).

Despite the attractiveness of the empirical nature of a survey-based, econometric model approaches they cannot be used to recommend optimal strategies for farmers that involve changes in practices outside of the range of those reported in a survey. On the other hand, because simulation models are mechanistic, they can be integrated with optimization or cost-benefit analyses frameworks to determine optimal management strategies for different ecological, economic, and risk preference parameters. However, these models require the availability of an ecological production function that can represent how changes in farm practices drive ecosystem service provision.

Crop and biogeochemical models have been widely used to generate the distribution of yields and/or profits. For example, models such as DNDC, APSIM (Agricultural Production System Simulator), and HERMES have been used to assess the risk faced by farmers under climate change scenarios (Graß, Thies, Kersebaum, & Wachendorf, 2015; Iqbal et al., 2018; Luo et al.,

2007; Yu et al., 2014). Another crop model used in previous risk assessment is CropSyst, Finger (2012) used this model to simulate maize yields for different levels of water and N application under different climate scenarios. Using the mean and variance of crop yields, they calculated the risk premium, which is the amount a grower is willing to pay to eliminate risk exposure due to changes in crop market prices (Finger, 2012).

### **1.8 Research questions and hypotheses**

Helping farmers to assess the benefits and costs associated with cover crop adoption in a changing climate might allow them to make informed decisions about cover crops use. The goal of this study is to evaluate the economic and environmental benefits provided by cover crops against the monetary and opportunity costs of adoption. Among the benefits of cover crops, this study focused on the value provided by cover crops through the provision of three ecosystem services: improved soil water storage, soil organic matter accumulation, and N retention, in four climate scenarios that include historical weather, no-drought scenario, drought scenario, and a hybrid scenario.

The research questions and related hypotheses were:

1. Do cover crops provide economic net benefits to farmers?

*Hypothesis 1: In a no-drought year, cover crops provide a positive net benefit to the farmers.*

*Hypothesis 2: Cover crop positive benefits are larger in extreme droughts.*

2. Do cover crops reduce economic risk to farmers?

*Hypothesis 3: In extreme droughts, cover crops reduce economic risk to farmers (i.e. year-to-year fluctuations in profits), through the regulating ecosystem services of soil water storage, N mineralization, and SOM accumulation.*

I used a simulation modeling approach to answer these research questions and test the hypotheses. I used the DNDC (DeNitrification-DeComposition) model as the ecological production function in my biogeochemical-economic model. The DNDC simulates water storage, soil organic matter accumulation, and reduction of nitrogen leaching, with and without cover crops, and generates yields. By doing so, it satisfies the production function approach method where changes in non-market ES need to be linked to changes in a marketed output (e.g. corn and soybean yields) and the marketed inputs (e.g. fertilizer rates). However, the DNDC needs to be calibrated and validated before being integrated with an economic model. Therefore, the specific objectives are as follows:

*Specific objectives*

- 1) Calibrate and validate the DNDC
- 2) Use the DNDC to generate yields with and without cover crop adoption, under four climate scenarios.
- 3) Integrate the DNDC yields with a profit (utility) maximization economic model, representing the point of view of a risk-neutral and a risk-averse farmer, with and without cover crop adoption, under four climate scenarios.

## CHAPTER II

### BIOGEOCHEMICAL MODEL DESCRIPTION

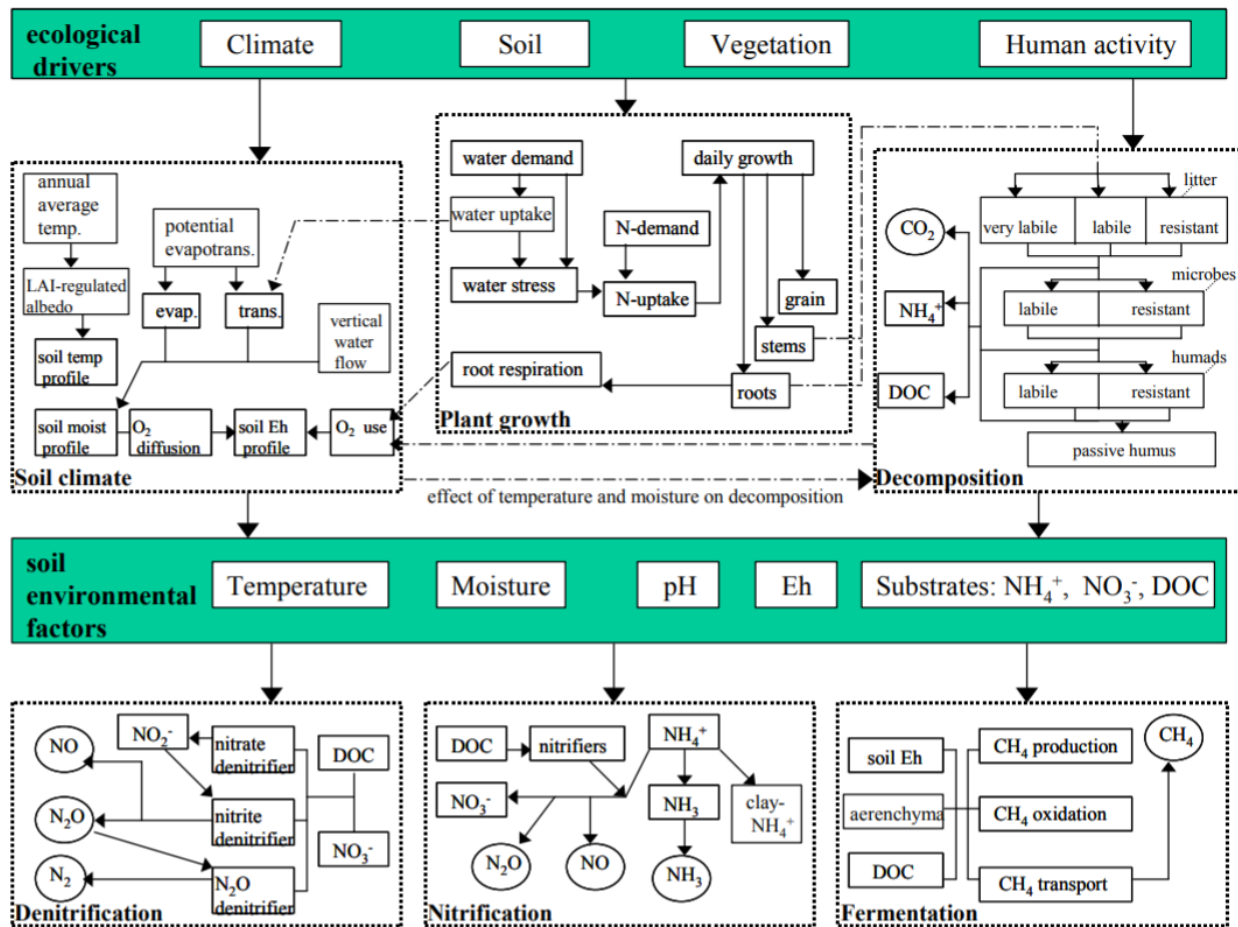
The DNDC (DeNitrification-DeComposition) model acts as the ecological production function of the biogeochemical-economic model. This chapter provides a general overview of the model, followed by a description of the most relevant DNDC sub-models. The inputs, outputs, and assumptions of the model are discussed at the end of this chapter.

#### 2.1 Overview of the DNDC model

The DNDC (DeNitrification-DeComposition) is a computer simulation model of water, carbon, and nitrogen cycles occurring in agro-ecosystems. The DNDC model was first used to simulate  $N_2O$ ,  $CO_2$ , and  $N_2$  emissions from agricultural soils in the U.S. (Li et al., 1992). The DNDC integrates ecological drivers, soil environmental variables, and biogeochemical reactions in one framework to predict soil trace gases. Li (2000) described the model as a spatio-temporal assembly of different environmental variables, especially soil moisture, that drive biogeochemical reactions in an ecosystem. The DNDC consists of two components that incorporates six sub-models (Fig. 1). The first component links ecological drivers to soil environmental variables and consists of: soil climate, crop growth, and decomposition sub-models. The second component links soil environmental factors to trace gases and consists of denitrification, nitrification, and fermentation sub-models (DNDC, 2019). In the DNDC, soils are represented as of discrete horizontal layers, down to 50 cm depth. Some soil properties are assumed to be uniform across all layers. For example, bulk density, porosity and hydraulic conductivity are assumed to be constant through depth of a soil profile. Other soil properties such as pH, soil moisture, soil temperature,

carbon and nitrogen pools are calculated in each soil layer using a daily time step. Often, researchers re-parameterize the soil and crop properties for local conditions based on empirical information and sometimes modify the model equations to better match dependent variables of the specific system (Giltrap et al., 2010).

Since its creation, the DNDC has been modified and adapted to include different scenarios and ecosystems. In 1994, a simple plant growth sub-model was added to the original version (Li et al., 1994). Later, a Crop-DNDC was developed to simulate the interactions between crops and C, N, and water cycles. In the Crop-DNDC model, crop growth is simulated by tracking physiological processes (phenology, leaf area index, photosynthesis, respiration, assimilation allocation, rooting processes, and N uptake) along with water and nitrogen stress (Zhang et al., 2002). The new algorithms introduced to the crop sub-model act as an alternative approach to the simple crop sub-model of the original version (Li et al., 1994). As result, the Crop-DNDC was superseded by the DNDC (version 9.5) (Gilhespy et al., 2014). Further improvements to the model include: modification of the soil evaporation equation to simulate the effect of different levels of surface residue cover, enhanced capacity for simulating exchangeable  $\text{NH}_4^+$ ,  $\text{NO}_3^-$  leaching, surface runoff, and soil erosion (Steiner, 1989; Deng et al., 2011; Li et al., 2012; Gilhespy et al., 2014). Additionally, the DNDC has improved the simulation of crop growth and alternative management practices such as slow release fertilizers, irrigation, and cover crops. Because of these improvements the DNDC is well-suited to predict the effect of alternative management strategies and the impact of climate change on agricultural production.



**Figure 1.** Schematic diagram of DNDC model structure (Li et al., 1994).

In the next sections, the most relevant processes in each of the four DNDC sub-models are summarized, including soil climate, crop growth, decomposition, and nitrification. These four sub-models are described in detail because they simulate the provision of our ES of interest: soil water storage, soil organic matter accumulation, and N retention. Further details about the model processes and mathematical equations are described in Li et al. (1992; 2006), and Zhang et al. (2002).

### *Simulating soil water storage: DNDC soil climate sub-module*

In the DNDC, soil moisture is calculated based on vertical water flow through each horizontal soil layer. The rooted soil profile has a default depth of 50 cm with 25 horizontal layers. The water sub-model time step is 30 min, but output variables are reported as a daily average. Water inputs to the sub-model are precipitation, surface inflow, and ice/snow melting. Water withdrawal from the soil profile is calculated based on transpiration, evaporation, and percolation to deeper soil depths. The model assumes moisture and texture are uniform through the soil layers. Another assumption is that all rain events have a constant intensity (0.5 cm/h) and start at midnight. If the rain intensity is higher than the soil saturated hydraulic conductivity, water will pond on the soil surface. Surface runoff is calculated based on the soil slope.

At the beginning of each time step, water flow is calculated in the soil layer by layer. Discharge rates in each layer are influenced by field capacity, porosity, water content, and two constant coefficients defining initial discharge flow and retention rate. The magnitude of these coefficients is related to soil texture, porosity, field capacity, and wilting point. For example, heavy soils with rich clay content tend to have higher field capacity, which translates into lower initial discharge flow and longer recession process. As soil water content decreases, discharge rate decreases. Drainage rate reaches its maximum when the soil is saturated during a rainfall event, and gradually decreases as soil water approaches field capacity (Tallakse's 1995). The water discharge rates are essential for modeling the water storage difference with and without cover crops.

The model includes a deeper water pool to capture drainage flow from tile lines. The deep-water pool is a function of soil porosity and the distance between the bottom of the soil profile and the drainage tiles. The discharge flow of the deep-water pool is divided into two fractions. A



fraction of the water flow is stored in the deep-water pool, and the rest is released from the pool to the tile drainage flow. The initial water volume in the deep-water pool is equivalent to the field capacity. If the water content in the deep-water pool is higher than the field capacity, a fraction of the excess water is released from the pool to the tile drainage flow. Both fractions were defined as functions of soil texture with clay content as an indicator (Tonitto et al., 2007).

Evapotranspiration (ET) is calculated using the Thornthwaite formula, in which potential ET is determined by monthly mean air temperature and then adjusted for daylight length relative to 12 hours (Dunne and Leopold, 1978). Potential transpiration is determined by daily crop water demand, which is based on the modeled daily crop increment biomass. Actual transpiration is determined by potential transpiration and soil water content. Potential evaporation is calculated as the difference between potential ET and actual transpiration. Evaporation is assumed to occur only for the top 20 cm of the soil profile. The major constraints for water movement are soil freezing and compaction.

#### *Simulating plant growth: DNDC plant growth sub-module*

The DNDC simulates plant growth with four major state variables and eight processes, where the state variables (stocks) are expressed as mass per unit area or as fractions and the processes are the representation of mechanistic processes describing the evolution of state variables over time. In the DNDC, the state variables include phenological development, Leaf Area Index (LAI), biomass, and N content of crop organs. The processes include phenological development, photosynthesis, respiration, assimilate allocation, rooting processes, water and N uptake. First, the crop assimilates atmospheric carbon through photosynthesis, then carbon assimilation produces N demand. The actual N uptake depends on the availability of inorganic N

in the soil. Carbon allocation and N demand is influenced by the phenological stages and water and N stress factor. The DNDC plant growth processes are as follows:

Phenological development is based on thermal time units. Thermal time is the summation of temperature that predicts plant growth. There are nine crop growth stages from emergence to maturity. The thermal time needed from sowing to emerge is calculated based on sowing depth. The thermal time needed for other stages are variety specific parameters or are estimated based on the thermal time of the former stages (Hanks et al., 1991; Jones, 1986; Ritchie et al., 1998).

Leaf Area Index is simulated as the difference between leaf area growth (associated with assimilate allocation) and leaf senescence (associated with phenological development and stress). Leaf Area Index growth is simulated using an exponential function of leaf number or thermal time units. Growth is then simulated according to the allocation of assimilates. Leaf senescence is estimated based on phenological stages and water and N stress factors (Brown, 1987; Ritchie et al., 1998)

Photosynthesis is simulated considering the direct and diffuse light separately (Spitters, 1986; Spitters et al., 1986). The response of photosynthesis to light is expressed as an exponential function with two parameters. The effect of temperature on photosynthesis is simulated as influencing the photosynthesis rate at light saturation and initial light use efficiency (Penning de Vries et al., 1988). The effect of atmospheric CO<sub>2</sub> concentration on photosynthesis rate is considered based on Goudriaan (1986). Photosynthesis is also influenced by water and N stress factors.

Plant respiration is simulated considering growth and maintenance respiration separately (McCree, 1970). Growth respiration is estimated based on the amount of assimilates available for

growth; and maintenance respiration is estimated based on temperature and biomass of crop organs (Svirezhev, 1992).

The difference between photosynthesis and respiration is the amount of assimilate available for allocation among crop organs. Assimilate allocation is simulated based on phenological stages (Brown, 1987; Svirezhev, 1992). First, the DNDC model estimates the partitioning of assimilate between roots and shoots. Then the model calculates the partitioning of shoots among leaf, stem, and grain.

Rooting process include the increase of root front depth, the distribution of root length density, and biomass in soil profile. The depth of the root front is limited to a maximum of one meter and is proportional to the thermal time before flowering. Root length density in a layer depends on new root growth and root senescence. New root growth is determined by the assimilate partitioned to root. Root senescence is assumed as 1-2% of the total root biomass. Root biomass is estimated based on root length distribution, follows an exponential pattern in soil profile, and is subject to constraint factors (Allan Jones et al., 2015). In each layer there are 5 rooting constraint factors, one is static and four are dynamic. The static factor is a direct input parameter for the effect of toxicity, coarse fragments, pan layers, and deficiency of other nutrients. The dynamic factors include the effect of soil strength, aeration, temperature, and N. Soil strength factor is based on soil bulk density, texture, and water content (Allan Jones et al., 2015). The aeration factor depends on soil moisture and sensitivity of plant to water saturation. The N factor is simulated based on Ritchie (1987).

