ADOPTION OF NITROGEN EFFICIENT ECO-INNOVATIONS BY U.S. CORN FARMERS

A Thesis

presented to

the Faculty of the Graduate School

at the University of Missouri-Columbia

In Partial Fulfillment

of the Requirements for the Degree

Master of Agricultural and Applied Economics

by

CATHARINE ELIZABETH WEBER

Dr. Laura McCann, Thesis Supervisor

MAY 2014

The undersigned, appointed by the dean of the Graduate School, have examined the thesis entitled,

ADOPTION OF NITROGEN-USE EFFICIENCY INNOVATIONS BY U.S. CORN FARMERS

presented by Catharine E. Weber,

a candidate for the degree of masters of agricultural and applied economics,

and hereby certify that, in their opinion, it is worthy of acceptance.

____

Associate Professor Laura McCann

____

Professor Ray Massey

____

Professor Stephen Anderson

DEDICATION

Praise the Lord. This graduate opportunity would not have been possible without the support of my family and friends. Thank you Mom and Dad for believing so strongly in me. I was extremely fortunate to teach and research during my time at the University of Missouri, which funded my education. Thank you to Dr. Laura McCann and Dr. Marc Strid for their support and belief in my abilities. I would also like to thank Dr. William Meyers, Dr. Tom Johnson, and Dr. Judith Stallmann. My experience in both Belgium and Italy would not have been possible without them. These trips to Europe greatly impacted both my education and outlook. I would also like to thank all students I had during my time at Mizzou.

Thanks be to God.

ACKNOWLEDGEMENTS

I would like to acknowledge the extraordinary efforts of my adviser, Dr. Laura McCann. Her attention to detail and dedication to the success of her students has positively impacted both me and the following thesis. I would like to acknowledge my two thesis committee members Dr. Ray Massey and Dr. Stephen Anderson for their contribution to my research and analysis. I would also like to acknowledge the United States Department of Agriculture (USDA) National Institute of Food and Agriculture (NIFA) for their funding of this study. Their research funding helps shape the future of American agriculture and the ecosystem it operates in. Thank you to the USDA National Agricultural Statistics Service (NASS) office in Columbia, MO for sharing their computer space. Finally I would like to acknowledge the University of Missouri-Columbia which has been an amazing institution for research and collaboration.

Table of Contents

List of Figures

List of Tables

ABSTRACT

Anthropogenically introduced nitrogen has compromised environmental quality, but is an essential element for crop production, particularly corn production. Increasing nitrogen use efficiency by adopting eco-innovations such as nitrogen soil testing, plant tissue testing and nitrogen transformation inhibitors can ameliorate this problem. Data from the 2010 USDA Agricultural Resource Management Survey of corn producers was used to examine the factors affecting adoption of these practices. Twenty-one percent of the 1840 corn farmers had adopted nitrogen soil testing, three percent had adopted plant tissue testing and ten percent had adopted nitrogen inhibitors. A multivariate probit regression found significant results for each category of explanatory variable that was examined. Older farmers were less likely to adopt nitrogen soil testing and nitrogen inhibitors. Farmers who did not obtain external nitrogen recommendations were less likely to adopt all three practices than farmers who received recommendations from a crop consultant. Those who received recommendations from fertilizer dealers were less likely to adopt nitrogen soil testing. Those who indicated that high prices influenced their decision to plant corn on that field were more likely to adopt plant tissue testing but less likely to adopt the other two practices. All regions were more likely to adopt nitrogen soil testing than the Midwest. Those who adopted conservation tillage were more likely to adopt nitrogen inhibitors and those who received conservation payments were more likely to adopt nitrogen soil testing and plant tissue testing. Adoption was also associated with the adoption of several other technologies.

Chapter 1 — Introduction

1.1 Motivation

In the past decade the United States has increased corn production as increasing demand has raised prices (USDA 2014a). This demand has spurred farmers to bring millions of more acres into production[1]. Increased capacity can be coupled with new innovations that allow for increasing productivity per acre and better environmental stewardship (Pingali 2012; FAO 2002). But despite food security and economic benefits of increased U.S. corn production, there is increasing concern regarding biodegradation of aquatic ecosystems due to agricultural chemical inputs (Galloway *et al.* 2004; Mitsch *et al.* 1999).

Anthropogenically introduced nitrogen for agricultural production has compromised water quality, biological diversity, and threatens human health all over the world (Robertson and Vitousek 2009; Galloway *et al.* 2004). Nitrogen fertilizer is largely produced by the Haber-Bosch process allowing for the dramatic increase in world food production in the last century (Sutton *et al.* 2011; Townsend *et al.* 2012). Nitrogen is an essential element for plant life and therefore in agriculture—meaning it cannot be replaced by technological substitutes, as chlorofluorocarbons were substituted in industrial processes by non-ozone depleting chemicals (Mosier *et al.* 2001).

From 1961 to 2011, nitrogen fertilizer consumption in the US increased by 324% (USDA 2013). Corn is the most widely planted crop and receives the highest nitrogen

[1] Reference Appendix 1 for official USDA numbers regarding acres, prices, and production.

application rates per acre (Ribaudo *et al.* 2012). The 2013 crop year saw an estimated 87.2 million acres of corn harvested for grain that yielded almost 14 billion bushels—a 5 billion bushel jump from 2002 (USDA 2014b).

Annual nitrogen application provides crops with needed nutrition. But over-application (i.e. exceeding agronomic fertilizer targets) can occur because added nitrogen can serve as a form of insurance or risk management at a relatively low cost compared to potential yield loss (Williamson 2011; Billen *et al.* 2013). The USDA estimated that in 2006 approximately 65% of surveyed cropland did not follow nitrogen best management practices (Ribaudo *et al.* 2011). This, coupled with other factors, makes agriculture in the U.S. and many other countries the leading source of non-point source pollution in surface and coastal waters (Warner 2008; OECD 2001).

Additional nitrogen from agriculture has changed the global nitrogen cycle leading to severe impacts on aquatic systems and the organisms that rely on them (Billen *et al.* 2013). Nitrogen can be lost in surface and ground water leading to excess plant biomass and a depletion of oxygen (Billen *et al.* 2013; Chambers *et al.* 2011). A growing mobilized nitrogen imbalance has increased the need for greater nitrogen use efficiency (NUE) (Galloway *et al.* 2004; Robertson and Vitousek 2009; Vitousek *et al.* 1997). NUE is the quantitative measure of grain produced per unit of fertilizer applied (Ciampitti and Vyn 2011) and will be used throughout this study when discussing agricultural eco-innovations.

Farmers can increase NUE by adopting best management practices (BMPs), nitrogen-efficient plant varieties, precision agriculture, and other eco-innovations that diminish environmental externalities (Mosier *et al.* 2001; Tscharntke *et al.* 2012; Ribaudo *et al.* 2012; Chen *et al.* 2008). Eco-innovations or technological environmental innovations, change the ecological properties of a society's metabolism (Huber 2008b). Changing a society's metabolism refers to "new *technologies and practices* that change the operative structures and ecological properties of production and consumption, and thus relieve strain on resources and environmental sinks" (Huber 2008a:361).

Innovations that protect health and the environment can include reducing negative externalities of contamination, increasing biological safety, and improving long-term ecosystem health (Kemp and Volpi 2008). Agricultural eco-innovations can possibly decrease cost and/or increase yield by being more efficient with inputs and reducing capital, labor, and energy-using outputs. A broad classification of agriculturally-based innovations includes: mechanical innovations (e.g. improving tractor equipment), biological innovations (hybrid seeds), chemical innovations (more efficient fertilizers), agronomic innovations (new tilling practices), biotechnological innovations (genetically modified organisms), and precision technologies (GPS and variable-rate technology) (Sunding and Zilberman 1999). Adoption of such innovations over time has changed global agricultural productivity (McBrantney, Whelan, and Ancev 2005; McBride and Daberkow 2003).

Just as economic analysis takes into account the added cost and value at each stage of production, agricultural benefits and impacts need to consider all stages in order to capture truly eco-efficient farming practices. Knowledge of environmental processes, minimization of non-renewable inputs, and collective action towards natural resource solutions can be brought into a broadened sustainable production perspective as society continues to face decreasing energy supplies and increased environmental pollution (Elliot and Cole 1989; Pretty 2008). Therefore, analyzing adoption of agricultural eco-innovations is critical in both understanding and adjusting the way we present information and develop policy relating to agriculture and the environment. The section below presents specific research questions and overall goals of this study.

1.2 Specific Research Questions

- What are determining factors affecting adoption by corn farmers of nitrogen soil testing, plant tissue testing, and nitrogen transformation inhibitors?
- How do these factors compare to previous agricultural innovation adoption studies?
- How do these research results help to improve farm practices, and educational outreach to promote voluntary adoption of environmentally sound practices that ultimately improve water quality?

In order to understand factors that may influence adoption of NUE innovations, we must first understand the context and biological processes that occur. Examination of nitrogen fertilizer use and its relationship with the environment will be covered in the next chapter. Chapter 3 is a literature review on adoption and diffusion of innovations and their role in moving society towards a more sustainable farming system. Survey information and analytical methods are found in Chapter 4. Summary statistics, CART models, and multivariate regression results are analyzed and discussed in Chapter 5. Chapter 6 provides conclusions and final thoughts on this research.

Chapter 2 — Background

Part of the problem in targeting agricultural nitrogen non-point source pollution is its complex nature and its widespread effects over millions of heterogeneous agents. Complexity of the nitrogen cycle "provides multiple points of management intervention; on the other hand, it hides interactions among different processes" (Robertson and Vitousek 2009:99). The multifaceted framework and diverse stakeholder base creates a *wicked* problem (Rittel and Webber 1973).

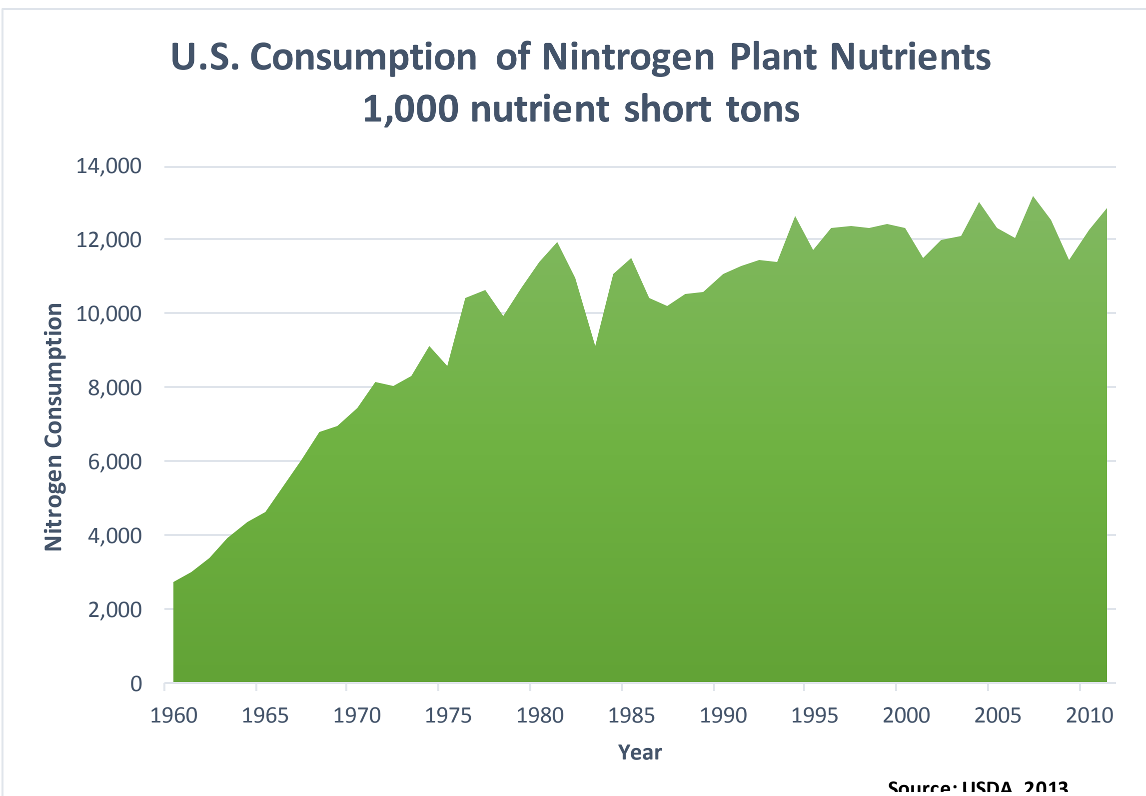
Classic problems in science and mathematics usually operate in restrained or "tame" environments where laws and theories are predictable and measurable (Rittel and Webber 1973:160). Wicked problems are illustrated as having unpredictable outcomes and incorporating multiple user groups representing a variety of desired outcomes (Batie 2008). Non-point source pollution from agriculture is a wicked problem. There is no ultimate solution, only a resolution of pollution mitigation by users (Arias *et al.* 2000).

2.1 Nitrogen and Agriculture

Agricultural history helps to explain the problems, policies, and productivity we have today (David, 1994). Therefore a basic historical introduction is critical in understanding the depth and breadth of environmental challenges linked to farm production. Regarding nitrogen, increasing use of fertilizers on crops started in the 19th century (Melillo 2012). Between the 1840s and 1930s hundreds of millions of tons of nitrogen-rich guano and sodium nitrate (NaNO3) were shipped to farmers in North America and Europe from Peru and Chile.

This increase in agricultural productivity during the Industrial Revolution is characterized by some as the 'First Green Revolution' (Melillo 2012). Historians usually refer to the *Green Revolution* as the array of programs and policies that increased production and synthetic inputs that occurred in the 1960s and 70s. US *Green Revolution* policies led to a fertilizer-intensive approach of food and fiber production that has had a profound anthropogenic impact on the global nitrogen cycle (Pretty *et al.* 2010). The USDA has been tracking plant nutrient fertilizer consumption since the 1960s. Figure 1 shows the dramatic increase nitrogen use over a fifty year period.

Figure 1



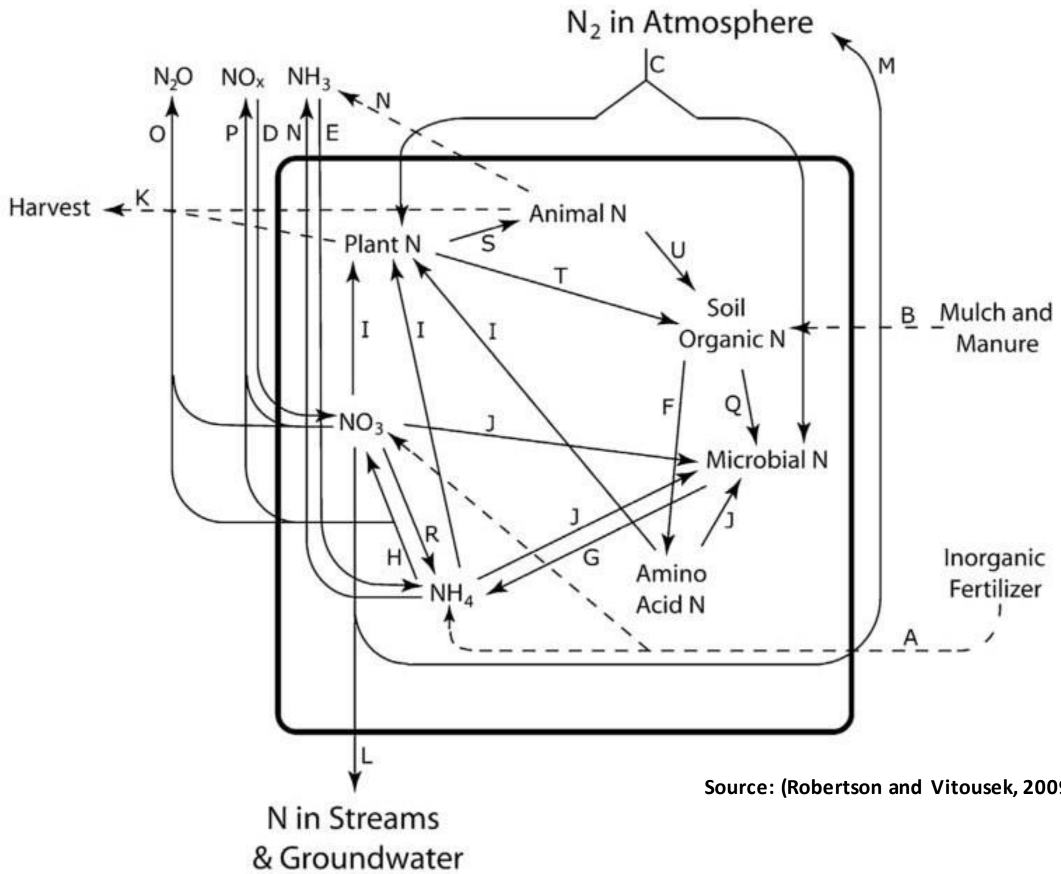
2.2 The Nitrogen Cycle

A rudimentary introduction to the nitrogen cycle is essential for implementing proper agricultural nutrient management and grasping the far reaching effects unnaturally high amounts of reactive nitrogen have on the surrounding ecosystem (Field 2004). When discussing nitrogen in general, N can be used as an abbreviation. When specifically discussing *reactive* nitrogen, many scientific papers use Nr as an abbreviation (Galloway *et al.* 2004), which includes biologically active ammonium (NH_4^+) and nitrate-nitrogen (NO_3^-).

Nitrogen (N) is a limiting element in many terrestrial and aquatic ecosystems (Galloway *et al.* 2004). N is essential in agriculture because it promotes greater plant growth and increases crop quality (Mitsch *et al.* 1999). Reactive nitrogen (Nr) that escapes agricultural production negatively impacts terrestrial, fresh water, marine ecosystems, and human health (Connor *et al.* 2011; Galloway *et al.* 2003).

Nitrogen cycles in different chemical states between the atmosphere, soil, and plants (Borton and Porter 2008). Nitrogen gas (N_2) is the most common gas in the atmosphere, making up 78% by volume in dry air (Field 2004). A corn plant will only readily uptake two forms of Nr; ammonium (NH_4^+) and nitrate-nitrogen (NO_3^-) (Nelson and Huber 1992). Two of the largest sources of nitrogen in the farm system are not readily used by plants, air and dead organic matter (DOM). The N_2 double-bond in the atmospheric nitrogen gas is hard to break and therefore unusable by plants (Bardgett 2005). Over 90% of N in soil can be trapped as DOM which cannot be readily processed by plants. Plants will instead uptake ammonium or converted inorganic nitrogen in the soil that has occurred via mineralization or N-fixing bacteria. The nitrogen cycle as it relates to water pollution and agriculture is shown in figure 2 below.

Figure 2- Complexities of N Cycle



Source: (Robertson and Vitousek, 2009)

Naturally introduced nitrogen can come from nitrogen fixing bacteria, soil microorganisms, and lighting strikes (Field 2004). Legumes can help accumulate plant-useable nitrogen in the soil by hosting a symbiotic bacterium that converts organic nitrogen to inorganic nitrogen in the root zone (Connor *et al.* 2011). Rotating legume crops (like soybeans) with corn can help to both naturally replenish N in the soil and prevent crop specific diseases (Billen *et al.* 2013; Pretty 2008). Lightning can add Nr to the soil from volatized nitrogen in the atmosphere, but is only considered an important source of Nr in areas that lack other large Nr sources (Galloway *et al.* 2004) and therefore is an insignificant Nr source for intensive industrial agriculture.

2.2.1 Anthropogenic Changes

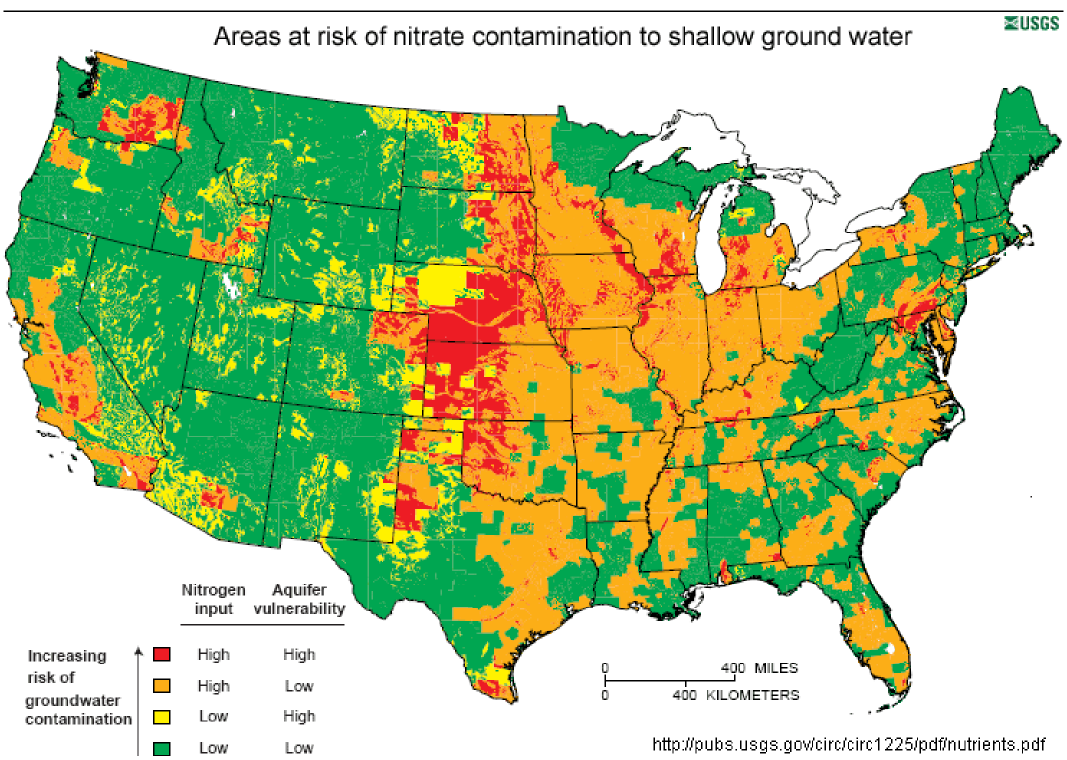
Anthropogenic changes to the global nitrogen cycle can involve both redistribution of natural Nr sources or Nr from industrial fixation. As mentioned earlier, sodium nitrate can be mined and used as an Nr source. But until the late 1800s, nitrogen-fixing legumes and animal manure were primary sources of fertilizer for crop fields (Sutton *et al.* 2011). In the past, it was common to have both field crops and livestock—so waste manure was available on-site (Schroder 2005). Manure has benefits beyond Nr, including micronutrients and organic matter that helps build soil organic matter (Beckman and Livingston 2012). But its nutritional content can be unpredictable and depending on factors like proximity to manure source and manure state (solid or liquid) can be relatively expensive to apply compared to fertilizer from industrial fixation (Schroder 2005; Beckman and Livingston 2012).