Crop water uptake depends on potential transpiration, uptake capacity, and soil water availability. Transpiration is determined by LAI and climate. Uptake capacity is determined by soil moisture, root length, and root distribution. The major assumption in this process is that roots

are uniform sinks with a specific uptake capacity. Soil moisture influences the actual uptake capacity. Water stress factor is based on the ratio of actual water uptake and potential transpiration demand (Brown, 1987).

Crop N uptake depends on crop demand and uptake capacity. Crop demand is based on the optimum daily crop growth and the plant C/N ratio. Any time the plant has low N concentration; plant growth will be reduced. A similar principle is used for estimating N stress. Nitrogen demand includes deficiency demand and new growth demand. The actual N uptake depends on  $\text{NO}_3^-$  and  $\text{NH}_4^+$  concentration in the root zone and water availability. Crop N pools are divided into shoots, grain, and roots. The major assumption in the crop N pools is that shoots and roots have the same relative concentration compared to their critical concentrations (Ritchie et al., 1998).

After harvest, all root biomass is left in the soil profile and the above-ground crop residue remains as stubble in the field. The residues incorporation provides the inputs for the soil biogeochemistry sub-module (DNDC, 2019).

#### *Simulating soil organic matter accumulation: DNDC soil decomposition sub-module*

Decomposition in the DNDC model is calculated at a daily time step in each layer. The outputs variables of this sub-model are SOM,  $\text{CO}_2$ ,  $\text{NH}_4^+$ , and dissolved organic carbon (DOC). SOM is calculated as the summation of crop residues, microbial biomass, humads (i.e. active humus), and passive humus (Li et al., 1994).  $\text{CO}_2$  is the product of microbial respiration during the decomposition process.  $\text{NH}_4^+$  is the N that was attached to the carbon lost due to microbial respiration and N in excess if that needed to grow microbial biomass. DOC consists of the decomposed microbial biomass and humads. DOC helps to recycle carbon back into microbial biomass and serves as an indicator of the amount of soluble carbon available in the soil (Li et al.,

1994). The decomposition sub-model is essential to differentiate soil organic matter accumulation with and without cover crops. At the same time, this sub-model captures the reduction in N fertilization rates with the use of cover crops.

Decomposition occurs as first order-kinetics and depends on the pool size, the specific decomposition rate, soil clay content, N availability, soil temperature, and soil moisture (Molina et al., 1983). The pools of organic matter consist of cover crop residues, cash crop residues, microbial biomass, and humads. The crop residues are partitioned into three pools consisting of very labile, labile, and resistant. The microbial biomass and humads are partitioned into labile and resistant pools. During the decomposition process, each pool decomposes independently (Hunt, 1977; Jenkinson, 1977).

When decomposition occurs, the carbon is either released as CO<sub>2</sub> or incorporated into other carbon pools. For example, as the crop residue pools decompose, the carbon release is either respired as CO<sub>2</sub> or incorporated into the microbial pool. First, the model calculates the amount of CO<sub>2</sub> produced. Then, 90% of the carbon is incorporated as labile microbial biomass and the other 10% as resistant microbial biomass (Gilmour et al., 1985). The same principle applies when microbes die and their biomass decomposes, 20% of the carbon is respired as CO<sub>2</sub>, 60% is reincorporated into new microbial biomass, and 20% is transferred to the resistant humads pool (Molina et al., 1983). When the resistant humads pool decomposes, 40% of the carbon is transferred to the stable humus pool, 40% is converted as CO<sub>2</sub>, and 20% is reincorporated into microbial biomass (Gilmour et al., 1985; Molina et al., 1983).

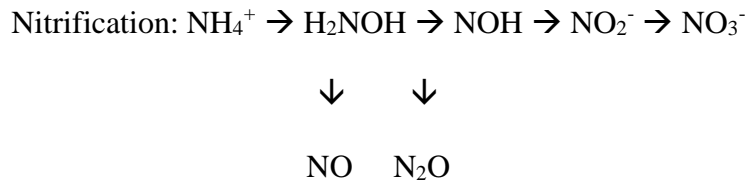
Soil moisture and temperature can delay the decomposition process (Nyhan, 1976). This is because of the effect of water and temperature on microbial activity. Nitrogen availability and clay content are also limiting factors in the decomposition (Molina et al., 1983). For example, high soil

clay content and low N availability reduce decomposition rates (Bouwman, 1990; Molina et al., 1983). Decomposition only occurs in aerobic conditions. During rain events (i.e., anaerobic condition), the decomposition sub-model pauses, and the denitrification sub-model runs until the top 20 cm of the soil has an average of water content less than 40% of porosity or until denitrification sub-model run out of substrates (Bremner & Shaw, 1958; Li et al., 1994).

*Simulating soil N retention: DNDC soil nitrogen cycling sub-modules*

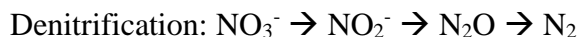
The DNDC model simulates nitrification and denitrification processes. The DNDC model includes an “anaerobic balloon” that divide soil into aerobic and anaerobic parts based on moisture conditions. Base on kinetics the model predicts the soil aeration status by calculating oxygen or other oxidants in the soil profile. The substrates located in the aerobic part are subject to nitrification and the substrates located in the anaerobic part are involve in denitrification (Li et al., 1992b; Li, 2000; Li et al., 2006).

Nitrification is the microbial oxidation of ammonium (NH<sub>4</sub><sup>+</sup>). The key elements controlling nitrification are soil temperature, soil moisture, pH, and NH<sub>4</sub><sup>+</sup> concentration. The model predicts nitrification rates by tracking nitrifier activity and NH<sub>4</sub><sup>+</sup> concentration. The turnover rate of NH<sub>4</sub><sup>+</sup> oxidizers are calculated based on DOC concentration, temperature, and moisture (Li et al., 1992b; Li, 2000).



Denitrification is the sequential reduction of nitrate (NO<sub>3</sub><sup>-</sup>) to dinitrogen (N<sub>2</sub>) driven by denitrifying bacteria under anaerobic conditions. Denitrification rates are controlled by soil

moisture, redox potential, temperature, pH, and substrate concentration (e.g. DOC,  $\text{NO}_3^-$ ,  $\text{NO}_2^-$ , NO and  $\text{N}_2\text{O}$ ). The model simulates the growth rates of denitrifiers based on soil DOC and nitrogen oxides. The growth rate of denitrifiers is independent for different substrates. DOC generates competition among bacteria. The death rates of denitrifiers are a constant fraction of the total biomass.



Nitrogen leaching is part of the N biogeochemical sub-model. The N concentration in the leachate depends on several buffering mechanisms. These mechanisms include N assimilation/dissimilation by soil microbes and N adsorption/desorption in clay mineral or/and organic matter. The  $\text{NH}_4^+$  ions are easily assimilated or adsorbed. The assimilated  $\text{NH}_4^+$  in the microbial pools can be released back into the soil when the microbes die or during SOM decomposition. The adsorbed  $\text{NH}_4^+$  in the clay particles can be released through chemical equilibrium. The  $\text{NH}_4^+$  released into the soil liquid phase can be quickly transformed to  $\text{NO}_3^-$  by nitrifiers. Although,  $\text{NO}_3^-$  can be reused by microbes, the anion does not have affinity to the soil adsorbents. This creates a better chance for  $\text{NO}_3^-$  to move to the leaching water flow. Because  $\text{NO}_3^-$  is highly soluble, when a rainfall occurs it is leached into deeper layers with the soil drainage flow (Li et al., 1992b; Li, 2000; Li et al., 2006). This process captures the difference on N retention with and without cover crops.

### *Input requirements*

The main input parameters required by the DNDC are divided in four major categories: location, climate and weather, soil, and farming management practices. The DNDC provide some default soil parameters based on average values for U.S. soils (Giltrap et al., 2010). The mandatory

input parameters for which default values are not provided are location, climate weather data, soil bulk density, pH, and SOC at the surface (0-10 cm) and management practices. Selecting land use, crop type, soil texture, and management practices alongside with the main required inputs, provide sufficient detail to run the model (Gilhespy et al., 2014).

### *Output variables*

The DNDC generates outputs with daily time steps. The daily outputs include soil climate, soil water, soil C and N pools/fluxes, crop growth, and field management. The annual reports include crop growth/yield, soil C and N pools/fluxes, and water balance for the simulated site. Finally, the multi-year summary presents the major annual pools or fluxes across the simulated years (Gilhespy et al., 2014).

### *DNDC limitations and assumptions*

Because models are a simplification of the real world and by the tradeoffs that occur when trying to represent more complexity in a model, mechanistic models such as the DNDC are limited by incomplete scientific understanding of key processes. Therefore, the full mechanistic complexity of the real world is not accurately represented in ecosystem models and several assumptions are made. Here we listed the most relevant assumptions and limitations of the DNDC model related to our study:

- In the DNDC all rain events have constant intensity (0.5 cm/h). In the real-world rain intensity can vary. If rain intensity is higher, more water pond in the soil surface and higher erosion occurs. This means that DNDC might be underpredicting soil erosion rates without cover crops and therefore, underpredicting the benefits of cover crops use,



- The plants in the DNDC don't die. If in the real-world plants die due to water deficit, in the DNDC model plants stop growing only for the days that the plant experienced water deficit and the model allows the plant to re-grow after a rain event occurred. This optimistic view of the model is common in most agricultural models. However, it is still possible to make inference about the soil processes and yields lost due to water stress. This indicates that during extreme droughts the soil water storage benefits of cover crops might be underpredicted.
- Most crop and biogeochemical models have limited ability to simulate long-term, management-induced changes in soil hydraulic properties. In the DNDC, infiltration rate and available water are determined by soil structural characteristics such as bulk density and texture. These are fixed input parameters that don't change over the simulation period. This limits our ability to account for cover crop soil water storage benefits in the short-term. Therefore, in our study we evaluated soil water storage benefits after 10 years of cover crop use (long-term effect of cover crop use).
- The mechanistic controls on soil organic carbon stabilization and destabilization remain incomplete. As a result, the full mechanistic complexity of SOC accumulation is not accurately represented in any biogeochemical model, including the DNDC.

## CHAPTER III

### METHODS: BIOGEOCHEMICAL-ECONOMIC MODELING DESCRIPTION

This chapter describes the biogeochemical-economic model. Focus is put on the impact of cover crops on the DNDC sub-models' processes. The economic model with its mathematical representation is included.

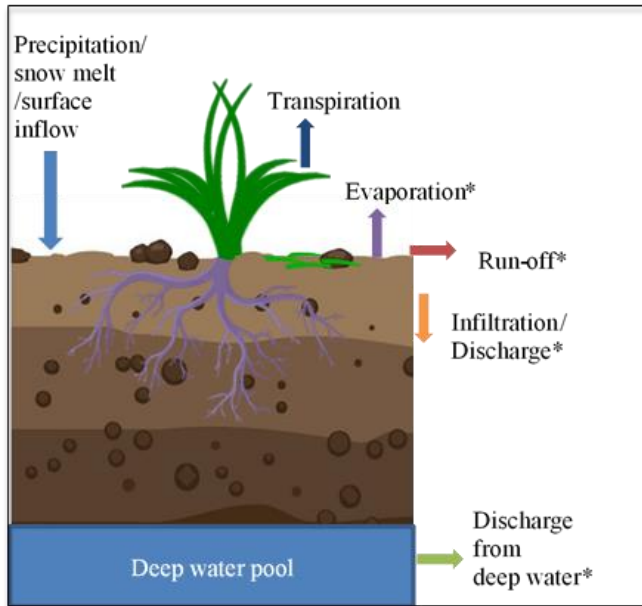
#### 3.1 Biogeochemical modeling: DNDC

##### *The DNDC sub-models influenced by cover crops*

In this study, the DNDC model was used as the biogeochemical model to simulate how changes in soil organic matter, soil water dynamics, and N leaching affect crop yields when a farmer adopts cover crops. Although the denitrification and fermentation sub-models can capture the effects of cover crops in greenhouse gas emissions, the outputs of these sub-models are not related to our research questions. Therefore, we focused only on four sub-models: soil climate, soil N cycling, decomposition, and crop growth.

The effect of cover crops on processes in the soil climate sub-model is driven by increased wilting point and field capacity values via the improvement of soil structure. The soil climate sub-model provided information on soil water dynamics including daily soil moisture. The main processes simulated by the soil climate sub-model are transpiration, evaporation, water run-off, and infiltration (Fig. 2). These processes are influenced by input parameters such as wilting point, clay content, and field capacity. Cover crops can increase the water retained in the soil by reducing the net evapotranspiration in the short-term and by increasing wilting point and field capacity values in the long-term. Cover crop residues in the top layers reduce evaporation rates by reducing

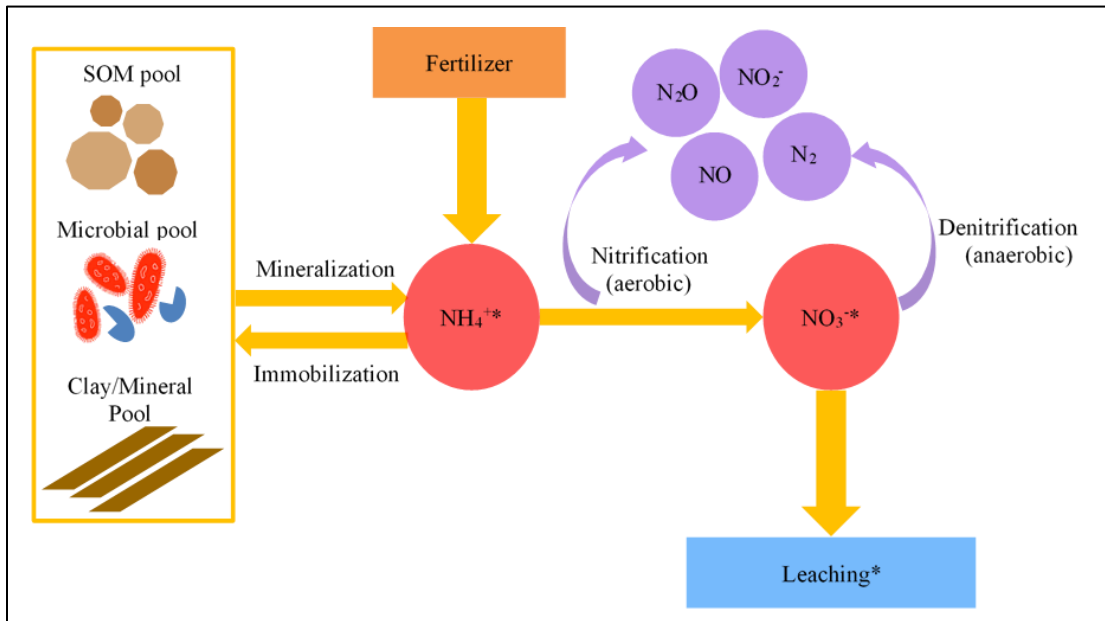
soil exposure to solar radiation. At the same time, higher wilting point and field capacity values, decrease infiltration rates in each soil layer. Mechanistically, this allows the soil to retain more water (DNDC, 2019; Changsheng Li et al., 1992; Li, 2000; Zhang et al., 2002; Basche et al., 2018a).



**Figure 2.** Main processes of the DNDC soil climate sub-model. Asterisk (\*) represents the processes that are reduced under the influence of cover crops. Source: Li et al. 1992.