In 1908, the Haber-Bosch process allowed cheap ammonia fertilizer to be created on an industrial scale (Sutton *et al.* 2011). Humans' ability to produce massive amounts of Nr has allowed agriculture to feed the world—which cannot be discounted. However, producing massive amounts of Nr comes with a price. Both the intensive amount of energy (largely coming from fossil fuels) and the added Nr in the environment have led to increased pollution around the world (Sutton *et al.* 2011).

2.2.2 Water Quality and Agriculture

Nitrate-nitrogen is highly mobile in water (Mitsch *et al.* 1999). Areas that have shallow groundwater that is used for human consumption can be at risk of nitrate pollution from agriculture. Once nitrates pollute groundwater, users must remove high level of nitrates before consumption—forcing secondary costs (Ribaudo *et al.* 2011). High nitrate levels in water can cause heart disease and methemoglobinemia (blue baby syndrome) (EPA 2010). The EPA has set a maximum contaminant level for drinking water in the U.S. to 10 milligrams per liter (mg/l) for nitrate-nitrogen. Figure 3 below is a map from the U.S. Geological Survey that shows areas at risk of nitrate contamination to shallow ground water across the Continental U.S. (1999). Notice that areas known for intense agriculture, such as the Corn Belt, are dealing with higher levels nitrate pollution.

Figure 3 - Groundwater Nitrate Risk Map



Groundwater contamination is not the only environmental impact associated with movement of excess Nr. Eutrophication of surface waters can cause algae blooms, creating an oxygen level too low to support fish, shellfish, and other aquatic life (Field 2004). Excess mobile nitrogen leads to hundreds of hypoxic dead zones all over the world—many of which are directly related to increased fertilizer use (Field 2004; Billen *et al.* 2013). The decline of aquatic health in areas like the Gulf of Mexico has led to a decrease in recreational and commercial fisheries health affecting both the fishing industry and tourism (Mitsch *et al.* 1999).

2.3 Mitigating N Loss in Agriculture

A crop field can lose applied fertilizer or naturally occurring nitrogen to water sources by soil erosion, denitrification[2], runoff, volatilization, and leaching. Farm managers can take steps to minimize these losses by adjusting practices and adopting technology. Fertilizer applications can be timed and administered to foster efficient plant uptake before Nr leaches below the root zone (Connor *et al.* 2011). Leaching can be minimized by adjusting tile drainage and field contours which can decrease water movement on the surface and in subsurface soil (Mitsch *et al.* 1999).

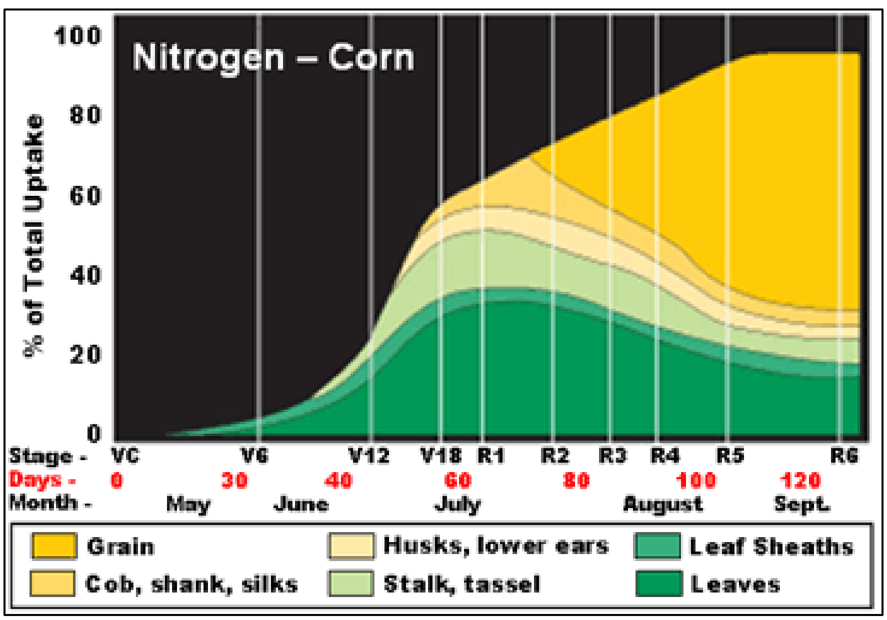
Depending on a variety of factors, commercial nitrogen fertilizer is usually applied in one or more of the following forms: nitrate, ammonia, ammonium, or urea (Mengel 1986). Nitrogen fertilizer can come in dry and liquid forms with application method varying from

[2] Denitrification is a natural process "carried out by microorganisms in anaerobic conditions with nitrate acting as a terminal electron acceptor, result[ing] in the loss of nitrogen as it is converted to gaseous nitrous oxide (N_2O and molecular nitrogen (N_2)" (Mitsch et al. 1999:43).

surface to subsurface application. A farmer may choose to apply some or all fertilizer in the fall well before planting season because of better soil conditions, time savings, and labor and equipment demands (Randall and Vetsch 2005).

Timing, rate, nitrogen form, and application method are all valuable components of N management because a plant's need for nutrients changes throughout the growing season. Figure 4 on the following page shows the varying nitrogen uptake in a typical corn plant. N uptake is relatively low at planting then rapidly increases at the end of June. In corn, one bushel can contain approximately 1 pound of nitrogen with close to half that nitrogen in the grain (Martin, Waldren, and Stamp 2006). Adequate and timely plant-available nitrogen affects both grain number and grain weight (Liu *et al.* 2011).

Figure 4- Timing of nitrogen uptake in corn



Source: Iowa State University Extension

From a managerial perspective, crop nutrition must focus on meeting the nutritional needs of the plant not just applying a certain rate to a field (Connor *et al.* 2011). This means using the right amount of fertilizer at the right time. Proper timing and quantity can minimize nitrogen losses and decrease the farmer's fertilizer cost (Ribaudo *et al.* 2011). Some methods include side-dressing, variable rate N applications, and nitrogen-transformation inhibitors. But farmers must take a holistic approach by incorporating a variety of technologies and practices if mitigation of non-point source pollution is to be observed on a large scale (Mitsch *et al.* 1999).

2.4 Three Dependent Variables: NUE Innovations

Three nitrogen-use efficiency innovations were selected as dependent variables in the following adoption study. These three nitrogen efficient technologies have not been extensively studied: nitrogen soil testing, plant tissue testing, and nitrogen transformation inhibitors. A detailed description of each technology helps to explain both their value and role in increasing NUE in a farming system.

2.4.1 Nitrogen Soil Testing

A common tool for increasing NUE is the nitrogen soil test, which can use field-level data to help farmers decide on application quantities (Williamson 2011). This is both the oldest and most common of the three technologies being examined (Ribaudo *et al.* 2012). Soil testing determines the level of available nutrients in the soil (Peters and Laboski 2013). Nitrogen soil testing predicts the amount of plant-available nitrogen in the soil so preseason and in-furrow side-dressing applications can be more precise (Brouder and Mengel 2003). The Natural Resource Conservation Service (NRCS 2012) recommends soil nitrate and organic N testing as part of annual nutrient management practices to reduce nitrogen loss. It is recommended that at least one sample per five acres be taken (NRCS 2012), costing anywhere from $20-50 for each nitrogen soil test (MU-Extension 2012; Rutgers 2014).

Previous 2001 and 2005 ARMS data showed corn farmers that use soil testing can reduce overall commercial fertilizer application compared to non-adopters (Williamson 2011).

2.4.2 Nitrogen Transformation Inhibitors

In conjunction with this informative tool, nitrogen transformation inhibitors can be an added input to fertilizer applications in order to decrease volatilization and leaching (Upadhyay and Tewari 2011). This practice can be especially valuable for fall nitrogen applications (Frazen 2011). Both nitrogen transformation inhibitors and controlled-release fertilizer are recommended by NRCS as nutrient management conservation practices (2012). There are three classifications of nitrogen transformation inhibitors and controlled-release fertilizer.

Nitrification inhibitors (NI) are chemicals that help reduce the transformation of nitrogen in the ammonium form to the nitrate form, and thus reduce losses of reactive nitrogen. These chemicals kill or interfere with the metabolism of bacteria that cause nitrification (Trenkel 2010). The enzymes that convert ammonium to nitrate are blocked, helping delay the conversion to prolong nitrogen in the root zone since nitrate is more mobile and susceptible to leaching. A common NI is N-Serve® by Dow AgroSciences which costs an estimated $8 an acre (Dow 2014).

Urease inhibitors help to block the enzyme urease from converting urea to volatile ammonia (Trenkel 2010). Ammonium is converted to ammonia gas in the soil until it reaches equilibrium. When this gas is exposed at or near the surface, the gas can volatilize and be blown away, decreasing the overall nitrogen content in the soil and under certain conditions increasing N_xO emissions (Upadhyay and Tewari 2011). The urease inhibitor can be applied to anhydrous ammonia, dry urea, and manure (Frazen 2011). A popular urease inhibitor is Agrotain® which also costs about $8 an acre depending on fertilizer application rate (Jackson 2012).

Finally, controlled-release urea is a urea pellet that is covered in a material that slows the microbial activity around dry urea (Trenkel 2010). Thickness and imperfections in the coating slow release time and therefore delay plant-available nitrogen (Schwab and Murdock 2010). One coating type can be made of sulfur, which can be expensive. Another is PCU or poly-coated urea, which is a polymer coated urea that releases when adequate temperatures and/or moisture levels dissolve the outer coating. A leading PCU coated fertilizer called ESN® is priced at around $0.10/lb. higher than uncoated urea (Silva 2011). Different studies have found that the increased cost of nitrogen transformation inhibitors can be offset by preservation of fertilizer (Upadhyay and Tewari 2011; Frazen 2011).

2.4.3 Plant Tissue Testing

Along with detailed soil information, plant tissue testing gives farmers' quantitative nutrient content information (Schulte and Kelling 2013). Samples can be taken at different stages in the growing season, providing in-season feedback on both macro- and micro-nutrients, thus helping to diagnose early health problems and gage the effectiveness of a fertility program (McGinnis *et al.* 2013). This technique measures the essential nutrients being used by the plant—which they cannot obtain from soil tests because of weather, chemical factors, and genetic variability (Ma *et al.* 2005; Schulte and Kelling 2013). A plant tissue sample will contain leaves from a minimum of 20 randomly selected plants from an area or field of interest. Each analysis typically costs $10-30 (McGinnis *et al.* 2013; MU-Extension 2012).

2.5 Other Innovations for Nitrogen Management

Table 1 in Chapter 4 lists all the variables used in this study and provides a brief description. The following section is designed for readers without a strong agriculture background. Included is an introduction to precision agricultural technology and three technology variables used in the regression that complement the practices of interest.

2.5.1 Precision Agriculture

Generically defined, precision agriculture (PA) is "that kind of agriculture that increases the number of (correct) decisions per unit area of land per unit time with associated net benefits" (McBrantney *et al.* 2005:8). This enhanced management strategy helps inform and improve farm-level decisions (Batte and Arnholt 2003). Precision farming can improve input selection for seed, pesticide, fertilizer, irrigation, and other inputs (Koch and Khosla 2003). Enhanced selection can then be economically optimized to enhance efficiency of application area and timing (McBrantney *et al.* 2005; Koch and Khosla 2003). Both impacts on farm inputs help to tailor management decisions to field needs—hopefully resulting in less environmental impact (Schimmelpfennig and Ebel 2011).

2.5.2 Satellite Soil Maps

Satellite soil maps are field-level maps farmers can acquire that contain a variety of information (depending on the source). Simple maps can be used to get a general idea of soil type in a field. Alternatively in-depth maps can be created through agriculture service agencies that give details on soil types and management systems, drainage patterns, organic concentration, and management zones (SIC 2013). These types of maps aid in both in-season and pre-planting decisions that ultimately make field management more precise and efficient.

2.5.3 Remote Sensing

For farmers, remote sensing assesses their fields without physically touching them. Specifically,

> "Remote sensing is the practice of deriving information about the Earth's land and water surfaces using images acquired from an overhead perspective, using electromagnetic radiation in one or more regions of the electromagnetic spectrum, reflected or emitted from the Earth's surface" (Campbell and Vynne 2012:6).

These remote sensing images can be taken from satellites and aircraft, giving the field manager an aerial view. Though this technology has existed since the 1950s, further advancements and benefits including decreased cost have made it recently appealing to the agricultural sector (Nowatzki *et al.* 2004). Now plant health can be determined by be comparing the spectral signatures from energy the crop reflects to known signatures of nutritional value.

Remote sensing can also be combined to create geospatial data that pinpoints areas on the images with GIS (geographical information system) and others like it. This geospatial overlay began in the 1980s but did not fully mature until the mid-2000s (Campbell and Vynne 2012). Farmers can use images to look for nutrient deficiencies, diseases, water deficiency or surplus, weed infestations, insect damage, hail damage, wind damage, and herbicide damage (Nowatzki *et al.* 2004:1). These images are usually interpreted through a company or extension service that provides a farmer with a color scaled map showing nutrient deficient areas on his or her field. This information can then be relayed to variable rate technology (VRT) applications for precise fertilizer and pesticides applications (Nowatzki *et al.* 2004).

2.5.4 Variable Rate Fertilizer

Variable rate fertilizer technology is a site-specific management tool that allows operators to vary the application rate of fertilizer across their field. This technology relies on other management practices to be fully implemented which may include soil testing and GPS guidance (NDSU 2013). Field zone application maps and GPS in-cab helps to accurately execute variations in fertilizer application across fields (Zhang *et al.* 2010). Farmers can also hire consultants to create maps and develop variable rate fertilizer plans (Batte and Arnholt 2003). For application simplicity, fields are commonly divided into zone management areas with different soil types, yield goals, and application rates (NDSU 2013; Zhang *et al.* 2010). This technology can increase NUE and has the potential to increase profitability (Colaco *et al.* 2012).

2.6 Background Conclusions

This chapter briefly summarized the foundation of scientific and agricultural knowledge needed to further explore adoption of NUE eco-innovations by farmers. Understanding the nitrogen cycle and its relationship to agriculture and surrounding ecosystems will aid in grasping both the magnitude and urgency of increased Nr agricultural non-point source pollution. Chapter 3 will now build on this dialogue by discussing adoption of innovations and highlighting predictors in adoption of agricultural eco-innovations.

Chapter 3 — Literature Review

3.1 Introduction

Adoption of innovation research made exponential progress in the mid-1950s. Early sociology and economic literature tended to approach this topic from different directions. Sociologists focused heavily on social ties and information channels while early economists focused more on macro effects of innovations' impact on economic productivity (Antonelli 2003; Rogers 2003). Everett M. Rogers' now classic book, *Diffusion of Innovations* (published in 1962 and updated in 1971, 1983, 1995, and 2003) is referenced by most researchers in the field of adoption of innovations. Today, adoption and diffusion literature is very much a multi-disciplinary research effort with books and articles in rural sociology (Prokopy *et al.* 2008; Rogers 2003), economics (Pannell *et al.* 2006; Ruttan 1997), business (Baptista 1999), and marketing (Tidd 2010; Goldenberg *et al.* 2010).

3.2 Innovation

"An innovation is an idea, practice, or object that is perceived as new by an individual" (Rogers 2003:12). This means that innovations maybe a disembodied process or an embodied product (Sunding and Zilberman 1999), like a new way to till a field (*disembodied*) or a GPS guidance system (*embodied*). In some cases, an embodied innovation can further be separated as the tool that embodies the technology or *hardware* (GPS system in a tractor) and the knowledge base for the tool or *software* (actually operating it) (Rogers 2003).

An innovation has five main characteristics; (1) relative advantage, (2) compatibility, (3) complexity, (4) trialability, (5) observability (Rogers 2003). These characteristics are critical for individual adoption decisions of an innovation or technology[3]. In analyzing relative advantage it is useful to differentiate primary and secondary attributes of an innovation (Tidd 2010). Primary attributes are invariant and intrinsic to a particular innovation, regardless of adopter perspective. Whereas secondary attributes vary with the adopter perception of compatibility and relative advantage. The difference in secondary attributes across a potential adopter population is known as the "attribute gap" and the size of this gap sometimes can indicate innovation success (Tidd 2010:21).

Compatibility of an innovation involves the degree to which an innovation is compatible with a potential adopter in both values and experience (Rogers 2003). Complexity deals with the level of understanding needed to adopt an innovation. Trialability involves the degree to which a potential adopter can experience the innovation, decreasing uncertainty. Finally, observability is concerned with visibility of an innovation—influencing peer-to-peer networks (Rogers 2003).

3.2.1 Eco-Innovation

The term eco-innovation will be defined from Kemp and Pearson's 2007 study as the,

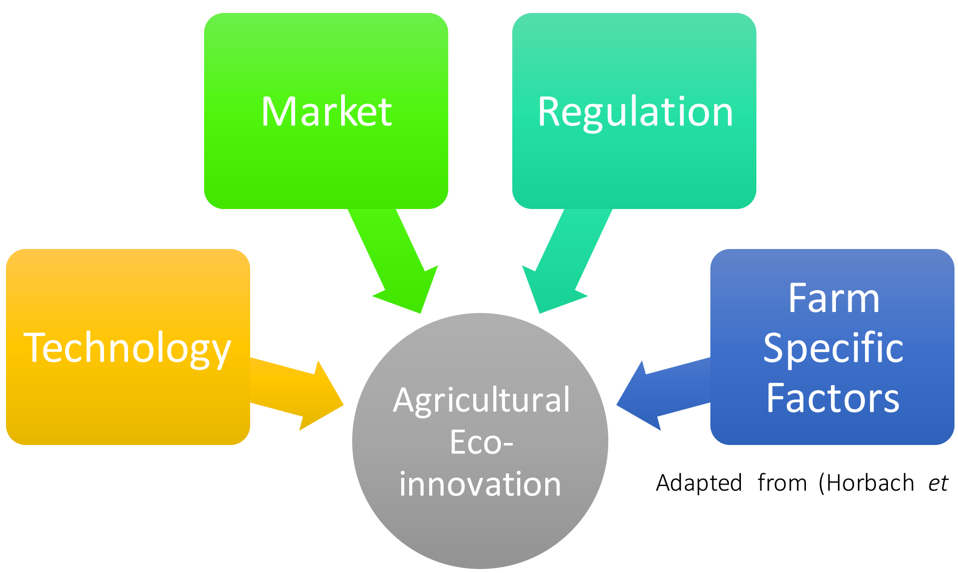
> "[T]he production, application or exploitation of a good, service, production process, organizational structure, or management or business method that is novel to the firm or user and which results, throughout its life cycle, in a reduction of environmental risk, pollution and the negative impacts of resource use (including energy use) compared to relevant alternatives" (7).

[3] It is important to note that though innovation and technology are sometimes used synonymously, technology is "a design for instrumental action that reduces the uncertainty in the cause-effect relationships involved in achieving a desired outcome" (Rogers 2003)

Recall from Chapters 1 and 2 that environmental problems are very complex and more often there are less harmful alternatives rather than true solutions. Two key points to this definition; 1) it restates our original innovation definition 2) it adds a caveat of reducing negative environmental impact *compared to* relevant alternatives. Therefore an innovation does not have to be created specifically for environmental benefit, but rather if it does reduce negative environmental impact (*compared to alternatives*) can be brought under the umbrella of eco-innovation.

All innovations are shaped by their environment. They are influenced by social systems, knowledge, previous technologies, ecological constraints, market conditions, infrastructure, etc. (Kemp and Pearson 2007; Rogers 2003). Determinants of eco-innovations come from four main sources: technology, market, regulation, and farm specific factors. This simple framework is adapted for agriculture from Horbach *et al.* (2012) in Figure 4.

Figure 4- Determinants of Agricultural Eco-innovation



Adapted from (Horbach *et al.* 2012)

These determinants can play a big role in the development of eco-innovations. Current technologies can be enhanced and refined. The market can demand more precise technologies that increase yield as corn prices increase. Farm regulations can prohibit federal subsidies unless certain conservation practices are met. Farm specific factors may dictate need for in-season fertilizer applications or efficient irrigation technology due to geographic location (Frazen 2011).

All four broad determinants impact the five characteristics of an innovation. Therefore to fully understand adoption of an eco-innovation, one must understand the innovation itself and its surrounding factors. These determinant factors can directly relate to factors influencing farmer adoption and diffusion of eco-innovations.

3.3 Adoption and Diffusion

Rogers (2003:5) defines diffusion as “the process by which an innovation is communicated through certain channels over time among members of a social system. It is a special type of communication, in that messages are concerned with new ideas”. While interconnected, adoption and diffusion are individual concepts (Metcalfe 1988). Adoption “is generally considered to be the decision to do or acquire something” (Tidd 2010:5) i.e. the *process of decision making*. Diffusion is “concerned with how the economic significance of a new technology (i.e. market share) changes over time” (Leite and Teixeira 2011:126). Thus, adoption is an *individual* (micro) concept and diffusion is an *aggregate* (macro) concept.

The generic pre-diffusion phase is made up of two parts; invention and development (Goel 1999). The pre-diffusion phase is viewed as complete by researchers when adoption has reached a threshold percentage of the population (Rogers 2003). This indicates that an innovation is available for adoption on a large scale, marking the beginning of the diffusion curve (Easingwood and Lunn 1992; Tidd 2010).