Cover crops have a direct effect on the N sub-model. In the DNDC model, the amount of  $\text{NO}_3^-$  that is available in the soil is immediately leached during a rain fall event. At the same time, the model predicts the nitrification process by tracking nitrifier activity and  $\text{NH}_4^+$  concentration. The  $\text{NH}_4^+$  ions are easily assimilated by microbes or adsorbed in clay particles. The assimilated  $\text{NH}_4^+$  in the microbial pools can be released back into the soil when the microbes die or during SOM decomposition. The adsorbed  $\text{NH}_4^+$  in the clay particles can be released through chemical equilibrium. The  $\text{NH}_4^+$  released into the soil liquid phase can be quickly transformed to  $\text{NO}_3^-$  by nitrifiers. Although,  $\text{NO}_3^-$  can be reused by microbes, the anion does not have affinity to the soil

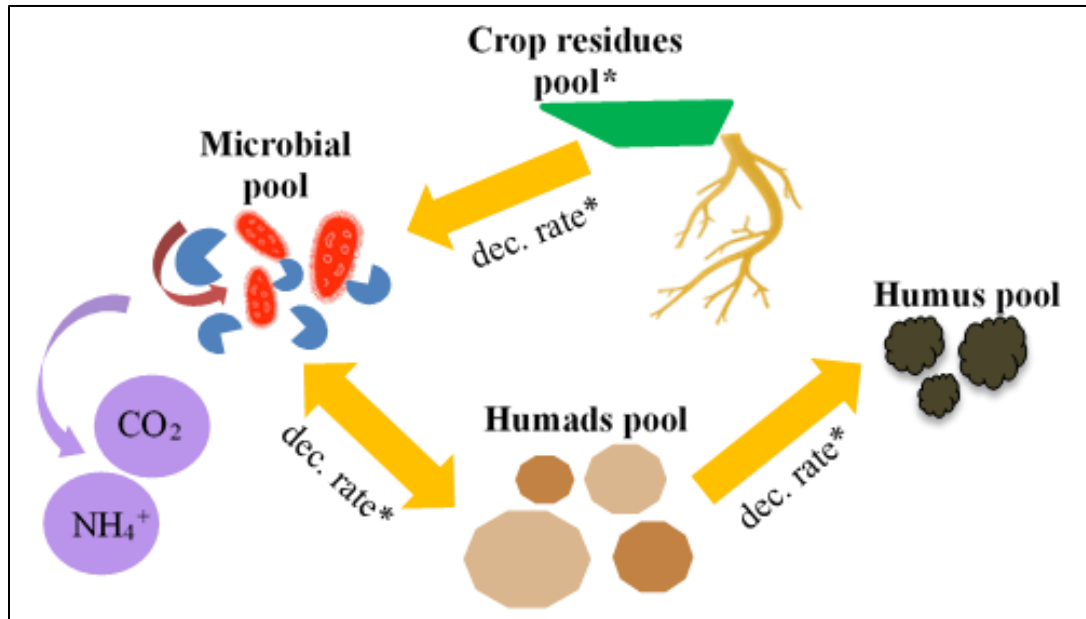
adsorbents. This creates a better chance for  $\text{NO}_3^-$  to move to the leaching water flow (Fig. 3). Cover crops reduce the amount of  $\text{NO}_3^-$  and  $\text{NH}_4^+$  that is left in the field after the harvest of cash crops. Cover crops incorporate this inorganic N into their biomass, increasing soil organic nitrogen. During decomposition, the N contained in the cover crops recycles back into the soil through mineralization and has the potential to contribute additional N to subsequent cash crops, thereby reducing the N fertilization need for these crops (Li et al., 1992b; Li, 2000; Li et al., 2006).



**Figure 3.** Main processes of the DNDC soil nitrogen sub-model. Asterisk (\*) represents the processes and stocks that are reduced during cover crop growth. Source: Li et al. 1992.

Cover crops have direct and indirect effects on processes in the decomposition sub-model. Cover crop residues serve as inputs to the decomposition sub-model, directly increasing SOM. In the DNDC model, SOM is defined as the summation of crop residues, microbial biomass, humads, and humus (Fig. 4). Therefore, adding shoots and roots of cover crops increase SOM. The indirect effect of cover crops in this sub-model is through water retention. Soil moisture can delay decomposition rates due to the effect of excess water on soil microbes. For example, high soil

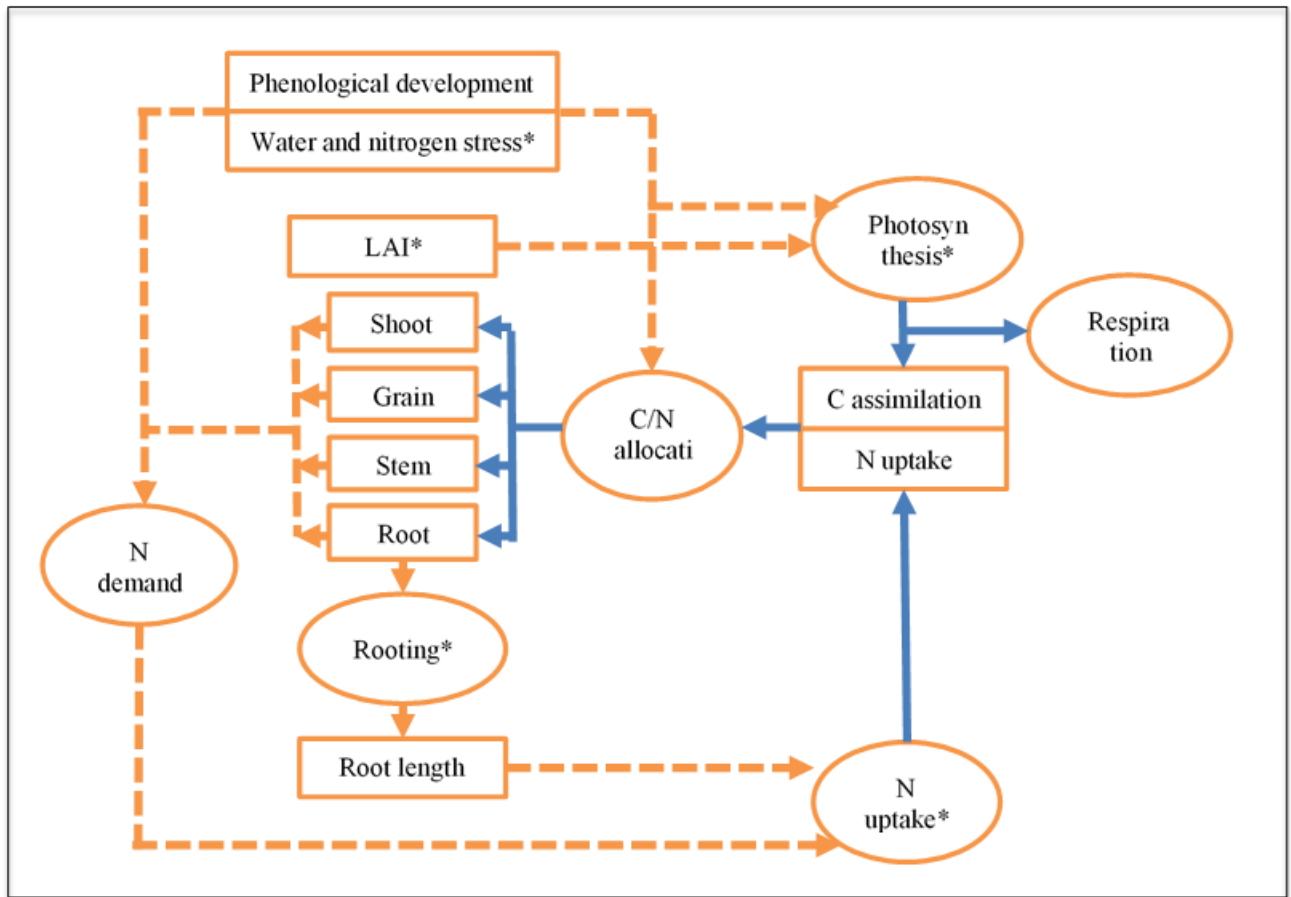
moisture can cause anaerobic conditions in the soil, resulting in decomposition delay. Additionally, cover crops provide a source of N. During the decomposition processes, N that was attached to respired carbon ( $\text{CO}_2$ ) is partially mineralized to ammonium ( $\text{NH}_4^+$ ). Thus, cover crops provide multiple benefits by increasing SOM and serve as a source of N for the subsequent crop (DNDC, 2019; Li et al., 1992; Li, 2000; Zhang et al., 2002).



**Figure 4.** Soil organic matter pools and their transformation processes considered in the DNDC model. These SOM pools increase with the use of cover crops. Asterisk (\*) represents the decomposition processes indirectly influenced by cover crops. Source: Li et al. 1992.

Cover crops also influence the crop sub-model, mainly by improving soil water, SOM, and by reducing N leaching (Fig. 5). Cover crops indirectly affect the leaf area index, photosynthesis, rooting process, water uptake, and N uptake. First, the leaf area index, photosynthesis, and rooting process are influenced by limiting factors of soil water and N content. Since cover crops increase water retention, water may be less of a limiting factor in the cash crop growth processes. Second, the crop water uptake process depends on the root growth and the availability of water in the soil.

Because cover crops increase both the rooting process and the water retained in the soil, the cash crop water uptake capacity also increases. Finally, the N uptake process is influenced by N concentration and water availability in the root zone. Cover crops increase cash crop N uptake by providing additional mineralized N from cover crop residues and by improving soil moisture. Therefore, overall cover crops have a positive effect on the cash crop processes (DNDC, 2019; Changsheng Li et al., 1992; Li, 2000; Zhang et al., 2002).



**Figure 5.** Scheme of the crop sub-model. Rectangles are for state variables and circles for processes; solid lines are for matter flow and dash lines are for information flow. Asterisk (\*) represents the processes influenced by cover crops thru water retention ecosystem services. Source: Zhang et al. 2002.

### 3.2 Economic model

The DNDC sub-models described above were used to simulate cash crop (i.e. corn and soybean) yields, with and without cover crops. When simulated with cover crops, these sub-models explicitly account for the ecosystem services provided by cover crops, namely water retention, soil organic matter, and reduction of N leaching. This section incorporates the simulated cash crop yields in a risk-neutral farmer's profit function that includes the price of corn and soybean, the costs of corn and soybean production, the costs and benefits of adopting cover crops, and a discount factor (Eq. 1). Using historical weather and price data, the simulated yearly profits and standard deviation across 10 years were used to calculate the expected utility of a risk-averse farmer, that is a farmer who is averse to year-to-year fluctuation in profits.

#### *Risk-neutral farmer's profit function*

The objective function of a risk-neutral farmer is to maximize the farm's Expected Net Present Value (ENPV), that is the NPV average over 10 years. The decision variables for the farmer in this model are whether to adopt cover crops and the amount of N fertilizer used for corn production. Both decisions occur at the beginning of the simulation and are fixed over the years. The amounts of N fertilizer available to the farmer to choose from are 90, 100 and 110 kgN/ha and application occurs every other year. We used historical corn and soybean prices, N fertilizer cost, herbicide cost, and cover crop seed costs. The risk-neutral farmers' objective function can be represented mathematically as follow:

$$\max_{\{n_{f,0}, u_0\}} \text{ENPV} \sum_{t=0}^{10} \rho^t \cdot [(p_t \cdot Y_t - n_{f,0} \cdot c_{N,t} - C_{Y,t}) - u_0 \cdot (EQIP_t - c_{u,t} - E(c_{u,t}))] \quad (1)$$

Subject to:  $Y_t = f(SWC_t, SOM_t, N_t)$

where  $n_{f,0}$  is the quantity of fertilizer applied at  $t=0$ , which takes the values of 90,100, and 110 kgN/ha;  $u_0$  is a binary variable that equals 1, if the farmer decides to plant cover crops at  $t=0$  and 0 otherwise; ENPV denotes the expected value, over 10 years, of the net present values for the farmer;  $t$  denotes years;  $\rho^t$  is the discount factor applied to the profit values in each year  $t$ ;  $p_t$  is the cash crop output price, which alternates every year between corn and soybean prices and fluctuates over years;  $Y_t = f(SWC_t, SOM_t, N_t)$  is the cash crop yield simulated by the DNDC model, which is a function of soil water content ( $SWC_t$ ), soil organic matter ( $SOM_t$ ), and N retained by the cover crop ( $N_t$ );  $c_{N,t}$  is the unit N fertilizer cost, which fluctuates across years  $t$ ;  $C_{Y,t}$  is the total cost of cash crop production, excluding fertilization costs, which also fluctuate across years; ( $EQIP$ ) is a yearly revenue term representing the revenues a farmer generates from planting cover crops in the form of a the cost share program payments ( $EQIP_t$ );  $c_{u,t}$  is the direct cost of adopting cover crops, which include seed, planting, and termination costs;  $E(c_{u,t})$  is the expected value of cover crop maintenance, computed based on the probability of the cover crop becoming a weed and requiring maintenance. All total costs are assumed to be linear in input quantities (i.e., calculated by multiplying unit costs with quantity).

#### *Risk-averse farmer's utility function*

To represent the utility function of a risk-averse farmer, we used the certainty equivalent (CE) measure. The CE is the sure amount of money that has the same utility as the expected utility of a risky alternative. Based on Expected Utility Theory and as in Finger (2012), we assumed that a risk-averse farmer seeks to maximize the CE, as follow:

$$CE = ENPV - \pi \quad (2)$$

where  $ENPV$  is the expected net present value (Eq. 1); and  $\pi$  is the risk premium. In the case of a risk-averse farmer,  $\pi > 0$ .



According to Pratt (1964), a risk premium is the amount of money the farmer is willing to pay to eliminate risk exposure and can be approximated as follows:

$$\pi = \frac{\gamma \cdot \sigma_{NPV}^2}{2 \cdot ENPV} \quad (3)$$

where  $\gamma$  is the coefficient of relative risk aversion;  $\sigma_{NPV}^2$  is the year-to-year variance of the NPV over a time horizon of 10 years. The year-to-year NPV variance is due to the variation in soil water, N retention, and SOM dynamics and therefore yields over the years  $t = 0, \dots, 10$ .

We generated NPV data over 10 years and computed the expected value over the 10 years and the variance across years. We then computed the CE measure for a moderately risk-averse farmer ( $\gamma = 2$ ). Combining the Equations (3) and (4), we get the following CE expression:

$$CE = ENPV - \frac{\gamma \cdot \sigma_{NPV}^2}{2 \cdot NPV} \quad (4)$$

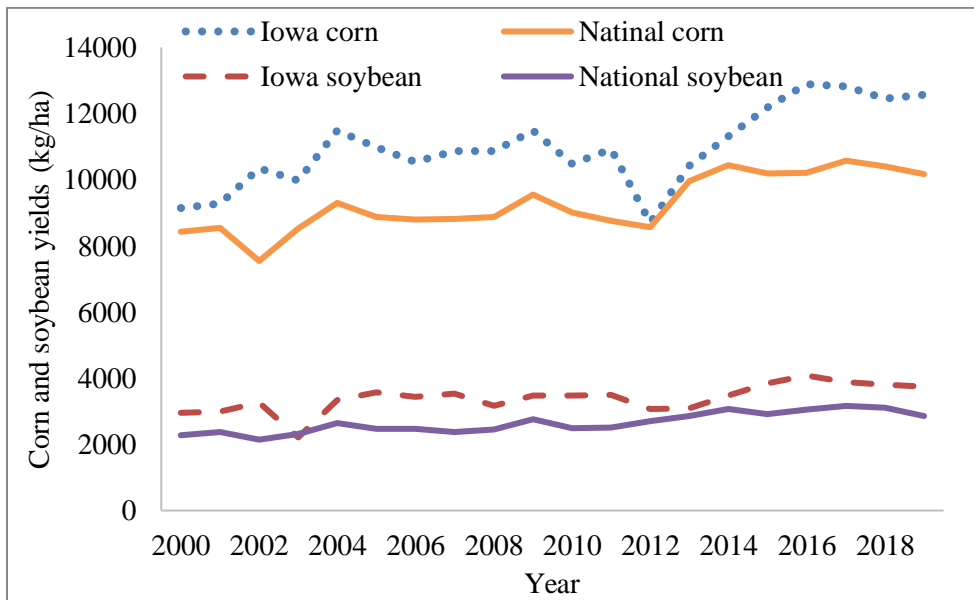
where  $ENPV$  is the expected NPV; and  $\sigma_{NPV}^2$  is the variance of the NPVs observed over 10 years.

## CHAPTER IV

### MODEL APPLICATION

#### 4.1 Study site for model application

Iowa was selected as a representative state to study the economic and environmental benefits of cover cropping. Iowa is a major producer of maize and soybean in the Midwest. Since 2000, Iowa corn and soybean production has been higher than the national average except in 2003 and 2012, when major droughts occurred (Fig. 6). Iowa also represents a region of high N pollution and is a member of the Mississippi River/Gulf of Mexico Watershed Nutrient Task Force that aims to reduce nutrients leaching into watershed and ultimately, the Gulf of Mexico (Iowa Department of Agriculture & land stewardship, 2018).



**Figure 6.** Average corn and soybean production in Iowa compared the U.S. national average (kg/ha) from 2000 to 2018. Source: USDA Survey data from 2000-2019.

## 4.2 Field data

In this section, we briefly explain the methods used for data collection at the field site needed to parameterize the DNDC, as reported by Kaspar et al., 2007; and Kaspar et al., 2012; Basche et al., 2016a; Basche et al., 2016b.

The site used in this study is located Boone County, IA (ISUAG; 42.05°N, 93.71°W). The two predominant soils on this site are Canisteo (fine-loamy, mixed, super-active, calcareous, mesic Typic Endoaquolls) and Nicollet (fine-loamy, mixed, super-active, mesic Aquic Hapludoll) (USDA Soil Conservation Service, 1991). This site has a long history of corn-soybean rotations dating back to 1999. Maize was planted in the spring of even-numbered years and soybeans in the spring of odd-numbered years. In 2000, a treatment of cereal rye cover crop with no-tillage was established. Plots sizes of 30.5 x 42.7 m were arranged in a randomized complete block design with four replicates. The cereal rye cover crop was established by drilling or aerial seeding after cash crop harvest in the fall and was terminated with glyphosate prior to cash crop planting (Basche et al., 2016a; Basche et al., 2016b; Kaspar et al., 2007; Kaspar et al., 2012).

At the field site, subsurface drainage tiles of 7.62 cm diameter were installed at 1.2 m depth in 1999. Soil moisture sensors were installed in three of the four replicates in 2008. Two treatment were selected based on data availability on management, soil characteristics, and N leaching. These treatments included a no-tillage corn-soybean rotation either without cover crops (noCC) or with cereal rye cover crop (CC). Empirical data was collected from published studies. These data consisted of crop and soil measurements. Crop measurements included biomass, total N and C for cover crop, and yields for maize and soybeans. Soil measurements included soil water content, water flow in tile drainage and nitrate leaching ( $\text{NO}_3^-$ ). Information about agronomic management is summarized in table 1.

**Table 1.** Agronomic management practices used at the field site during the study period (month/day).

<b>Year</b>	<b>Cash crop</b>	<b>Cash crop planting</b>	<b>Cash crop harvest</b>	<b>Cover crop planting</b>	<b>Cover crop termination</b>	<b>Total N applied (kgN/ha)</b>	<b>Cover crop seeding method</b>
2004	Maize	4/28	10/4	10/6	4/16	246	Drilled after harvest
2005	Soybean	5/6	9/30	9/30	4/25	0	Drilled after harvest
2006	Maize	5/4	10/20	10/24	4/21	225	Drilled after harvest
2007	Soybean	5/22	9/26	9/28	5/10	0	Drilled after harvest
2008	Maize	5/14	10/28	10/29	4/29	198	Drilled after harvest
2009	Soybean	5/22	9/28	9/28	5/21	0	Drilled after harvest
2010	Maize	4/29	9/16	9/17	4/19	198	Drilled after harvest
2011	Soybean	5/18	9/29	9/30	4/23	0	Drilled after harvest
2012	Maize	5/4	9/19	9/4	5/13	197	Aerial seeding
2013	Soybean	5/23	10/20	9/4	4/10	0	Aerial seeding

Source: Basche et al., 2016a; Basche et al., 2016b; Kaspar et al., 2007; Kaspar et al., 2012.

### *Crop measurements*

Corn and soybean yields were determined to evaluate the effect of cover crops. Grain weight was converted to yield per area by standardizing to 15.5% moisture basis for corn and 13% moisture basis for soybean. Cover crop biomass sampling was done prior to termination. Frames of 0.76 x 0.50 m were used to define the sample area. Two representative samples per plot were collected. The rye cover crop was cut by hand using grass clippers, dried, and weighed for dry

biomass calculation. Subsamples were ground for total C and N analysis (Kaspar et al., 2007, 2012).

### *Soil measurements*

Soil moisture was measured to determine the effects of cover crops on soil water content. Soil moisture was measured at a soil depth of 5 cm from 2008 to 2014. Hourly soil moisture was measured using a Theta Probe soil moisture sensor (Model Type ML2x, Delta-T Devices, Cambridge, United Kingdom). Voltage measurements were converted to a dielectric constant then to volumetric water, using the calibration equation for Des Moines Lobe soils (Kaleita et al., 2005). During the growing season (April-October), average daily soil water content was reported in  $\text{mm}^3/\text{mm}^3$  (Basche et al., 2016a).

Field capacity and permanent wilting point were measured to determine the long-term impacts of cover crops on soil water properties. Field capacity is defined as the water retained in the soil at -33 kPa pressure, which represents the ability of the soil to retain water after internal drainage ceased and is also considered the upper limit of plant available water (Basche et al., 2016a; Hillel, 1992; Veihmeyer & Hendrickson, 1927). Permanent wilting point is defined as the water retained at -1500 kPa, which represents the soil wetness at which point a plant cannot recover turgidity and is also considered the lower limit of plant available water (Basche et al., 2016a; Hillel, 1992; Veihmeyer & Hendrickson, 1927). These measurements were analyzed using intact soil cores of 7.6 x 7.6 cm at 4-11.6 cm depth. Cores were analyzed at the Soil, Water and Plant Testing Laboratory at Colorado State University using a Decagon WP4C Water Potential Meter (Decagon Devices, Inc, Pullman, WA) (Basche et al., 2016).

Nitrate leaching ( $\text{NO}_3^-$ ) was measured from the drainage water. Water samples were measured on a weekly basis using Lachat Autoanalyzer (Zellweger Analytics, Lachat Instrument Division, Milwaukee, WI). The method's lower detection limit for  $\text{NO}_3^-$  was 0.3 mg N L<sup>-1</sup>. Mass of  $\text{NO}_3^-$  in drainage water was calculated by multiplying the  $\text{NO}_3^-$  concentration of each proportional water sample by the volume of water discharged during the time the sample was collected (Kaspar et al., 2007, 2012).

### **4.3 Biogeochemical model initialization and parametrization**

In this study, the DNDC model was used to simulate crop yields, soil water content (SWC), soil organic carbon (SOC), and nitrogen leaching ( $\text{NO}_3^-$ ) under a corn-soybean rotation with cover crops (CC) and without cover crops (noCC) in an Iowa farm.

The parameter values used to initialize the model were based on site-specific field measurements supplemented with information from the literature (Table 2). The values reported by Basche et al. (2016a, 2016b) and Parkin & Kaspar (2004) were chosen as they demonstrate the effects of cover crops on soil properties and are from the same experimental plots located at the a research farm in Boone County, IA.

To better capture mineralization from cover crop residues, we increased decomposition rates by 15% in the CC treatment. This modification allows the transformation of recalcitrant pools (humus) to more available pools (microbial), allowing us to incorporate the new theories of SOM decomposition, where SOM pools are based on microbial residues with faster turn-over-times rather than chemically recalcitrant pools with slower turn-over times (Grandy & Neff, 2008; Kallenbach et al., 2015; Schimel & Schaeffer, 2012). While there are multiple unknowns about SOM

decomposition, this modification was conservative enough to not overpredict cover crop benefits in terms of C and N cycling (according to our sensitivity analysis; Appendix).

**Table 2.** DNDC model initialization and parametrization.

<b>Parameter</b>	<b>Unit</b>	<b>Cover crop estimate</b>	<b>Control estimate</b>	<b>Reference</b>
Soil pH	Unitless	6.60	6.60	Basche et al., 2016a
Bulk density	g/cm <sup>3</sup>	1.30	1.30	Basche et al., 2016a
Field capacity	wfps	0.65	0.60	Basche et al., 2016b
Wilting point	wfps	0.36	0.35	Basche et al., 2016b
Clay fraction	%	27.00	27.00	Basche et al., 2016b
SOC (0-10 cm)	%	2.99	2.99	Basche et al., 2016a
Bulk C/N	Ratio	10.75	10.75	Parkin & Kaspar, 2004
Slope	%	1	1	Basche et al., 2016a
SOC decomposition	%	15	0	Assumed

#### **4.4 Biogeochemical model calibration and validation**

For model calibration and validation, we utilized field measurements collected at the field site (Table 3). The climate data used to initialize the model was collected from the Iowa Environmental Mesonet (IEM, 2020). The model simulation was started 4 years before the introduction of the treatments. Similar to the field site, we initialized the model with a corn-soybean rotation and a N application rate of 250 kgN/ha applied to corn. During the fifth year of

simulation, in the DNDC model the cover crop was planted, and the residues were incorporated with a litter burying tillage method the same day of cover crop termination. This tillage method was included in the simulation because the cover crop residues were not incorporated in the DNDC model N cycling without tillage. At the same time, tillage is one of the most common practices in the Midwest. The burying tillage method incorporates the N and C of cover crop residues and accelerates decomposition rates in the model. To separate the effects of cash crop residues from cover crop residues on the soil properties, all cash crop residues were removed in the model. Following the DNDC manual, field measurements reported as kg of dry matter were converted to kgC by multiplying by a factor of 0.4, assuming that 1 kg of dry matter is equal to 0.4 kgC (DNDC, 2020).

Model calibration included choosing parameters values that minimize the difference between observed and simulated corn and soybean yields, cover crop biomass, and soil water content. In order to assess model performance in terms of volumetric soil water content using data from Basche et al., 2016, we assumed that water filled pore space (wfps) is equal to the volumetric soil water content divided by porosity calculated from bulk density at 5 cm depth (porosity = 0.51) (USDA, 2012). The changes made to crop parameter values as a result of calibration are outlined in Table 4.

After model calibration, corn yield response to N fertilizer was validated using the values reported by Sawyer & Barker, 2013. For both treatments, we used the average of corn yield response to 0, 45, 90, 135, 190, and 225 kgN/ha in Iowa during 2000-2013 (Sawyer & Barker, 2013). These values were selected as they represent the typical corn-soybean rotation found across the Midwest. The same values were used in CC treatment because fewer field experiments are evaluating the corn yield response to different N fertilizer rates and non-legume cover crops.



Model performance was evaluated using the Root Mean Squared Error (RMSE) and index of agreement (I). These indices were calculated using the equations reported in Legates & McCabe, 1999. Other applied indicators of model performance included plotting and/or discussing cumulative drainage volume and N loss to drain flow; predicted and simulated yields; and predicted average and standard deviations compared to observed values.

**Table 3.** Dataset used for model calibration and validation.

<b>Output variable</b>	<b>Data used for calibration</b>	<b>Data used for validation</b>	<b>Reference</b>
Soil water content (wfps)	2008 (DOY 110-250) at 5 cm depth	2009-2013 (DOY 110-250) at 5 cm depth	Basche et al., 2016
Cover crop biomass N and C (kgN/ha and kgC/ha)	2004-2010	NA	Kaspar et al., 2007, 2012; Basche et al., 2016.
Corn and soybean yields (kgC/ha)	2004-2013 from no-cover crop treatment.	2004-2013 from cover crop treatment.	Kaspar et al., 2007, 2012; Basche et al., 2016.
Tile drainage (mm) and N leaching (kgN/ha)	2004-2010	NA	Kaspar et al., 2007, 2012.
Corn response to N fertilizer	NA	2000-2013 from no-cover crop treatment.	Sawyer, 2015.; Sawyer & Barker, 2013

**Table 4.** Input parameters to optimize cash crop yields and crop N uptake.

<b>Input parameter</b>	<b>Unit</b>	<b>Corn</b>	<b>Soybean</b>	<b>Rye</b>
Max biomass	kgC/ha	4500 <sup>*</sup>	1500 <sup>*</sup>	1000 <sup>*</sup>
Grain biomass fraction	%	0.36 <sup>*</sup>	0.35 <sup>a</sup>	0.20 <sup>*</sup>
Leaf biomass fraction	%	0.22 <sup>a</sup>	0.22 <sup>a</sup>	0.23 <sup>a</sup>
Stem biomass fraction	%	0.22 <sup>a</sup>	0.22 <sup>a</sup>	0.23 <sup>a</sup>
Root biomass fraction	%	0.20 <sup>a</sup>	0.21 <sup>a</sup>	0.34 <sup>*</sup>
Grain biomass C/N ratio	%	45 <sup>*</sup>	10 <sup>a</sup>	10 <sup>*</sup>
Leaf biomass C/N ratio	%	80 <sup>a</sup>	45 <sup>a</sup>	13 <sup>*</sup>
Stem biomass C/N ratio	%	80 <sup>a</sup>	45 <sup>a</sup>	13 <sup>*</sup>
Root biomass C/N ratio	%	80 <sup>a</sup>	24 <sup>a</sup>	50 <sup>*</sup>
Optimal temperature	°C	22 <sup>*</sup>	25 <sup>a</sup>	18 <sup>b</sup>
Water demand	g water/ g dry matter	90	350	250
N demand	kgN/ha	200 <sup>*</sup>	230 <sup>*</sup>	311 <sup>*</sup>

Superscript indicates source of the selected value: <sup>a</sup> DNDC, 2020; <sup>b</sup> Basche et al. 2016b; <sup>\*</sup>obtained at the moment of calibration.

#### **4.5 Economic model initialization and parametrization**

The cost parameter values used for economic model initialization were based on data from different sources (Table 5).

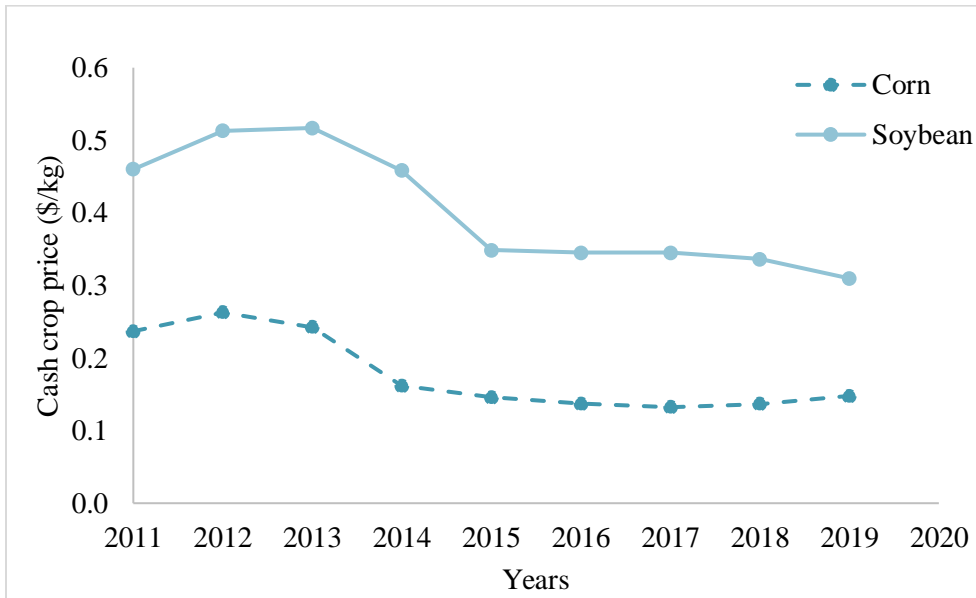
Several assumptions were made when selecting the cover crops benefits and costs parameters (Table 5). First, it's rational that farmers select the highest payments first, until they are disqualified from a program. Therefore, in the model, the farmer receives payments in the first three years through EQIP (fixed at 84.57 \$/ha), that are higher than those received in the following years (fixed 37.5 \$/ha; IDALS), and the last two years (fixed at 26.25 \$/ha; CSP). The duration of enrollment in each program was based on guidelines an regulation of each government program. For example, farmers are only eligible to receive up to three annual payments through EQIP. Lastly, the farmer cover crop planting and termination methods were drilling and herbicide, respectively. These methods were the same over the 10-year simulation experiment.