Diffusion of an innovation is typically conveyed by a generic S-shaped curve. The curve stylizes the common phenomenon observed, where diffusion rate rises then falls over time. This is presumed to occur in an atmosphere of "democratic equality of opportunity in respect to the interacting issue" (Dodd 1955:398). The S-shaped curve commonly starts after the pre-diffusion phase which is marked at a population adoption percentage (ex. 10%) (Geroski 2000).

3.3.1 Epidemic Model

The epidemic model has been a widely used in explaining diffusion (Tidd 2010; Meade and Islam 2010). Time distributions of adoption can result from "contagious" information about profitability or efficiency. Relating to medicine, contagion or epidemic models for disease are used as a proxy for modeling the spread of information (Antonelli 2003). However, the epidemic model is unrealistic in that adoption is assumed to occur in a static homogenous population were everyone is equally likely to *catch the disease* (Coombs *et al.* 1987), starting at introduction and ending at saturation (Meade and Islam 2010; Goel 1999; Rogers 2003).

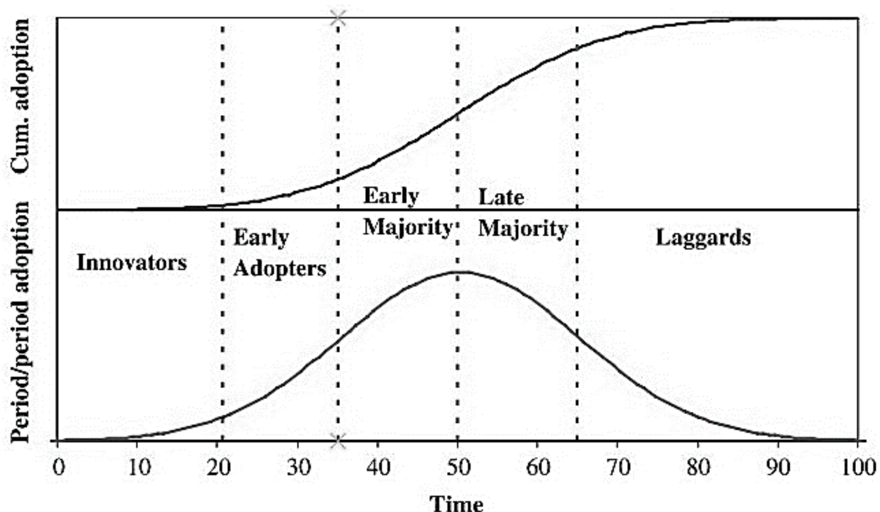
The S-shaped or sigmoid curve is common in explaining a diffusion pattern in a population (Barnett 2011). A special case of the logistic function is shown as a diffusion equation below. The *P* is the cumulative number of adopters or percent of population and *t* is time where *t*=1 is maturity of diffusion (Barnett 2011:104; Menard 2009).

$$\boldsymbol{P_t} = \frac{\mathbf{1}}{\mathbf{1}+\boldsymbol{e^{-t}}} \qquad (1)$$

The initial growth stage of early adopters to majority adopters ($0 < t < ½$) is exponential. The growth begins decaying exponentially after 50% (saturation) and then continues to slow ($½< t < 1$) until t=1, when growth stops (Barnett 2011). It is important to point out that empirically, this late growth usually occurs slower than an S-shaped model would predict. Asymmetric properties stem from varying diffusion rates in the population group (Geroski 2000). A related theory is that of imitation. Schumpeter viewed imitation as the methodological driver of technology diffusion (Schumpeter 1934), where entrepreneurial innovation successes lead to *imitation* of that innovation in the market.

The S-shaped curve can be used to divide adopters into groups by measuring the relative rate of speed at which an innovation is adopted and thus the innovativeness of that society (Rogers 2003). Rogers (2003) describes *innovativeness* as, the ability of a person to adopt new innovations in comparison to their social system. “Adopter categories, the classifications of member of a social system on the basis of innovativeness, include: (1) innovators, (2) early adopters, (3) early majority, (4) late majority, and (5) laggards” (22). Rogers characterized early adopters as better educated, have more upward social mobility, higher social status, larger-sized units or in this case farms, and have greater wealth compared to later adopters (Diffusion of Innovation 2003:288). Below in figure 5, a graph displaying both S-curve diffusion (on top) and adopter categories (in center) which show the relationship between cumulative adoption and number of adopters in each of the five periods. These labels include generalized character contrasts “but are often crude caricature rather than empirical taxonomies, and reflect a strong innovation bias” (Tidd 2010:9).

Figure 5 - Stylized Diffusion Curve



Source: (Meade and Islam 2010)

Another way of describing a typical diffusion study is by substituting *t* in the previous equation for –α-β*t*, where α determines the starting point of the diffusion curve and β is the slope of the curve, shown in equation 2 below (Coombs *et al.* 1987:122). This allows for varying start times and various rates of diffusion to be entered into the S-shaped equation. Different β-coefficients were used in this type of equation for Grilliches’ hybrid corn study (1957) mentioned later in this chapter.

$$\mathbf{x(t)} = \frac{\mathbf{1}}{\mathbf{1+e^{(-\alpha-\beta t)}}} \qquad (2)$$

3.3.2 Bass Model

A well-known diffusion model called the Bass model was developed by quantitative marketing scientist, Frank Bass (Meade and Islam 2010). Bass (1969) suggested individuals are influenced by a desire to innovate (coefficient, *p*) and a need to imitate other individuals in the industry (coefficient, *q*), prefaced by Schumpeter's theory of imitation (1934) as a vehicle for diffusion. This imitation effect is also called an epidemic or contagion effect (Meade and Islam 2010). These coefficients form an S-shaped curve driven by proportion of adopters at time *t* (A(*t*)), where (*q*/*p*)>1. This model (equation 3, below) assumes that the adopting individuals are homogenous and fully connected; therefore a macro-level model could be construed (Bass 1969).

$$\boldsymbol{A(t)} = \frac{\mathbf{1} - \mathbf{exp}[-(\boldsymbol{p}+\boldsymbol{q})\boldsymbol{t}]}{\mathbf{1} + \mathbf{exp}\left(\frac{\boldsymbol{q}}{\boldsymbol{p}}\right)[-(\boldsymbol{p}+\boldsymbol{q})\boldsymbol{t}]} \tag{3}$$

Many econometricians criticized Bass's homogenous social model because it did not incorporate the economic factors like income that change overtime despite the fact it closely modeled diffusion data (Bass *et al.* 1994; Bonus 1973; Meade and Islam 2010). Rogers (1962) argued that normally distributed individual adoption model shape was observed because of a population relatedness to the innovation and how heterogeneous the population is in their propensity to innovate (*p*).

Bass's original model later evolved into the 'Generalized Bass Model' which included decision variables and hazard rate[4] (Bass *et al.* 1994). The model presumes that early

[4] Hazard rate is the "proportion adopting at time *T* given that adoption has not yet occurred" (Bass, Krishnan, and Jain 1994).

adopters are mostly influenced by media while the later adopters are persuaded by communication channels. This model is influential in economics and marketing (Tidd 2010), and produces a skewed S-shaped curve with necessary flexibility for heterogeneous attributes.

3.4 Technology and Adoption

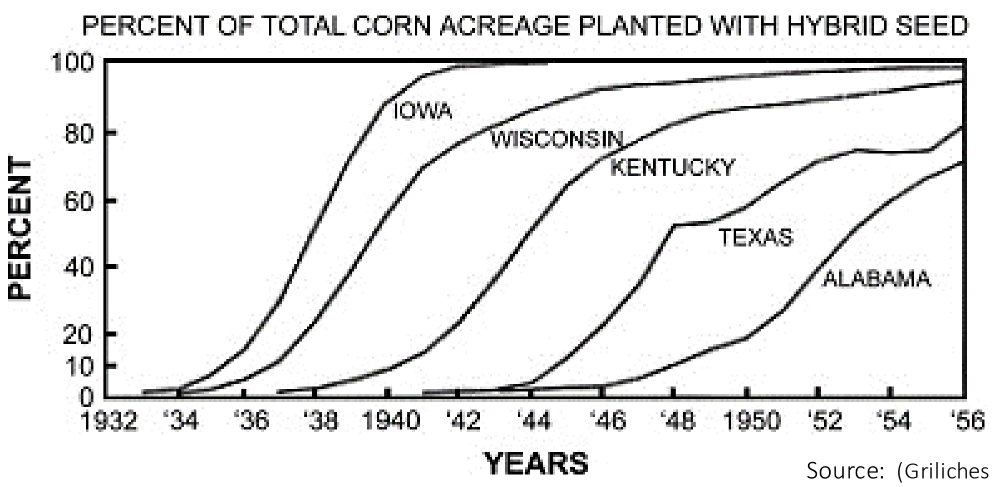
People and the environment are extraordinarily complex. The answers for improving ecosystem health by predicting human behavior are equally complex and must be calculated under uncertainty and with imperfect understanding. When integrating complex, nested systems into framework and theory, the extraordinary diversity and complexity of the world must be acknowledged (Ostrom and Basurto 2011). For adoption studies, this leads to particular variables of interest representing aspects of adoption from previous investigations typically focused on micro-level behavior (Rogers 2003). These variables could be education, age, time taken for adoption decisions, business practices, information source, comparative financial capabilities, and geographic location (Rogers 2003; Prokopy *et al.* 2008; Katz *et al.* 1963).

3.4.1 Previous Diffusion and Adoption Studies

A seminal study of diffusion of innovation was by Ryan and Gross (1943) in Iowa State's Department of Rural Sociology. "*Diffusion of Hybrid Corn in Two Iowa Communities*" attempted to explain the role of different communication channels and factors affecting the rate of adoption. The study used 259 respondent surveys to analyze adoption of hybrid corn technology. With adoption as the dependent variable, this study established the traditional research methodology used for future diffusion studies (Rogers 2003).

Sharing of information was the catalyst behind Grilliches' (1957) hybrid corn study. Griliches analyzed diffusion of hybrid seed in different states. Different states had different starting points based on a threshold of hybrid seed planted acres. A 10% threshold indicated proper development of regional varieties and adequate availability of seeds, allowing for spread of superior hybrids in a state. From this farmer adoption template, hybrid seed companies and public sector entities were guided by the expected returns on investment, projection of technology development, and anticipated yield (Griliches 1957). The results of this five state study are shown in Figure 6. Notice the different years used as starting times for each state and their S-shaped diffusion curve.

Figure 6- Diffusion of Hybrid Corn



Source: (Griliches 1957)

3.5 Influential Variables in Adoption of Agricultural Technology

Analyzing adoption behavior of a society as previously described allows for conservation efforts to be better aimed and carried out instead of forcing a one-size fits all approach to outreach and policy (Cooter *et al.* 2012; Miller *et al.* 2008; Soule 2001). "The key to successful fact-based decision-making is not simply the capture of facts as data, but the relationship of that data" (Weber 2005:19). This means scientific reasoning should be behind every selected independent variable followed by critical analysis of those findings.