**Table 5. Model initialization and parametrization (\$/ha).**

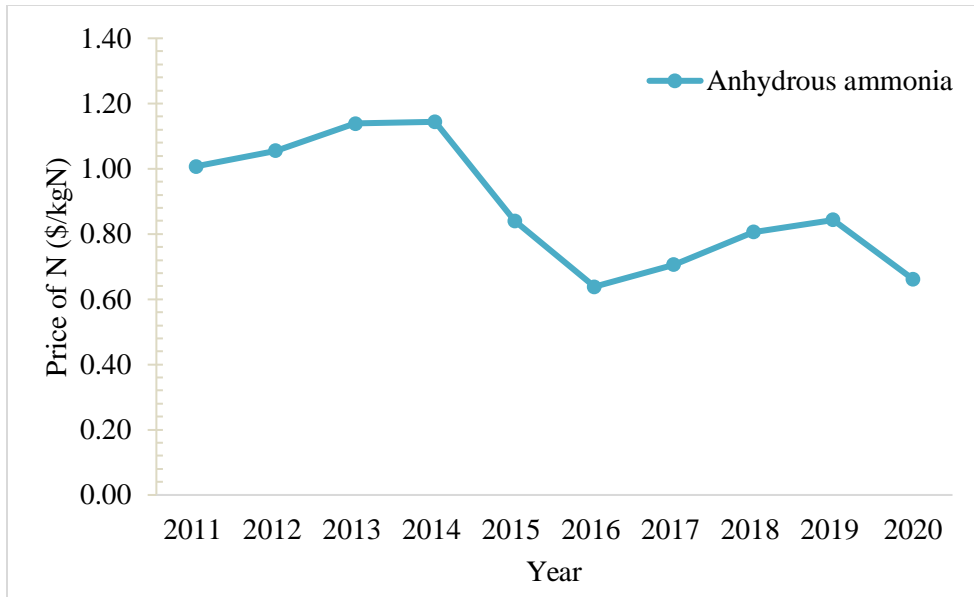
<b>Parameters</b>	<b>Value</b>	<b>Source</b>
N application cost	0.60	Plastina et al. 2018
<i>Cover crop benefits</i>		
EQUIP	84.58	Sawado & Plastina, 2017
CSP Enhancement	26.25	Sawado & Plastina, 2017
IDALS cost-share	37.50	Sawado & Plastina, 2017
Saving cost of reduced compaction	16.00	Pratt et al. 2014
Saving cost of reduced erosion	16.88	Plastina et al. 2018
<i>Cover crop planting costs</i>		
Seeds	44.25	Plastina et al. 2018
Drilling to standing crop	32.75	Plastina et al. 2018
<i>Cover crop termination costs</i>		
Herbicide	20.18	Plastina et al. 2018
Extra labor costs to apply herbicide	13.85	Plastina et al. 2018
Other termination expenses	4.93	Plastina et al. 2018
<i>Weed maintenance cost</i>		
Cost of maintaining cover crop in case it becomes a weed	3.21	Pratt et al., 2014

The baseline discount factor per year ( $\rho^t$ ) selected was 0.0961, which is equivalent to a yearly discount rate,  $r$ , of 4%, where  $\rho = \frac{1}{1+r}$ . The cash crop prices ( $p_t$ ) of corn and soybeans were

based on the U.S average prices received by the farmers (Fig. 7) (USDA-NASS, 2020). The unit of N fertilizer cost ( $c_{N,t}$ ) was based on average Iowa farm prices of anhydrous ammonia (Fig. 8) (USDA-NASS, 2020; IA Farm bureau, 2020). The total costs of cash crop production ( $C_{Y,t}$ ) were based on average costs for farms in Iowa (Plastina and Duffy, 2011-2020). These costs include cash crop seeds, herbicide and insecticide application, crop insurance, machinery (fixed and variable), and labor cost (Plastina and Duffy, 2011-2020). The cash crop prices, and input costs were based on data from 2011 to 2020 (USDA NASS 2020). We assumed that the farmer will not receive government payments for income losses, such as ARC-CO in any year.



**Figure 7.** U.S average cash crop prices received by farmers from 2011 to 2019. Source: USDA-NASS, 2020.



**Figure 8.** Average U.S. farm prices of anhydrous ammonia (\$/kgN) from 2011 to 2020. Source: USDA-NASS, 2020; Iowa Farm Bureau, 2020.

We compared the total cost of cash production in Iowa used in this study based on data from Iowa (Duffy (2011-2014) and Plastina (2015-2020)), with total costs reported in Indiana (Dobbins and Langemeier, 2011-2020) and Illinois (Schnitkey, 2011-2020).

The values used in this study were within the ranges reported in the literature. The highest production cost for corn was \$1247 ha<sup>-1</sup> and the lowest at \$1087 ha<sup>-1</sup>. Soybean production costs ranged from \$581 to \$832 ha<sup>-1</sup> (Table 6 and 7).

**Table 6.** Corn production budget in Iowa, Indiana, and Illinois reported in \$/ha.

<b>Year</b>	<b>Iowa</b>	<b>Indiana</b>	<b>Illinois</b>
2011	1204	993	588
2013	1258	1155	1290
2015	1209	1115	1455
2017	977	1055	1403
2019	1091	1118	1500
<b>Average</b>	1148	1087	1247

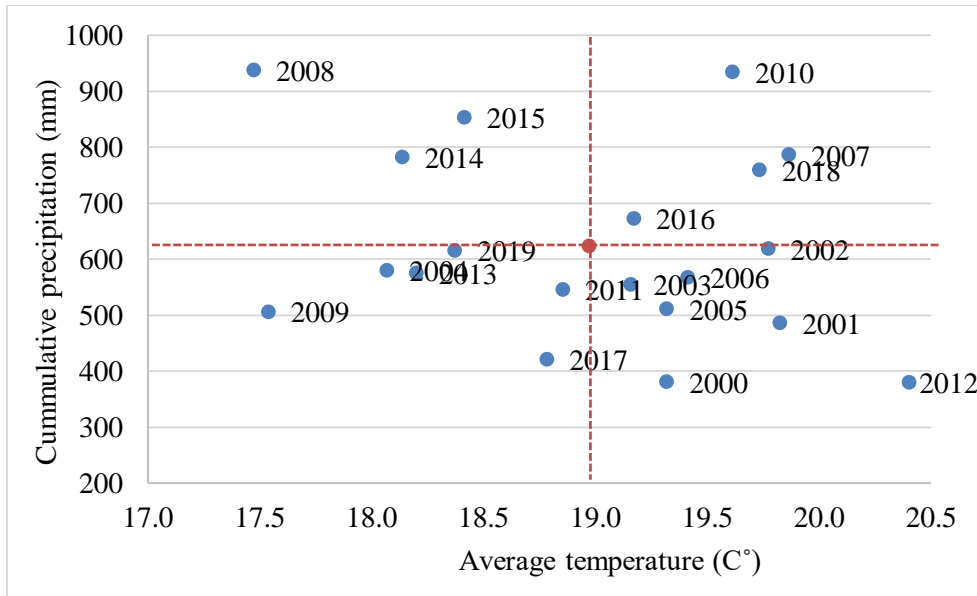
**Table 7.** Soybean production budget in Iowa, Indiana, and Illinois reported in \$/ha.

<b>Year</b>	<b>Iowa</b>	<b>Indiana</b>	<b>Illinois</b>
2012	733.2	607.5	757.5
2014	684.6	567.5	875
2016	637.5	507.5	852.5
2018	615.9	637.5	787.5
2020	635.0	587.5	887.5
<b>Average</b>	661.2	581.5	832.0

#### **4.6 Climate scenarios**

To simulate potential climate scenarios impacts on yields and management decisions, we considered three weather scenarios that reflect the trends in historical and future climate data. Daily precipitation and air temperature data were collected from Iowa Environmental Mesonet from

2000 to 2019 (IEM, 2020). During the growing season (defined as DOY 100-250), the average cumulative precipitation was 624 mm and the average air temperature was 19 °C (Fig. 9). The driest and hottest year was 2012 with cumulative precipitation of 380 mm and an average air temperature of 20.40 °C. The coldest and wettest year was 2008 with cumulative precipitation of 938 mm and an average air temperature of 17 °C.

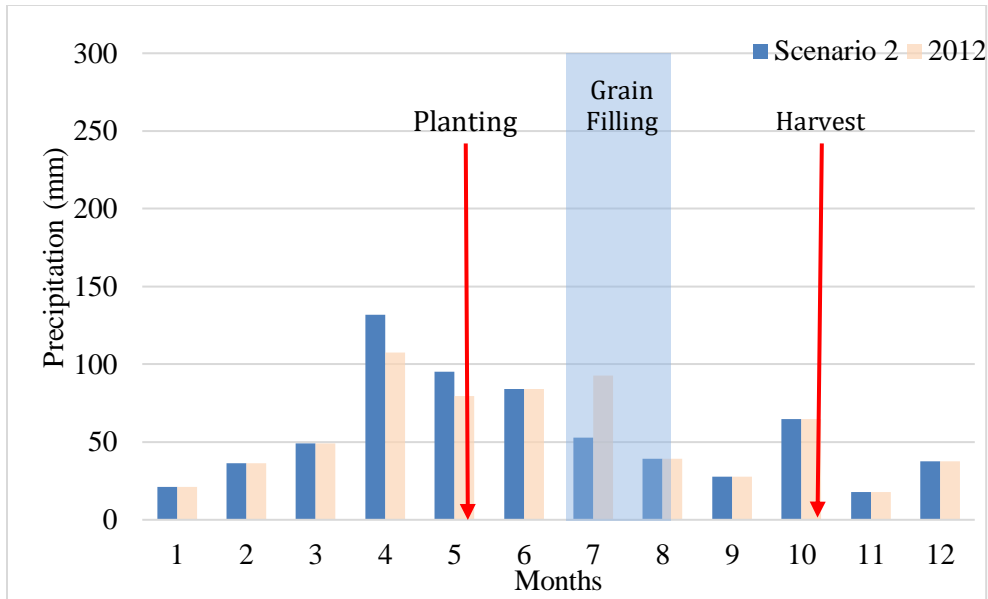


**Figure 9.** Average temperature and cumulative precipitation during the growing season (DOY 100-250) collected from 2000 to 2019 in Boone County, IA. Red lines represent the average temperature and average cumulative precipitation. Reported on Iowa Environmental Mesonet (2019).

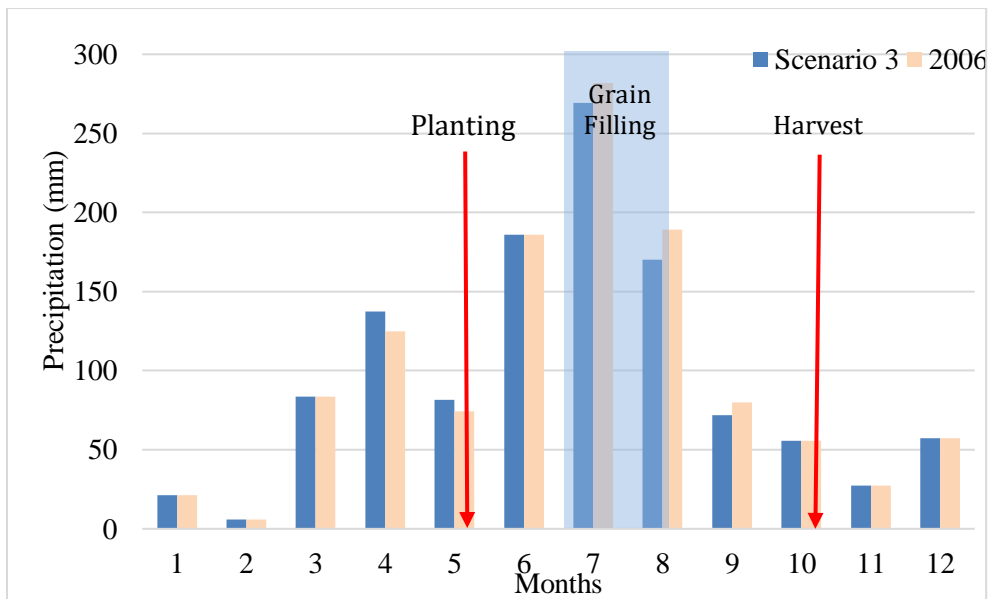
Based on historical weather and global warming scenarios, we created four weather scenarios for the 10 years of simulation described below. We chose a scenario-based approach, over an approach of simulated projected weather predicted by global circulation models. Projected weather data are inherently complex, highly uncertain, and difficult to interpret (Baum et al., 2020). In contrast, a scenario-based approach is simpler and avoids issues related to prediction.



- **Scenario 1:** Historical weather from 2004-2013.
- **Scenario 2:** Extremely dry years were created using the temperature and precipitation of 2012. To mimic a shift in precipitation patterns with longer periods of drought, we alternated the rain patterns by applying the cumulative precipitation every 15 days (14 days of drought followed by one day of intense rain). Additionally, we increased the amount of precipitation during spring and reduced the amount of precipitation at the end of the summer by 50% (Fig. 10). The total amount of precipitation during the entire year wasn't changed.
- **Scenario 3:** Reflect the most likely scenario in Iowa (Baum et al., 2020). To create this scenario, we used weather data from 2006 (selected to represent the average year). Similar to scenario 2, we alternated the rain patterns by applying the cumulative precipitation every 15 days (14 days of drought followed by one day of intense rain). Then, we increased precipitation by 10% in the spring and decreased 10% at the end of the summer (Fig. 11). Temperature was reduced by  $-0.5$  °C decrease in maximum and  $+0.5$  °C increase in minimum temperature.
- **Scenario 4:** A hybrid of scenario 2 and 3 where 8 years reflect the most likely scenario in Iowa and 2 years reflect drought during the corn growing season.



**Figure 10.** Monthly precipitation during extremely dry year (scenario 2) based on 2012 data.



**Figure 11.** Monthly precipitation during of the most likely scenario in Iowa (scenario 3) based on 2006 data.

#### **4.7 Sensitivity analysis to economic parameters**

In the Sensitivity Analysis section, we evaluated the model sensitivity to economic and management parameters, namely N fertilizer price, EQIP payments, cover crop adoption costs, and discount rates. The analysis of model sensitivity to alternative economic and management parameters is relevant, given the existing differences in production systems and conditions.

## CHAPTER V

### RESULTS AND DISCUSSION

#### 5.1 DNDC model performance

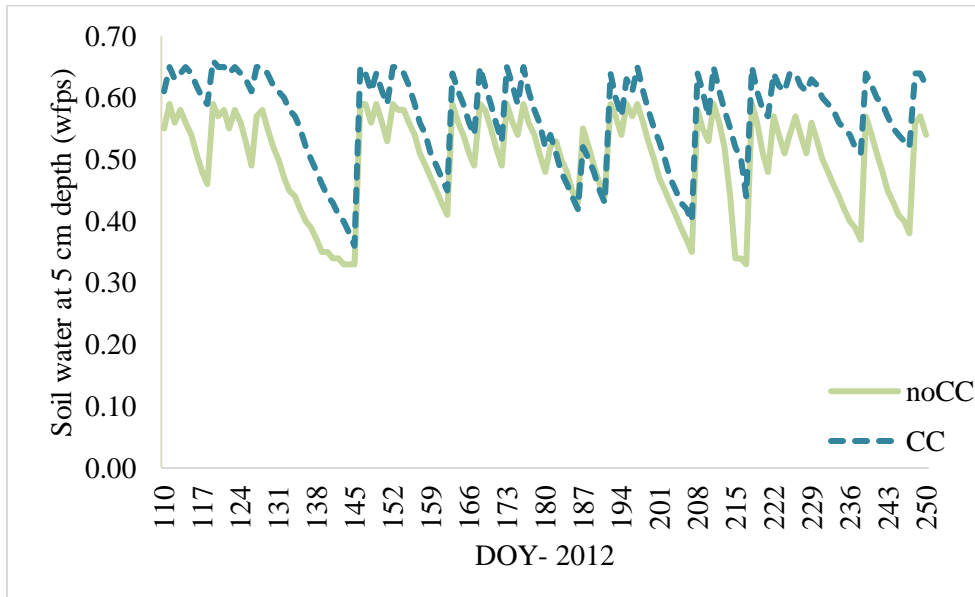
##### *Soil water content*

In the noCC treatment, model predictions at 5 cm depth had RMSE of 0.10 wfps and index of agreement of 0.44 during calibration, and RMSE of 0.08 wfps and an index of agreement of 0.69 during validation. The mean was slightly over predicted by 0.01 wfps in the noCC treatment (simulated mean = 0.52 wfps). The predicted standard deviation was 0.07 that differs from the observed by -0.02 (simulated stdev = 0.07) in the noCC treatment.

For the CC treatment, model predictions at the 5 cm depth had RMSE of 0.07 wfps and index of agreement of 0.73 during calibration, and RMSE of 0.12 and an index of agreement of 0.56 during validation. The mean was over predicted by 0.09 wfps in the CC treatment (simulated mean = 0.59), with a predicted standard deviation of 0.06 (simulated stdev = 0.06).

The DNDC model captured the pattern of increased soil moisture in CC compared to noCC (Fig. 12). Higher field capacity and wilting point values improved infiltration rates in the CC treatment. At the same time, the use of cover crop decreased evaporation and water run-off. The CC treatment reduced soil evaporation between 1-64% with greater reductions in dry years. Cover crop residues served as an impediment for water run-off, reducing run-off by 28% compared to noCC. Despite cover crop transpiration, which ranged between 17-170 mm and was related to biomass levels, the CC treatment had 7% more water than the noCC treatment at 5 cm depth. Even in a dry year when cover crop biomass and transpiration were high, the CC treatment still captured greater water benefits.

Previous modelling and field studies have demonstrated similar cover crop effects in water properties. The RZWQ model simulated soil water generally 2-6% greater in CC at a depth of 15 cm (Gillette et al., 2018). The APSIM model also predicted reduced soil evaporation and a small increase in soil water despite cover crop transpiration (Basche et al., 2016). Further, field studies also demonstrated that spring rainfall can restore soil moisture that was depleted during cover crop growing season (Basche, 2015).

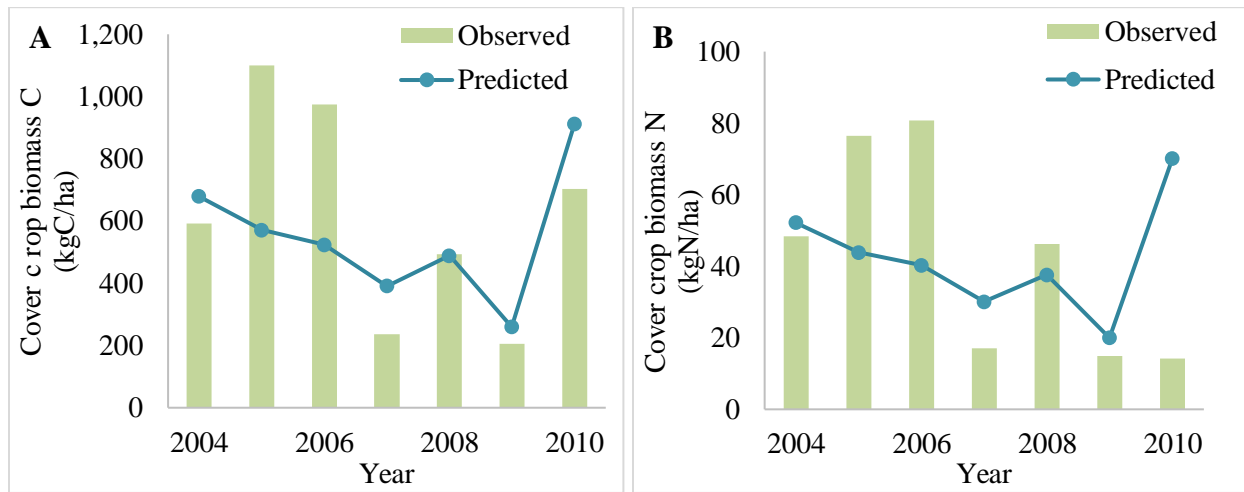


**Figure 12.** Simulated soil water content (wfps) at 5 cm depth during summer and spring in 2012 in the control treatment (noCC) and cover crop treatment (CC).

*Cover crop biomass C and N*

Average cover crop biomass C and N were under predicted by -151.1 kgC/ha and -10.0 kgN/ha. The predicted standard deviations were 213.0 kgC/ha and 11.2 kgN/ha that differs from the observed by -191.6 kgC/ha and -16.9 kgN/ha (Fig. 13). Model predictions of cover crop biomass had a RMSE of 326.7 kgC/ha and 22.3 kgN/ha during calibration. Model index of

agreement for cover crop biomass was 0.72 and 0.66 for C and N respectively ( $I > 0.50$ ). On average, the model captures the year to year variability of cover crop growth.

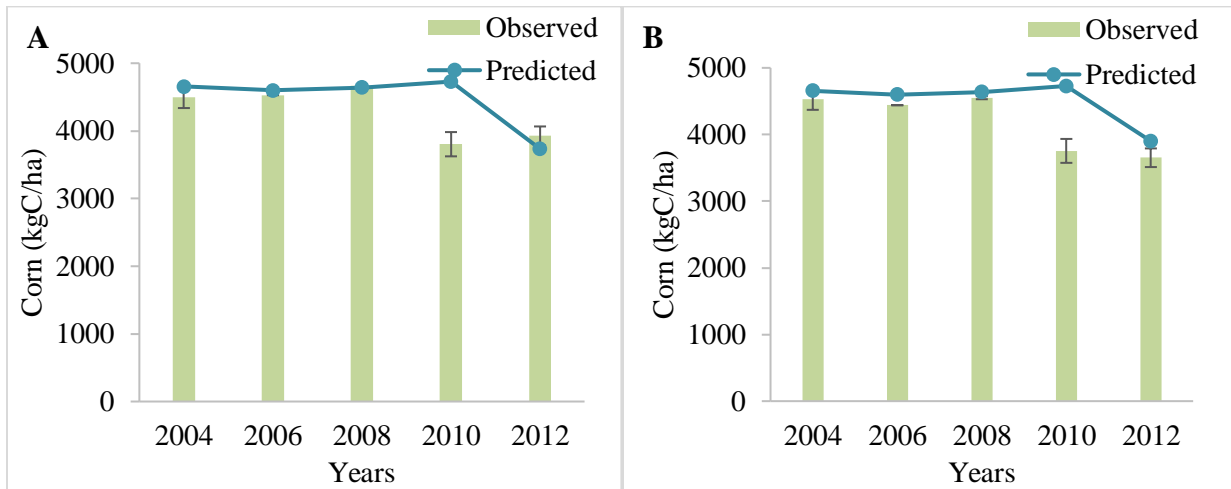


**Figure 13.** Observed (bars) and predicted (lines) cover crop biomass C (A) and N (B) from 2004-2010 during model calibration.

#### *Cash crop yields*

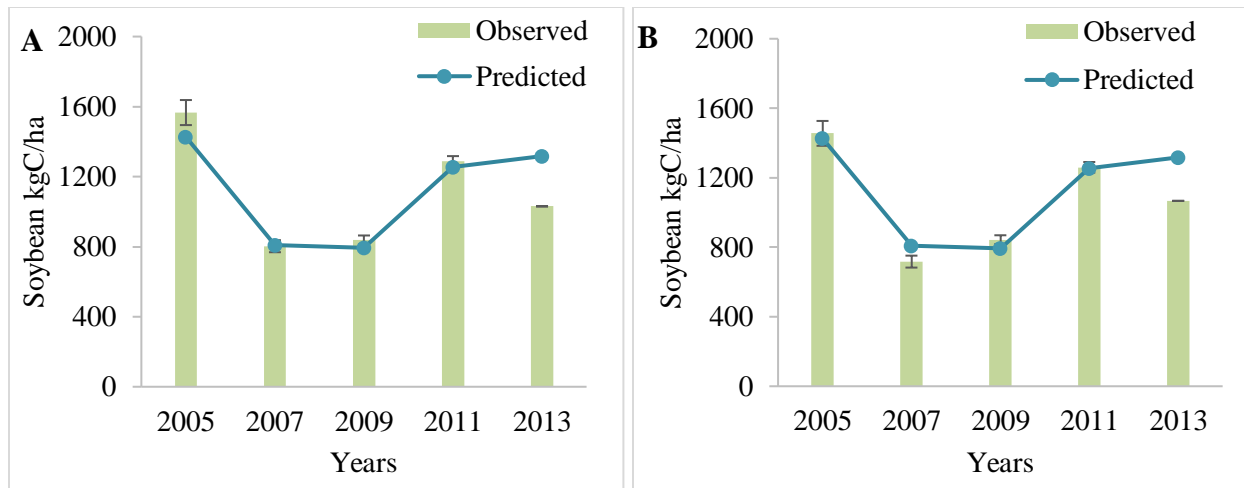
The average corn yields were over predicted by 319.6 kgC/ha. The predicted standard deviation was 341.0 kgC/ha, which is 102.6 kgC/ha lower than the observed. Higher observed corn yields were realized in 2004, 2006, and 2008 and lower yields occurred in 2010 and 2012. The model predictions for corn yields were similar to observed yields, except in 2010, where the model predicted higher yields than observed (Fig. 14). The error associated with over prediction of corn yields during 2010 was likely due to a fungal disease observed in the field that is not captured by the model (Kaspar et al., 2012). The model captured the yield reduction observed in 2012 when a major drought occurred. At the same time, the model captured the benefits of higher field capacity in 2012, where corn yields in the cover crop treatment (CC) were 166 kgC/ha higher than the control (noCC). This small difference between treatments was not observed in the field. Model

predictions of corn yields had a RMSE of 429.9 kgC/ha and 460.5 kgC/ha during calibration and validation respectively. The model index of agreement was 0.68 during calibration and 0.69 during validation. This index confirms that the model results were satisfactory ( $I > 0.50$ ). Overall, the DNDC model simulations for corn yields were in a good agreement with observations.



**Figure 14.** Observed (bars) and predicted (lines) corn yields from 2004-2012 during model calibration (A) and model validation (B). The error bars represent the standard deviation of the observed data.

The average annual soybean yields were slightly over predicted by 48.8 kgC/ha. The simulated standard deviation was under predicted (-5.4 kgC/ha lower than the predicted standard deviation; observed std. deviation = 300.1). Model predictions of soybean yields had a RMSE of 130.4 kgC/ha and an index of agreement of 0.94 during calibration, and RMSE of 121.8 kgC/ha and an index of agreement of 0.95 during validation (Fig. 15). Lower yields were observed and predicted in 2007 and 2009 due to a change in soybean cultivar (Kaspar et al., 2012).



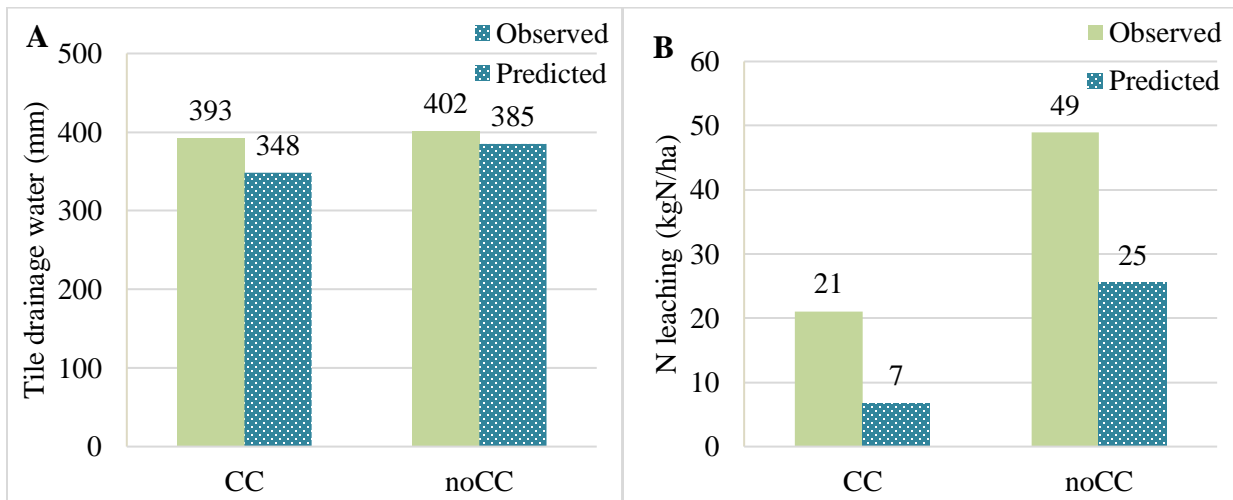
**Figure 15.** Observed (bars) and predicted (lines) soybean yields from 2005-2013 during model calibration (A) and validation (B). The error bars represent the standard deviation of the observed data.

#### *Annual tile drainage and N leaching*

Average annual tile drainage and N leaching were underpredicted by 4% and N leaching by 47% in the control treatment (noCC). Similarly, in the cover crop treatment (CC), annual average tile drainage and N leaching were underpredicted by 11% and 68% respectively (Fig. 16). The model performance was satisfactory for annual tile drainage, with an index of agreement of 0.93 and 0.90 for the noCC and CC treatment respectively. However, the index of agreement for N leaching through tile drainage was less satisfactory in both treatments (0.53 and 0.46 for the noCC and CC treatment respectively). The error in the predictions of N leaching through tile drainage is due to the model version that was used in this study (DNDC version 9). The DNDC version 9 does not mechanistically represent tile drainage and major model adjustment are needed to improve the predictions of N leaching under a tile drainage system (Tonitto et al., 2007).



Despite the low model performance, the model captured a reduction in N leaching under the cover crop treatment. This reduction in N leaching relates directly to the amount of cover crop N uptake during fall and spring. On average, annual N leaching in the CC was 26% lower than the noCC treatment. These results are within the ranges reported in the literature, where field studies across the U.S have reported a reduction in N leaching with cereal rye ranging from 13% to 94% (Kladivko et al., 2014).



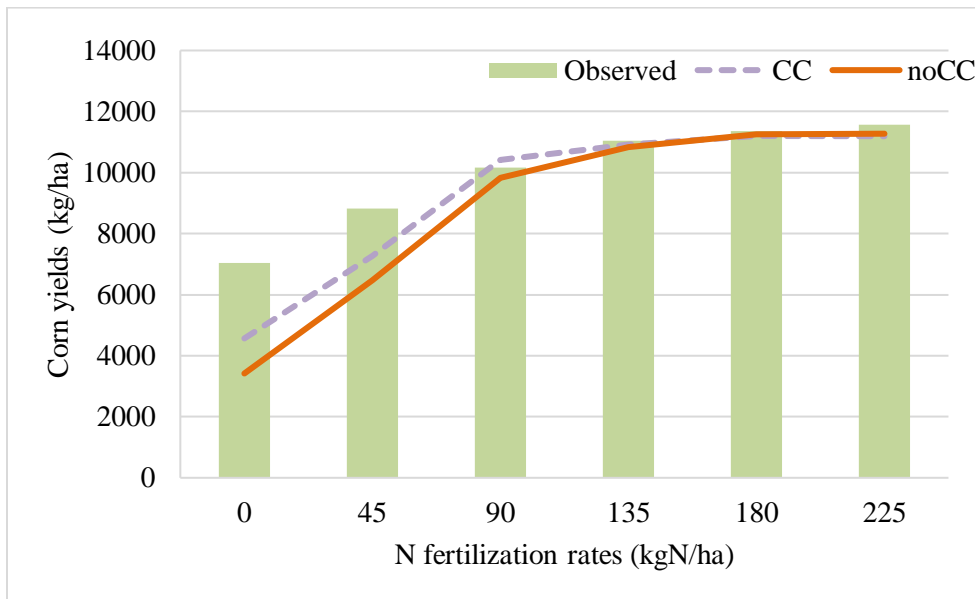
**Figure 16.** Observed and predicted annual average tile drainage (mm) (A) and N leaching (kgN/ha) (B) under cover crop (CC) and no cover crop (noCC) treatment.

## 5.2 DNDC model application

### *Yield response to N fertilizer*

The model captured the yield response to different N fertilization rates. The model results were satisfactory for both treatments, with an index of agreement of 0.86 and 0.92 for noCC and CC respectively. The RMSE was 710.9 kgC/ha and 484.8 kgC/ha for the noCC and CC respectively. The model captured the incremental yield increase with increasing N rates and as observed in the field. Eventually, there is no further yield increase with higher N rates (Fig. 17).

Similar to a field study conducted in Central Indiana, we found that non-legume cover crop have the potential to reduce the quantity of applied N fertilizer while maintaining corn yields (Hughes & Langemeier, 2020). The N rate needed to produce the maximum corn yield in CC was 10kgN/ha lower than the amount of N needed in noCC. This small difference was driven by higher mineralization rates in the CC treatment, where the input parameter of SOC decomposition rate was 15% higher.