However necessary, modeling adoption and diffusion of NUE and BMPs is challenging. In the case of nitrogen pollution, it is infeasible to involve every farmer (i.e. stakeholder) on an individual basis. Understanding user groups, behavior, and tendencies are then vital for prudent policy development and targeted outreach—increasing the need for eco-innovation adoption studies. Modeling adoption of agricultural eco-innovations that contribute to nitrogen mitigation can assist in taming this *wicked* problem.

Below are a series of important variables found in prior analyses of adoption of agricultural technology. Each section has a brief summary of synthesized research. Universality of variable influence on adoption is rare. Knowler and Bradshaw's (2007) synthesis of 31 empirical studies on conservation agriculture adoption found few if any universal variables that predict adoption. But these synthesized research findings help develop and justify hypothesized variables of influence particular to this study.

3.5.1 The Farmer: Education and Information

3.5.1.1 Information Sources

Understanding information inputs in the innovation processes contribute to understanding of the potential user's communication and collaboration trends as they are associated with adoption (Coombs *et al.* 1987; Mowery and Rosenberg 1979). The importance of communication channels and proximity to other adopters was shown in early technology adoption studies (Dodd 1955; Griliches 1957; Mansfield 1961; Ryan and Gross 1943).

A common source of information studied by agricultural economics and rural sociology is the amount of interaction or information a farmer has with an agricultural extension agency. This coincides to Rogers (1962), Grilliches (Hybrid Corn: An exploration in the economics of technological change 1957), and Ryan and Gross's (1943) original emphasis on proximity to communication channels and type of social ties. Prokopy *et al.* (2008) concluded that utilization of social networks and access to information are critical in increasing farmers' likelihood to adopt. Miller *et al.* (2008) found that a relationship or proximity to an extension agent was significant in increasing adoption. Other studies also found that contact with agricultural extension information sources increase the likelihood to innovate compared to farmers without extension contact (Wozniak 1986). But whether it be number of visits to an extension agency (Koundouri, Nauges, and Tzouvelekas 2006), or general communication (Wozniak 1986), the extension variable has been shown to have inconsistent significance (Daberknow and McBride 1998; McBride and Daberkow 2003; Saha *et al.* 1994; Soule 2001). However, since the early 1990s farmers have greater access to better information which could undermine the impact of the extension role with farmers (McBrantney, Whelan, and Ancev 2005; McBride and Daberkow 2003).

3.5.1.2 Human Capital and Education

Human capital and differences in knowledge of new technology have been shown to change the likelihood of adoption (Wozniak 1986; Khanna *et al.* 1999). Increasing human capital by higher education or training "enhances one's ability to receive, decode, and understand information, and that information processing and interpretation is important for performing or learning to perform many jobs" (Nelson and Phelps 1966:69). An increase in human capital creates a 'worker effect'—the marginal product of education, and 'allocative effect'—the allocative enhancement of current resources due to increased education (Welch 1970:42). Economic research has shown that an allocative effect has stronger analytical power than 'entrepreneurial capacity' (Huffman 1974; Welch 1970).

Farmers with more education get more additional benefit from information sources because of their heightened ability to 'decode information' (Huffman 1974). Huffman found that education and agricultural extension contact had a positive impact in nitrogen efficiency and hypothesized that agricultural extension agents can be "substitutes for some of the advantages associated with additional schooling" (96). In this context extension, consultant, contractor, or fertilizer dealer contact may increase human capital. But in today's high tech information age the role of personal interactions may be changing because of integration of user-friendly technology (i.e. cell phones, tablets, and farming applications) (Klerkx *et al.* 2012).

Education and information help decision makers overcome "resistance created by adoption costs and uncertainty" (Wozniak 1986:110). Feder and Slade (1984) found that larger farmers were more likely to allocate larger amounts of resources to the acquisition of education and information, leading to earlier adoption of new technology. Other studies confirmed education significance (Daberknow and McBride 1998; McBride and Daberkow 2003; Khanna 2001; Soule 2001; Huffman 1974; Koundouri *et al.* 2006; Gould and Saupe 1989)

But not all studies found education to be significant (Saha *et al.* 1994; Fuglie and Bosch 1995; Soule 2001). However the trend remains that as more adoption-related information is available and knowledge capital is better able to decipher the information—making adoption is more likely (Rogers 2003; Prokopy *et al.* 2008; Klerkx *et al.* 2012).

3.5.1.3 Age and Experience

Age and experience differ from education and have been found to have mixed results in adoption studies (Knowler and Bradshaw 2007). Commonly, age is thought to be negatively related to adoption because of shorter time horizons and lack of willingness to change (Roberts *et al.* 2004; Rogers 2003; Upadhyay *et al.* 2002a). Sometimes the particular technology matters; for example Gould, *et al.* (1989) found soil erosion was more likely recognized by older more experienced farmers but alternative tillage practices are more readily adopted by younger less experienced farmers. Wozniak (1986) found that though education was positively significant for use of a new cattle feed additive, experience was significantly negative—indicating that newer members of an industry may be more apt to try new things. But experience is commonly not a significant factor in eco-innovation adoption studies (Fuglie and Bosch 1995; Khanna 2001).

Torbett et al (2008) found that farmers over 50 were actually more likely to use precision farming technology for nitrogen fertilizer efficiency. They hypothesize that the experienced older farmers are able to "recognize and reap the benefits of improvements in N efficiency more than younger adopters" (Torbett *et al.* 2008:144). But a study done a decade earlier by Daberkow and McBride (1998) using the 1996 ARMS survey contrasted this notion, finding farmers under 50 were more likely to adopt precision technology. Other studies also support the generalized concept of younger farmers being more likely to adopt new practices than older ones (McBride and Daberkow 2003; Roberts *et al.* 2004).

A study by Napier and Tucker (2001) found that ability to recognize watershed issues had a weak but positively significant impact on adoption of watershed protection policies, but found no one factor extremely important to adoption. Other studies found experience was significant in influencing adoption decision of farmers (Ervin and Ervin 1982; Saha *et al.* 1994; Daberknow and McBride 1998). However, several studies did not find experience to be a significant factor whatsoever (Fuglie and Bosch 1995). These studies differed on particular innovations, but the variety of outcomes reveals the interaction of other influential variables on adoption.

3.5.1.4 Off-Farm Employment

Off-farm employment has been found to be negatively associated with adoption in a variety of studies and is usually associated with smaller farm size (i.e. part-time farmers) (Knowler and Bradshaw 2007). Off-farm income allows some farmers to increase household income, avoid income variability, and lower risk (Fernandex-Cornejo *et al.* 2005; Gould and Saupe 1989; Mishra and Goodwin 1997; Gould *et al.* 1989; Upadyay *et al.* 2002b).

Operators whose major occupation was off-farm employment were found to be less aware of new agricultural technologies (Daberknow and McBride 1998; McBride and Daberkow 2003; Gould and Saupe 1989; Gould *et al.* 1989). The reliance on off-farm income was negatively correlated with involvement in educational outreach, farm size, and receipts of government payments in a study of off-farm income and its effects on Kansas farmer characteristics (Mishra and Goodwin 1997). In a nationwide survey Fernandez-Cornejo *et al.* (2005) found adoption of herbicide tolerant soybeans to be positively related to off-farm income—interpreting this as a possible savings in management time for weed control. Again, innovation-specific attributes dictated the relation between adoption and off-farm income in many studies (Gedikoglu *et al.* 2011).

3.5.2 Location, and Size

3.5.2.1 Farm Size and Capital Accumulation

Theoretically, economies of scale would lead large firms (*farms*) to adopt innovations sooner because of their increased payoff to investment ratio (Antonelli 2003; Goel 1999; Leite and Teixeira 2011). Huffman's findings on nitrogen technology found economies of scale with adoption of nitrogen efficiency practices (Huffman 1974). A meta-analysis by Prokopy *et al.* (2008) suggests that BMP efforts should be directed toward farmers with larger acreages and more income and capital. Soule (2001) found N inhibitors and plant tissue testing were more readily adopted by farmers with high sales using the 1996 corn ARMS data.

Other similar studies also found the amount of land and capital was an influential variable (Feder and Slade 1984). A survey of conservation agriculture adoption found overall impact of farm size and capital holdings in studies inconclusive (Knowler and Bradshaw 2007) and farm size or acres in operation was found negatively correlated (Clay *et al.* 1998; Khanna 2001) or insignificant (Nowak 1987) in other research. Overall the innovation itself seemed to be important in the significance of farm size and adoption when evaluating conservation and environmental innovations.

In some adoption studies land ownership status has been assessed when predicting adoption. Based on Knowler and Bradshaw's survey of adoption literature (Farmers' adoption of conservation agriculture: A review and synthesis of recent research 2007), land tenure not been an important factor in assessing adoption. But in relation to the implementation of conservation practices, some studies did indicate that rented or leased land was negatively associated with adoption (Khanna 2001; Soule 2001). Upadyay *et al.* (2002a; 2002b) found insignificant negative impacts on land rented and conservation adoption—concluding that shorter time horizons could be affecting adoption of BMPs. The shorter time horizon of renters and adoption tends to be substantiated by the economic theory of rational choice.

3.5.2.2 Profitability

Profitability of an innovation as perceived by the farmer tends to be evaluated prior to adoption and can be significant in the decision to adopt or not adopt an eco-innovation (Napier and Tucker 2001; Prokopy *et al.* 2008). A study on watershed protection by farmers in three states found that profitability was the highest ranked factor in adoption decisions (Napier and Tucker 2001). Profitability from potential calculated yield based on theoretical implementation was also highly significant in predicting adoption in other agricultural innovation studies (Koundouri *et al.* 2006; Saha *et al.* 1994; Ryan and Gross 1943).

The potential valuation of profitability by a farmer can be sometimes far lower than the valuation of adoption to society (Ervin and Mill 1985; Napier and Tucker 2001). This is because the lack of social-benefit payment for adoption practices are not always present in the farmer's valuation (Ervin and Mill 1985; Koundouri *et al.* 2006). This can sometimes be due to a shorter planning horizon in calculating benefit compared to benefit by society (Gardner and Barrows 1985). This means that farmer's age and passage of the family farm is an added factor when calculating profitability as it pertains to the environment (Gardner and Barrows 1985; Robertson and Vitousek 2009).

3.5.2.3 Geographic and Location Dummy Variables

Geographic location dictates climate, restricts plant species, and can isolate demographic characteristics. Therefore, adoption rates can also vary by region (Griliches 1957; Rogers 2003). Making geography endogenous in an adoption model can be done with a number of variables; regional dummy variables, soil type, climate, average rainfall, proximity to a metropolitan area, etc. Khanna (2001) found that farm location both with state dummy variables and soil type was a key variable in influencing adoption of site-specific technologies. Farmers with higher quality soils had a higher probability of adopting, but greatest environmental impacts are generated on lower productive soils. This indicates potential societal benefit from a targeted educational outreach to farmers with lower quality soils (Khanna 2001).

Several studies found regional variables to be significant for the awareness of environmental problems and adoption of new techniques (Griliches 1957; Ribaudo *et al.* 2011; Roberts *et al.* 2004). Studies that examined fertilizer management or application techniques also found farm location to be a significant factor in management (Soule 2001). Other geographic-related variables like amount of precipitation, temperature and irrigation practices have been shown to be positively correlated with nitrogen management techniques (Soule 2001). In particular, studies found strong links between adoption and non-adoption of nitrogen management techniques based on wet climate/irrigation and dryer climates/non-irrigation (Fuglie and Bosch 1995).