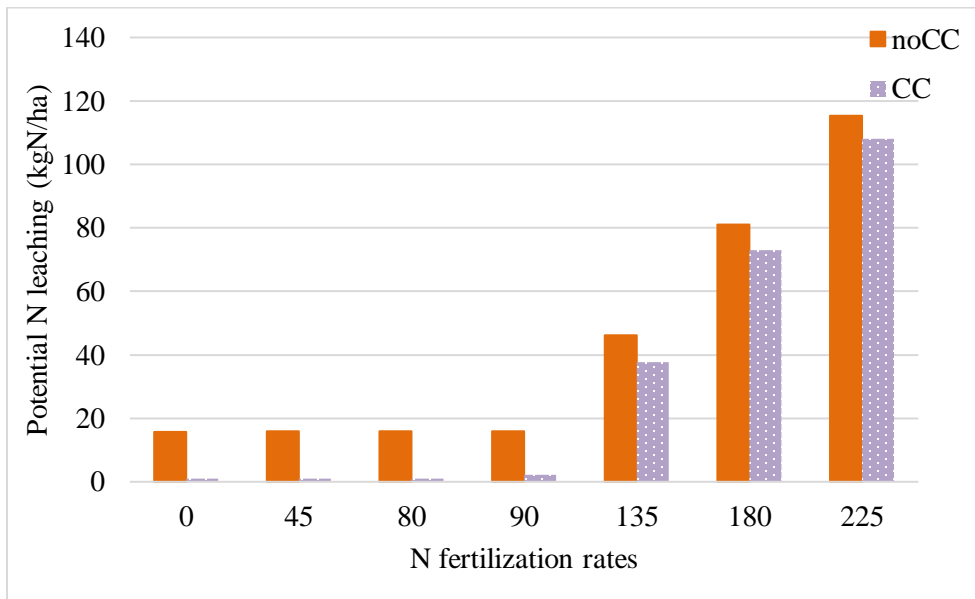
**Figure 17.** Observed (bars) and predicted (lines) yield response to N fertilization rates under cover crop (CC) and no cover crop (noCC) treatment.

#### *N leaching response to N fertilizer*

The model also captured the response of N leaching to different N fertilization rates. The model produced the pattern observed in the field where higher N fertilization rates result in higher N leaching (Fig. 18). At the same time, the model captured a reduction in N leaching under the CC treatment, which is consistent with Tonito et al. 2007. On average, cover crops reduced N leaching by 22% compared to noCC. However, the N leaching difference between treatments tended to

decrease when N fertilization rates increased. This decline is explained by the amount of N that cover crops can uptake from the soil given the short window for establishment and growth. Cover crops were terminated before achieving grain filling stages producing only 742 kg of biomass. Due to this short window for biomass growth and other weather limiting factors, cover crop N uptake was only 25 kgN/ha for all N fertilization rates. The conservative planting window utilized during the simulation, is likely the reason that the N fertilization rates did not influence cover crop growth in the early stages.

Previous studies have shown that increasing cover crop biomass leads to greater N retention. However, after producing 6,919 kg of biomass the benefits of reducing N leaching plateau (Finney et al., 2016). The simulation model results are consistent with these field observations.



**Figure 18.** Predicted potential N leaching response to N fertilization rates under cover crop (CC) and no cover crop treatment (noCC).

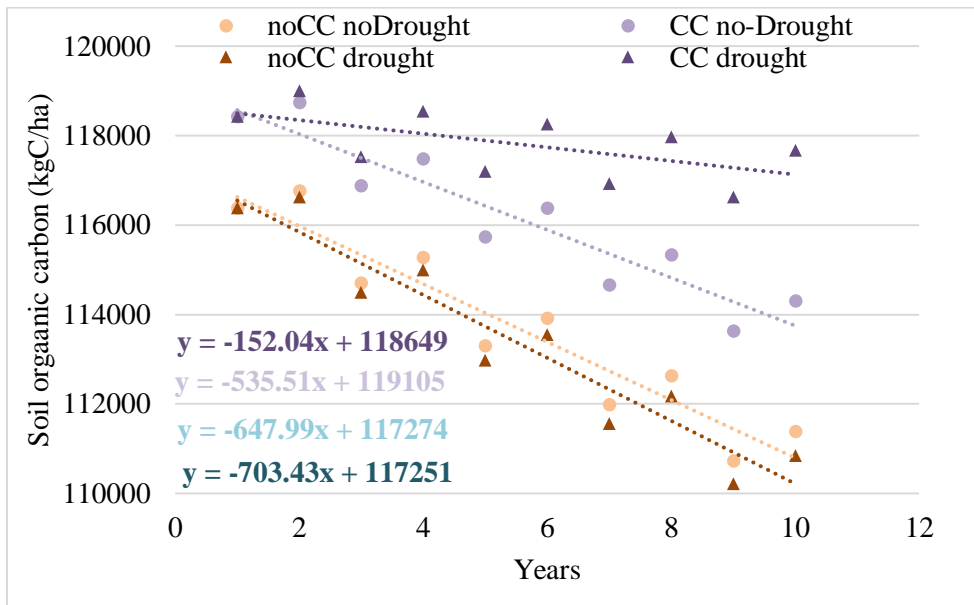
### *Nutrient cycling under drought vs no-drought years*

We evaluated the C and N cycling dynamics under two contrasting weather scenarios with and without cover crops. For this analysis, we used the extreme drought weather scenario (scenario 2 = drought) and the most likely future scenario in Iowa (scenario 3 = no-Drought). The amount of N fertilizer applied was the yield maximization rate, which is 90 kgN/ha to CC and 100 kgN/ha to noCC.

The DNDC model predicted carbon declines in both treatments and weather scenarios relative to the initial C stocks (Fig. 19). On average, the noCC treatment generated an additional loss of 889 kgC/ha, relative to the CC treatment under the no-drought scenario (annual loss of 37 kgC/ha/yr.). This represents a decline in carbon mass of 4% in the noCC treatment and 3% in the CC treatment over 10 years. This difference is greater in a drought year, with the noCC losing an additional 4,784 kgC/ha (5% decline) relative to the CC treatment (1% decline). The difference between CC and noCC is due the cover crop residues that served as inputs to the C cycle, whereas the noCC treatment had no additional inputs other than cash crop roots. Further, despite having higher soil organic carbon decomposition rates (15% higher), the CC treatment slow the rate of carbon loss. This reduction in C loss was magnified in a drought scenario, where cover crops produced above-ground biomass of 1,589 kg/ha or 39% higher than the biomass produced in the most likely scenario (no-Drought). Our results suggest that the incorporation of cover crops can help to slow the rate of carbon loss and more so in drought years.

Our results are consistent with those from other simulation models and long-term field studies. A 30-year field study in Montana, show that in plots with greater C input and lower tillage intensity slow the rates of carbon decline at depth 0-7 m (Sainju et al., 2015). Using the APSIM model, Basche et al., 2016 found that using cover crops can slow the rates of C decline by 3%

compared to bare fallows. However, other studies have shown that cover crops can increase soil C in the surface 0-30 cm by 17% compared to bare fallows (Austin et al., *in review.*). In our model simulation, the above-ground cash crop residues were completely removed from the field. A sensitivity analysis of the incorporation of cash crop residues captured a net increase in SOC with cover crops use (data in Appendix). Therefore, we conclude that cover crops have the potential to increase soil C stocks or to slow the loss in drought years.

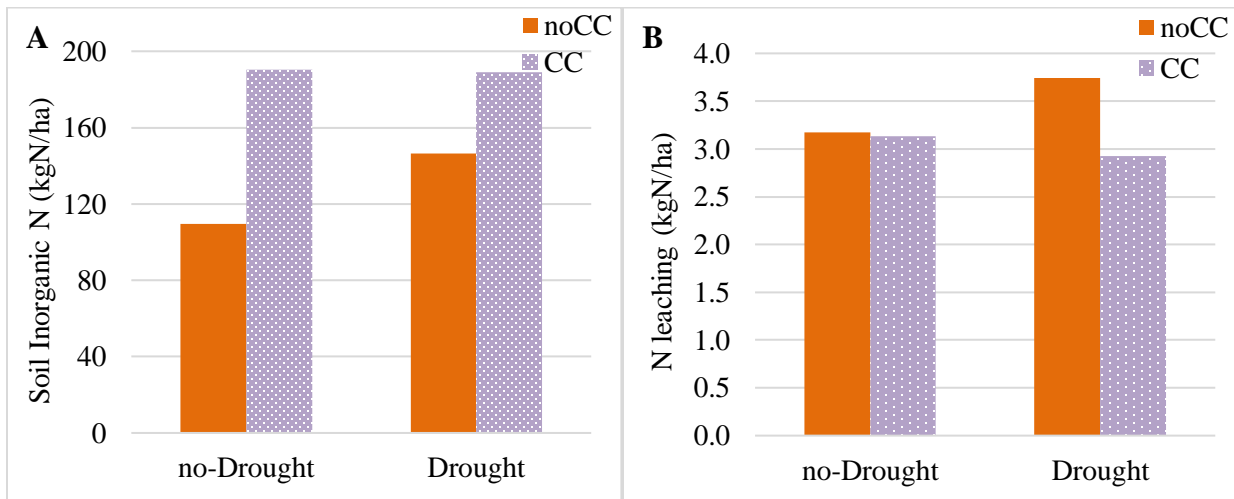


**Figure 19.** Soil organic carbon under two contrasting weather scenarios with and without cover crops.

Cover crops had a significant effect on the predicted Soil Inorganic Nitrogen (SIN) and N leaching. Under both scenarios, the CC treatment had consistently higher SIN and lower N leaching (Fig. 20). Cover crops increased SIN by 43% and 23% in the no-drought and drought scenario respectively. This increase in SIN is likely explained by the input residues and mineralization rates in the CC treatment. The greater mineralization rates were the result of the chosen input parameters (i.e., 15% higher SOC decomposition rates) and the low C:N ratio of the

cover crop biomass (~13). However, the noCC treatment increased SIN under the drought scenario. This slight increase is explained by the lower plant N uptake, where corn yields were 7.2% lower in the noCC treatment.

As previously discussed, N leaching predictions differ from the observations due to low model performance. However, the predicted patterns can still be interpreted cautiously to make general inferences about cover crops. Under both scenarios, cover crops reduced N leaching despite having considerably higher SIN. Moreover, this reduction was magnified in a drought year, when cover crops reduced N leaching by 26% compared to noCC. In the no-Drought scenario, cover crops reduced N leaching only by 1.2% compare to noCC. The reduction in N leaching in the CC treatment is likely explained by higher soil moisture that influenced plant N uptake and microbial assimilation.



**Figure 20.** Soil inorganic nitrogen (A) and N leaching under two contrasting weather scenarios with and without cover crops.

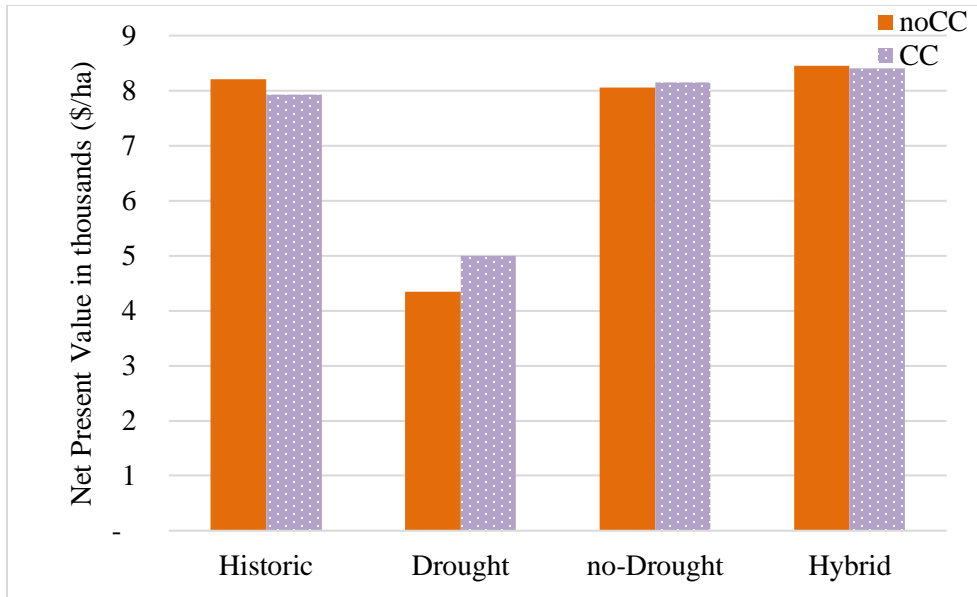
### 5.3 Biogeochemical-Economic model results

We first present results of the NPV of a conventional (noCC) and a cover cropped farm (CC) under historical and future climate scenarios. Then, we discuss the case of a risk-averse farmer.

#### *The economics of cover crops under different climate scenarios*

Under most climate scenarios, both farmers have similar NPVs. Under historical and Hybrid scenarios, the farmer that adopted cover crops had an NPV of -4% and -0.5% lower than the farmer that did not adopt cover crops. Despite generating a yield increase of 3% in the Hybrid scenario, the timing of the drought years influenced the farmer's NPVs. The discount factor of 4% reduced the effect of the yield increase in the NPVs, because the drought years occur on the fifth and ninth year of the simulation. If the drought years occur earlier in the simulation, the farmer that adopted cover crops would experience higher NPVs (Appendix).

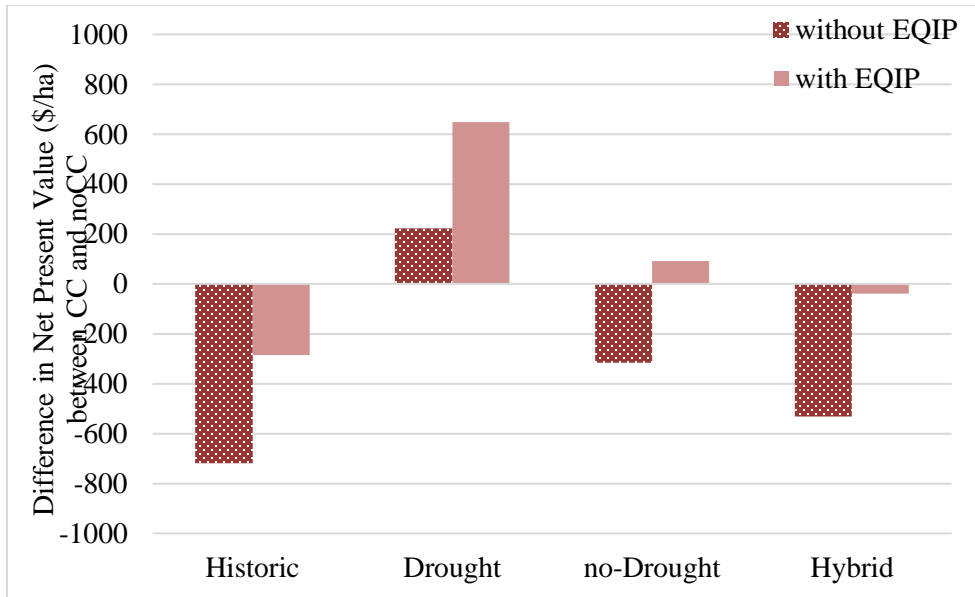
The ranking of NPVs is reversed in the most likely scenario (no-Drought scenario). In the no-Drought scenario, the farmer that adopted cover crops had a NPV of 1.1% higher than the farmer that did not adopt. Further, this difference increases when the farmer experiences a greater number of drought years. Under frequent extreme droughts (Drought scenario), the farmer that adopted cover crops had a NPV of 15% higher compared to the farmer that did not adopt cover crops (Fig. 21). The difference was explained by higher corn yields in the CC treatment, where corn yields were 15% higher under the Drought scenario. This yield increase is due to the CC ecosystem services of improved soil water storage, soil organic matter accumulation, and N retention.



**Figure 21.** Farmer’s Net Present Value (NPV) over 10 years under different climate scenarios. Historic scenario represents historical climate; Drought represents constant extreme droughts; no-Drought reflect the most likely scenario in Iowa (-10% precipitation during summer, +10% precipitation during spring); and Hybrid represents a combination of scenario 2 and 3.

The farmer's NPV changes significantly without government payments (i.e., EQIP). Under historical and Hybrid climate scenarios, the farmers that adopted cover crops had a NPVs of -\$286 and -\$39 ha<sup>-1</sup>, respectively, even when they receive EQIP payments. Only under the extreme drought scenario (Drought scenario), the farmer that adopted cover crops was better off by \$221 ha<sup>-1</sup>, even without receiving an EQIP payment. The biggest difference accrues when the farmer experienced two droughts in 10 years (Hybrid scenario). In the hybrid scenario, the farmer that receives EQIP payments for cover crop adoption had a NPV of -\$39 ha<sup>-1</sup> lower than the farmer that did not adopt. Moreover, the farmer that did not receive EQIP payments and adopted cover crops had a NPV of -\$532 ha<sup>-1</sup> than the farmer that did not adopt (Fig. 22). These results highlight the importance of EQIP payments to encourage cover crop adoption.

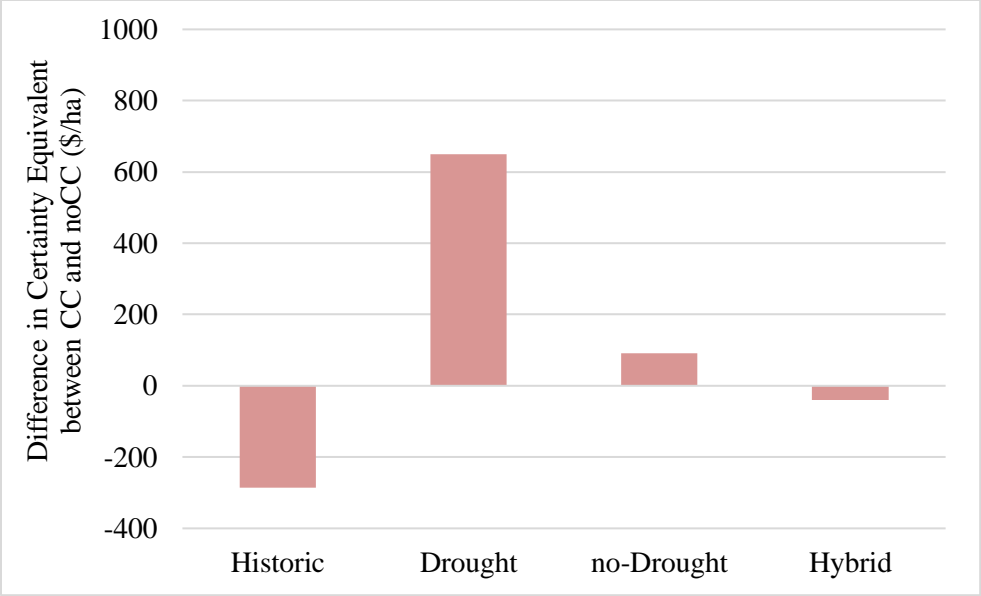




**Figure 22.** Difference in Net Present Value (NPV) over 10 years under different climate scenarios, with and without government payments (EQIP).

*The case of a risk averse farmer*

In the case of a risk averse farmer, we found that moderate risk aversion (risk aversion = 2) does not change the results of CC vs noCC from the baseline risk neutral case. Where the farmer only experienced a higher certainty equivalent measure when frequent extreme droughts occur (Drought) or in the most likely scenario (no-Drought) (Fig. 23).



**Figure 23.** Difference in Certainty Equivalent (CE) over 10 years under different climate scenarios for a risk averse farmer.

## CHAPTER VI

### CONCLUSIONS

In this thesis, we used an biogeochemical-economic model to evaluate the economic and environmental benefits provided by cover crops under different climate scenarios. The DNDC model acted as the ecological production function in the biogeochemical-economic model. It simulated changes in non-market ecosystem services (i.e., improved soil water storage, soil organic matter accumulation, and N retention) with and without cover crops and linked them to changes in marketed outputs (i.e., cash crop yields) and marketed inputs (i.e., N fertilizer).

Under most climate scenarios, both farmers have similar NPVs. Under historical and Hybrid scenarios (i.e., two years of drought), the farmer that adopted cover crops had an NPV of -4% and -0.5% lower than the farmer that did not adopt cover crops. The ranking of NPVs is reversed in the most likely scenario (no-Drought) and in the constant extreme drought scenario (Drought). In the no-Drought scenario, the farmer that adopted cover crops had a NPV of 1.1% higher than the farmer that did not adopt. Further, this difference increases when the farmer experiences a greater number of drought years. Under frequent extreme droughts, the farmer that adopted cover crops had a NPV of 15% higher compared to the farmer that did not adopt cover crops. This difference is explained by higher corn yields in the CC treatment, where corn yields were 15% higher under frequent extreme droughts. This yield increase is due to the CC ecosystem services of improved soil water storage, soil organic matter accumulation, and N retention.

Finally, using certainty equivalent measure to determine the expected utility of a grower who has moderate level of risk aversion, we found that a moderate risk aversion does not change the results of CC vs noCC from the baseline risk neutral case.

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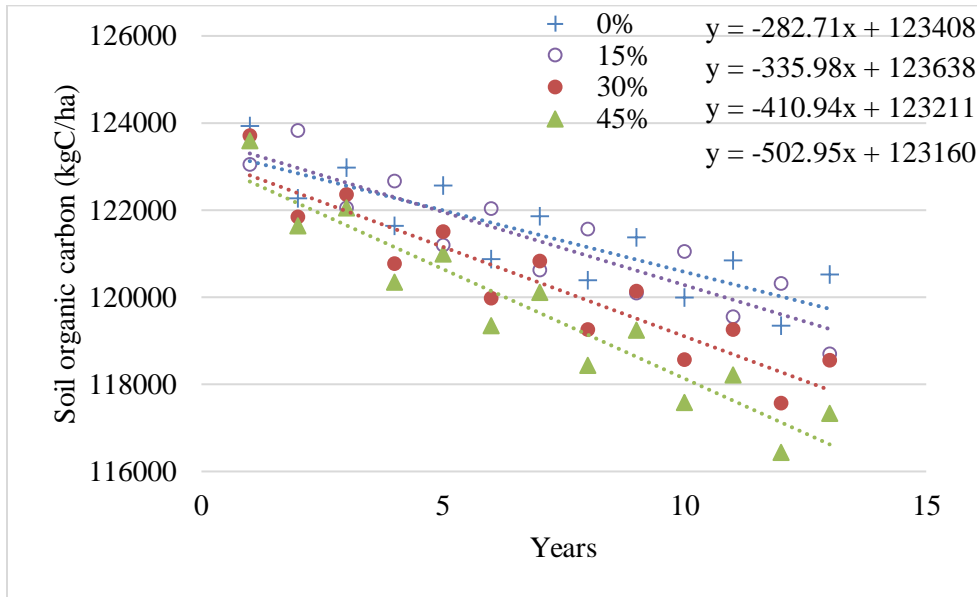
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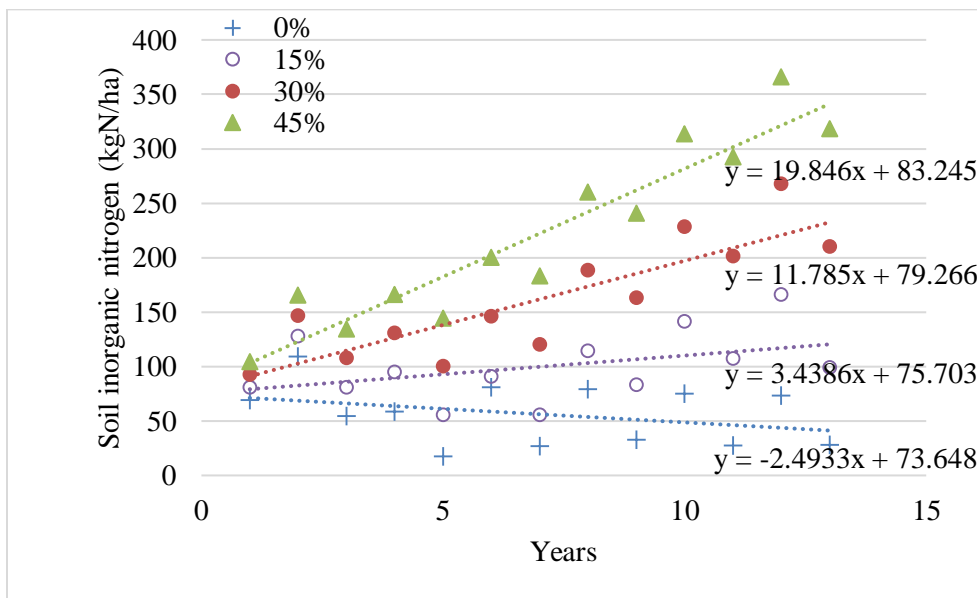
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## APPENDIX

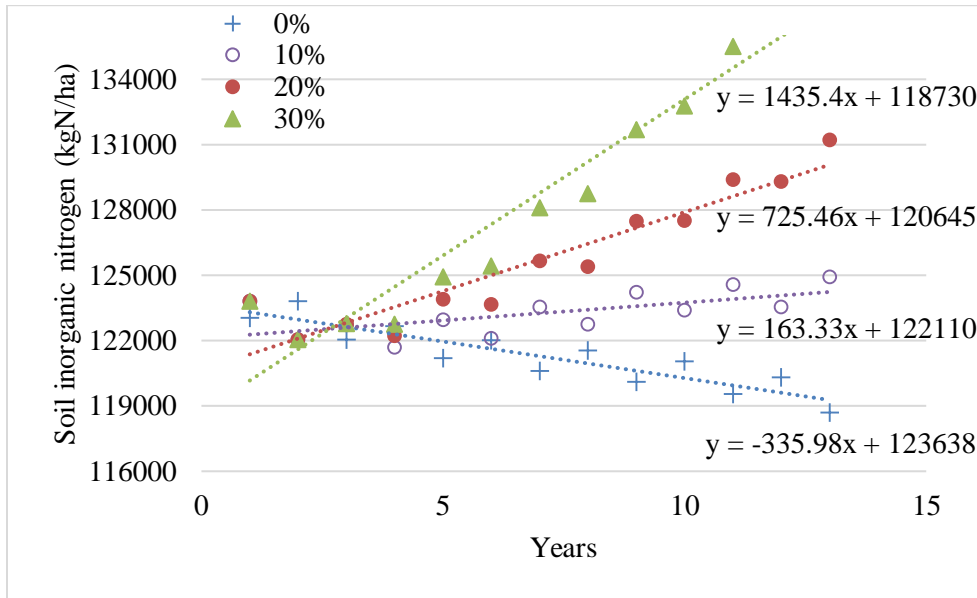
Appendix 1. Sensitivity analysis of SOM decomposition rates increase (in relation to the baseline) effect on soil organic carbon in the CC treatment.



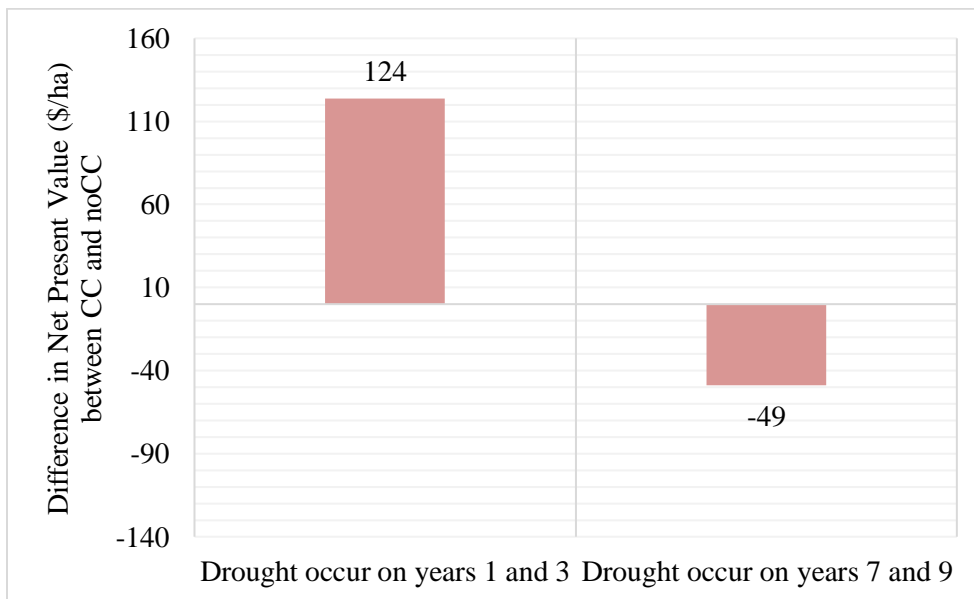
Appendix 2. Sensitivity analysis of SOM decomposition rates increase (in relation to the baseline) effect on soil inorganic N in the CC treatment.



Appendix 3. Sensitivity analysis of cash crop residues incorporation on soil organic carbon in the CC treatment.

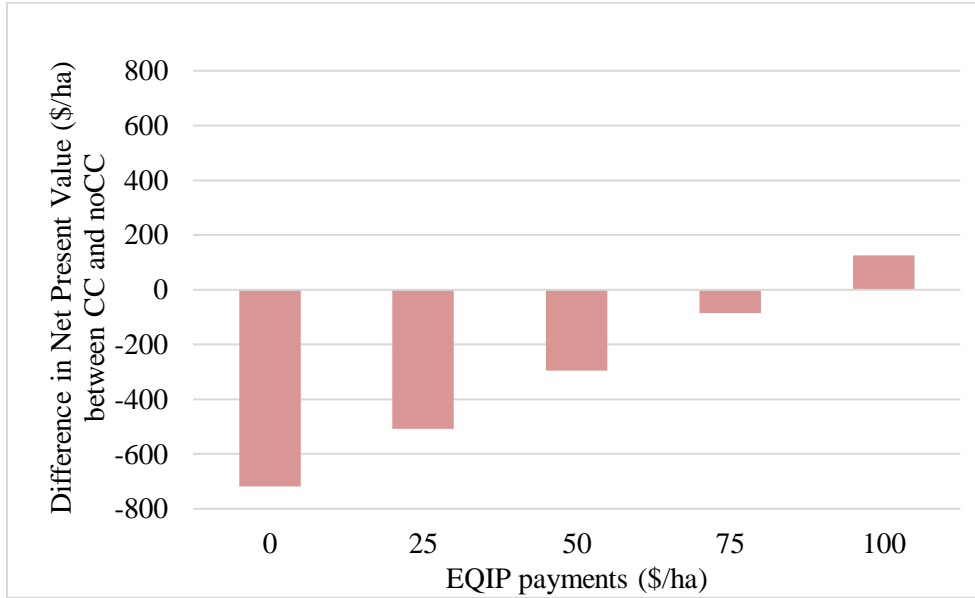


Appendix 4. Sensitivity analysis of timing of drought years effect on NPVs with a discount rate of 4%. Droughts occur during the corn growing season.

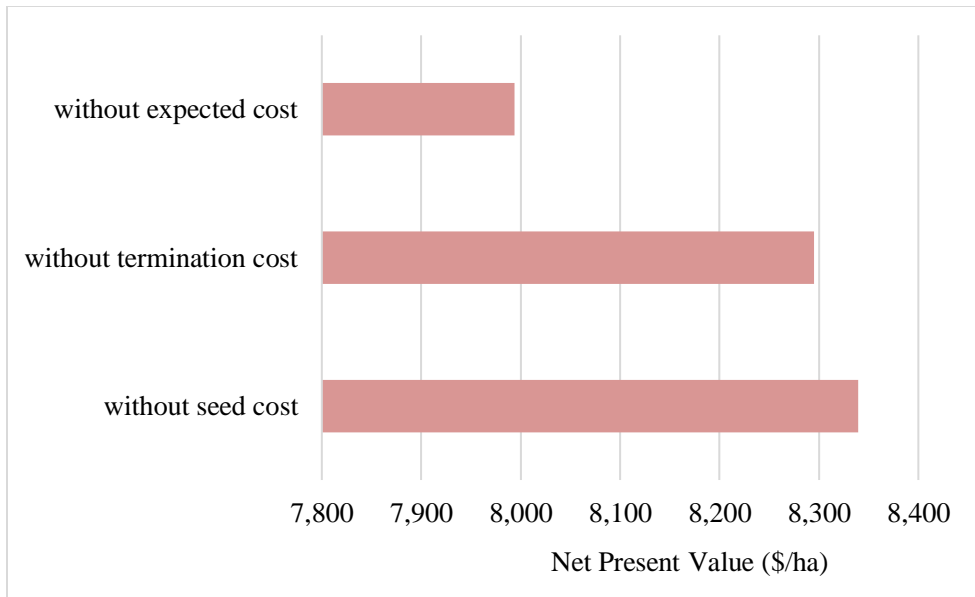




Appendix 5. Sensitivity analysis of EQIP payments under historical climate data.



Appendix 6. Sensitivity analysis of cover crop adoption costs.



Appendix 7. Sensitivity analysis of discount factor under historical climate data.