3.5.3 Technologies and Technology Bundling

Many times certain technologies will be used/adopted in bundles. A USDA publication using 2001 and 2005 corn ARMS (*Agricultural Resource Management Survey*) data showed that farmers who adopted GPS mapping systems had significantly higher yields than non-adopters (Schimmelpfennig and Ebel 2011). This also is true for both variable rate technology (VRT) and yield monitor adoption. VRT uses GPS readings to target specific application to parts of the field. Early on, many farmers found VRT complex, which hindered early adoption (Khanna *et al.* 1999; McBrantney *et al.* 2005). A Texas study found that younger farmers managing larger farms were more likely to adopt VRT (Napier and Tucker 2001). The 2005 Corn ARMS data showed that 12% of farmers had adopted VRT (Schimmelpfennig and Ebel 2011).

3.5.3.1 Farm Practices and Technology Bundling

Like technology, different farm practices can be adopted separately or in number. Schimmelpfenning and Ebel (2011) suggest a three-step adoption approach to precision agriculture practices starting with a yield monitor, then site-specific soil maps, and finally VRT. Soil test results can be incorporated into farm practices and fertilizer management technology.

Certain farm practices can be implemented to prevent soil erosion and nitrogen loss that also increase profit (win-win). Commonly modeled practices are no till or conservation till, cover crop adoption, soil testing, and filter or buffer strips (Upadhyay *et al.* 2002a; Buckley *et al.* 2012; Knowler and Bradshaw 2007). In Upadhyay *et al.* (2002a) adopters of more than one conservation practice were more significantly contrasted with non-adopters than single practice adopters were with non-adopters.

3.6 Importance of Further Adoption Studies

Extreme stress on environmental ecosystems or environmental *institutions* facilitates an opportunity for innovation, techno-scientific and behavioral modifications, along with adoption of better management processes and tools (Lach *et al.* 2005). Paramount to success is involving all users as owners of the problems (Arias *et al.* 2000). Their involvement is important for appropriate design elements along with establishment of a feedback loop for proposed and implemented solutions (Rittel and Webber 1973)—making research studies on these topics necessary in order to refine planned action.

3.6.1 Movement towards Mitigation

Many scientific fields use empirical phenomena to help bolster general laws (Ostrom 1991). But "economics is a different type of science, based on the power of deductive theories derived from a minimum number of basic assumptions about the individual and how individuals are related to one another and a physical world" (237). Because of this, economics becomes a powerful microscope for investigating social and environmental problems.

Under rational choice, the rational farmer has three main elements: 1) methodological individualism, 2) utility-maximization, and 3) existence of various institutional or strategic constraints on individual choice (Pollack 2006). This "theory of advice" helps inform individuals and institutions, about how best to achieve objectives, especially when it comes to environmental resources (Ostrom 1991:238). Naturally, as incentives and benefits change, farmer response to environmental problems may also change (Clearfield and Osgood 1986; Miller *et al.* 2008; Pingali 2012).

Farm sector diffusion of *labor-saving* and *productivity enhancing* innovations is fairly well studied (Rogers 2003). These two types of innovations can reduce marginal cost and as a result increase profit—making adoption in the farmer's self-interest (Miller, Mariola, and Hansen 2008). But environmental innovation does not always inherently increase efficiency and decrease cost, in fact adoption may increase farmer's cost and risk depending on the innovation (Knowler and Bradshaw 2007). Adding to this problem, environmental market failure can construct a scenario where society bears the cost of pollution while the landowner generates profit or a landowner bears the cost of pollution mitigation and society largely receives benefit (Miller *et al.* 2008; Anderson and Leal 2001).

Specifically for more environmentally sustainable adoption practices, individual adoption needs to be carefully analyzed. In economics, profit is not always the defining objective; instead perception of benefits to a farmer's personal utility curve is theorized (Miller *et al.* 2008). This complexity and adopter variance is why a variety of factors need to be examined when attempting to model conservation practices and eco-adoption (Knowler and Bradshaw 2007; Miller *et al.* 2008). The next chapter will discuss the methods used in this study to model eco-innovation adoption.

Chapter 4 – Methods and Hypotheses

4.1 USDA ARMS Survey

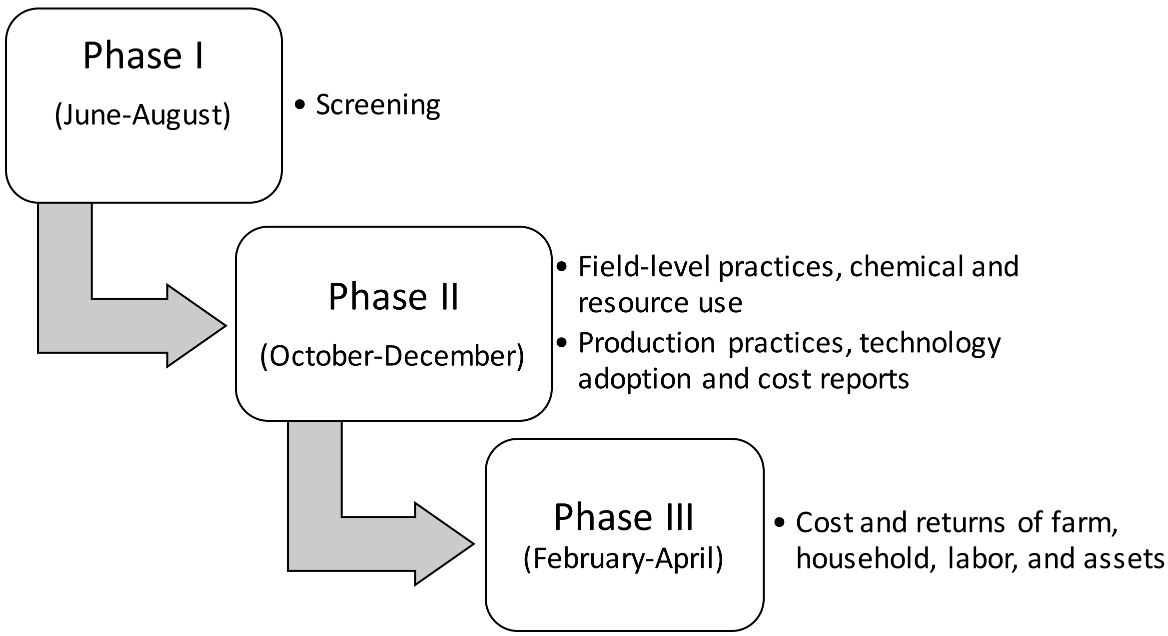
This study uses secondary data collected by the USDA. The Agricultural Resource Management Survey (ARMS) is the "USDA's primary source of information on the financial condition, production practices, and resource use of America's farm businesses and the economic well-being of America's farm households" (ERS 2012b). The survey is sponsored by the Economic Research Service (ERS) and the National Agricultural Statistics Service (NASS). The ARMS survey began in 1996 in an effort to combine USDA information on costs, practices, and returns, which had been collected since 1975 (ERS 2012b). Today ARMS data is used by the USDA and other government agencies to estimate agricultural statistics, monitor trends, and analyze policy and potential policy impacts by linking field-level descriptors of production to the economic characteristics of the farm operation.

The ARMS survey is a national survey of Continental United States farms. The survey covers specific crops on a rotating basis with major commodities (corn, soybeans, wheat, cotton, dairy, and hogs) being surveyed more frequently than others. This survey is sensitive because it contains spatial information; because of this, ARMS data is available to researchers on a limited basis. Researchers can request access to raw ARMS data "who have collaborative projects with ERS or NASS that contribute to USDA's public sector mission" (ERS 2012c).

4.1.1 Understanding the ARMS Survey

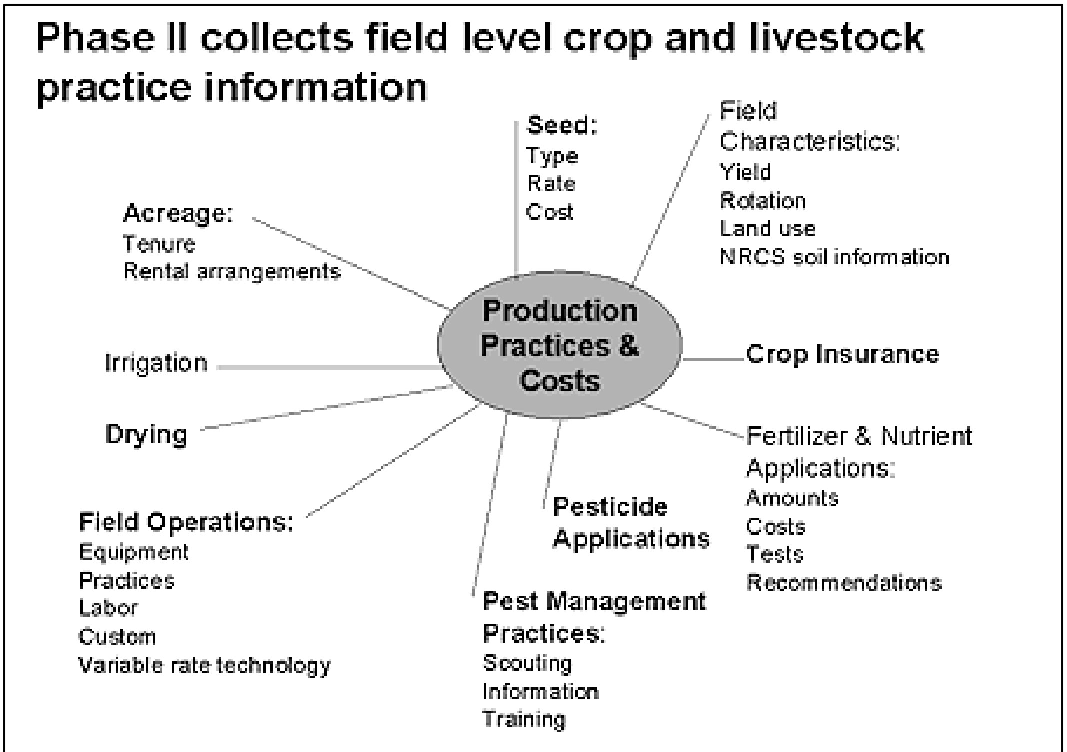
The survey is done in a series of one-on-one interviews with farm operators. It is important to note that the USDA generally considers a "farm" to be an establishment that sold or normally sells at least $1,000 of agricultural products in the course of a year (ERS 2012a). This survey is conducted in three phases as shown in the schematic below. Phase I is carried out during the summer of the reference year and is a "screening questionnaire

Figure 7 - ARMS Phases



used to improve survey efficiency" and does not go into the user data files (ERS 2012a). Phase II is completed in the fall and winter of the reference year. The second phase is similar to the former Cropping Practices Survey, collecting data at the individual field or production level. The Phase II survey is broken into a series of commodity surveys, shown in figure 8, that gather detailed information on production inputs, management practices, and commodity cost of production (ERS 2012a). Phase III data are collected in the spring of the

Figure 8 - ARMS Phase II Diagram



Source: USDA, (ERS 2012a)

year following the reference year to acquire costs of production and returns of investment. This phase is "designed to represent all U.S. farms and focuses on farm income and expenditures, farm financial arrangements, and other characteristics of the farm business and farm household" (ERS 2012a). Phase III also contains farm income, expenses, financial household data, and finance practices.

4.1.2 Survey Design and Quality

The ARMS survey is collected in a multi-phase process with probability-weighted survey sampling (ERS 2012a). The sample design is considered multi-frame because it uses two methods to select farms for the survey. A primary sample is taken from the NASS List Frame, which is a list of farms and information on type and size that is compiled from the

Census of Agriculture and other NASS surveys. The second sampling source helps to include farms that are not in the List Frame. This is done by randomly selecting farms that are in particular land use segments so the farmers of the target survey crop can be represented geographically (ERS 2012a). Variables from both sample selections are then cross-checked to make sure there are not duplicates. Using this sampling technique allows the survey to represent farmers accurately so as to extract statistics and trends and apply them to U.S. farm policy.

Survey data are collected in personal interviews by trained enumerators. The interviewer sits with the farm operator and a manual outline of the questionnaire that explains the procedure for each phase of the survey (ERS 2012a). The detailed directions help to aid interpretation of each answer so all surveyed farmers are asked the same type of question and give the appropriate response. Once the surveys are completed, the enumerators' questionnaires are reviewed by a superior for completeness, consistency, and error. The NASS supervisory statisticians further review each response before it is keyed into electronic format (ERS 2012a). Then a computer program will check for possible errors or outliers and if detected will then be further examined by a statistician.

4.1.3 The 2010 Corn Survey

The ARMS survey on US corn producers was completed in 1996, 1997, 1998, 1999, 2000, 2001, 2005, and 2010. ERS estimates that around 80 million acres of land in the heartland region are planted to corn, with the greatest percentage of the harvested crop going to livestock feed. The large impact of corn on the economy and the environment make US corn producers an important group to study—specifically the analysis of fertilizer use and BMPs (Daberknow and McBride 1998).

4.2 Decision Tree Analysis

Decision tree analysis helps explain the variation of a single variable of interest by one or more explanatory variables in the dataset (De'ath and Fabricius 2000). For the purposes of this study, all variables in the classification tree are either binary or categorical. Trees are represented graphically, starting with a rooted node of the single variable of interest and branching into leaves (or child nodes). These leaves represent a group and usually display summary statistics (De'ath and Fabricius 2000).

4.2.1 CART Analysis

Classification and regression tree analysis, or CART for short, is a nonparametric modeling method. CART models "recursively partition to find increasingly homogeneous subsets based on independent variable splitting criteria using variance minimizing algorithms" (Zheng *et al.* 2009:101). CART selects an independent variable with variance minimizing algorithms to best reduce deviation in response to the dependent variable (Herold *et al.* 2003). This selected independent variable creates a binary split that forms two stems. Each stem has a node called a child node that represents a group, in this case farmer groups. The method repeats itself from each node until no more sub-groups can be made that reduce deviation from the response variable or the number of observations in a node gets too small. The last nodes on branch are called terminal nodes. Tree growth can also be stopped by the researcher by limiting the minimum number of observations in a child node or limiting the number of stems a tree can have.

The CART models were created in IBM® SPSS version 9.2. The target or dependent variable is denoted a *Y* and the set of all predictor variables 1 through *M* are denoted as $X_m, m=1,\ldots.M$. Child nodes are formed from the target variable (*Y*) by variance minimizing algorithms that partition the data into homogenous subsets (Zheng *et al.* 2009; IBM 2011). These CART models can be observed in the following chapter with each of the three dependent variables selected in the research as a target variable.

4.2.2 Applicability of Decision Tree Analysis in this Study

CART analysis can be beneficial in complex and unbalanced datasets where variable relationships may be non-linear and have strong interactions (De'ath and Fabricius 2000; Bel *et al.* 2009). "The commonly used exploratory and statistical modeling techniques often fail to find meaningful ecological patterns" (De'ath and Fabricius 2000:3178), which can be an issue when analyzing a large dataset from a secondary source.

CART models have been used in ecology (Bel *et al.* 2009; Tittonell *et al.* 2008), medical research (Lewis 2000), and marketing analytics (Coussement *et al.* 2014). Particularly for marketing, decision trees can be valuable in segmenting customers, taking a heterogeneous group of customers and splitting them into smaller more homogenous groups in order to target customers and understand related behavior (McCarty and Hastak 2007). CART may detect interactions between variables that may be hard to detect using only regression techniques (Lewis 2000; Coussement *et al.* 2014). Businesses use decision trees “because of their combination of simplicity, transparency, and strong performance” (Coussement *et al.* 2014:2). They have the benefit of using many independent variables in the model which hinders the market researcher from altering the outcome with preconceived notions (Qi *et al.* 2008).

Tree analysis and probit regression are complementary, allowing for estimation of the entire group and segmentation of that group into smaller groups that help link farm characteristics and operator behavior (Qi *et al.* 2008). These two approaches together allow for better understanding of the drivers of farmer adoption in our survey.

4.3 Multivariate Probit Regression

The studies of adoption and factors that influence the probability of adoption commonly use a form of probit or logit model (Hahn and Soyer 2005). Focusing on NUE technology, a farmer either adopts (*y*=1) or does not adopt (*y*=0) a technology, forming the dependent variable. Then, given a variety of factors that influence adoption likelihood for a farmer $(x_1, x_2, x_3, \dots x_k)$, the probability of adoption is denoted as, $p_i = P(Y_i = 1|x_i)$ (Greene 2003). For probit models, we assume p_i is given by the standard normal distribution, $\Phi(x'\beta)$. The probit regression is as follows,

$$P(y = 1|x) = \Phi(x'\beta) \qquad (4)$$

Probit models have been favored for relative ease of computation and modelling of covariance structure (O'Brien and Dunson 2004; Khanna 2001). More explanatory variables can then be added to the model where $x = x_1, x_2, \dots x_k$ and $\beta = \beta_1 \dots \beta_k$ are coefficients for each corresponding *x* variable.

An analyst can extend the probit model to study adoption of two or more dependent variables. This allows for joint prediction of adoption choices. This paper follows Greene (Econometric Analysis 2003) in developing the multivariate probit model shown on the next page for three dependent variables;

$$y_1 = X_1\beta_1 + \varepsilon_1, \qquad y_1 = 1 \text{ if technology 1 is adopted, 0 otherwise,}$$

$$y_2 = X_2\beta_2 + \varepsilon_2, \qquad y_2 = 1 \text{ if technology 2 is adopted, 0 otherwise,}$$

$$y_3 = X_3\beta_3 + \varepsilon_3, \qquad y_3 = 1 \text{ if technology 3 is adopted, 0 otherwise,} \tag{5}$$

The error terms, variance, and covariance denoted as,

$$E(\varepsilon_1|X_1, X_2, X_3) = E(\varepsilon_2|X_1, X_2, X_3) = E(\varepsilon_3|X_1, X_2, X_3)=0, \tag{6}$$

$$Var(\varepsilon_1|X_1, X_2, X_3) = Var(\varepsilon_2|X_1, X_2, X_3) = Var(\varepsilon_3|X_1, X_2, X_3)=1, \tag{7}$$

$$Cov(\varepsilon_1, \varepsilon_2, \varepsilon_3|X_1, X_2, X_3) = \rho \tag{8}$$

The first two equations mean the error terms have a multivariate normal distribution where the expected values of the error terms equal zero and variances equal one. The ρ term represents covariance between the error terms. If this is found to be significant, the sign of ρ indicates the direction of the correlation (Greene 2003; Khanna 2001). In the case of our technologies, a positive ρ means that adoption of the first technology increases the likelihood of adopting the second.

Before interpreting the results in the following chapter, it is important to note that all three continuous variables (farmer's age, acres in operation, yield goal per acre) were transformed by a logarithm for the multivariate probit regression. This was done to shrink the range of the variables in order to converge the algorithm. The ConservationTillage binary variable was created to represent conservation, no till, and minimum till farmers, with zero being none of those three practices. The Filter/Buffer variable was combined in a similar manner, where one represents farmers with filter strips or riparian buffers to protect water quality. The remaining variables are binary and were not altered from the original USDA ARMS dataset.

4.4 Specific Hypotheses

Explanatory variables used in the regression model and their hypothesized signs are given in table 1 below. In our model, independent variables fall into four main categories: education and information, location and size, farm practices, and technology. Education and information predictors include higher level of schooling and sources of information (consultant, contractor[5], extension agents and fertilizer dealers). These variables assume a link between education and knowledge (Knowler and Bradshaw 2007) and have been shown to increase likelihood of adoption (Khanna *et al.* 1999); other similar studies found mixed results for both education and information sources (Daberknow and McBride 1998; McBride and Daberkow 2003; Saha *et al.* 1994; Soule 2001). Age is another commonly studied adoption indicator. Older farmers typically have shorter planning horizons (Roberts *et al.* 2004), but the influence age has on adoption probability can vary with the nature of individual innovations (Knowler and Bradshaw 2007; Torbett *et al.* 2008). For this study younger farmers are predicted to have a higher likelihood of adoption of NUE's based on an

[5] Contract farming means there is an agreement between a buyer and seller for farm products (FAO 2013). Contractors can supply technical advice and farm inputs.

increased time horizon and more time to learn-by-using the innovations (Rogers 2003; McBride and Daberkow 2003; Khanna 2001).

In addition to farmer characteristics and information sources, a variable called HighPrices was added as a proxy for farmer's motivation to plant corn in 2010 instead of another crop. This variable could be positively related to adoption of win-win technologies since these farmers are focused on increasing profitability, or it could be negatively related to adoption if the practices are viewed as just environmentally friendly. The last variable in this category is federal crop insurance which is predicted to be positively related to adoption. Federal crop insurance was not subject to environmental compliance in 2010 (Claassen 2012), however it can be thought of as a substitute for more nitrogen fertilizer application 'insurance' and may reduce overuse (Mulvaney *et al.* 2008; Huang *et al.* 2000; Ribaudo *et al.* 2011).

Location and size variables include regional dummy variables, with Midwest being chosen as the base since it is the largest corn producing region. Like similar studies, we expect that our three win-win technologies would have higher adoption rates in regions where they are most profitable (Beckman and Livingston 2012; Gedikoglu and McCann 2012). Other adoption studies using ARMS survey data that examined fertilizer management or application techniques found farm location to be a significant factor in management (McBride and Daberkow 2003; Khanna 2001; Chang and Boisvert 2009). As mentioned earlier, farm size and farm income can increase the likelihood of adoption in many cases based on economies of scale and increased ability to bear risk (Khanna 2001;

Roberts *et al.* 2004). The prediction in our model is that increasing farm size leads to increased likelihood of adoption.

Current adoption of farm practices can be an important predictor of NUE innovation adoption (Knowler and Bradshaw 2007). Environmental awareness has been found to be an indicator of likelihood of adoption, especially related to conservation practices like no till (Prokopy *et al.* 2008). Our study hypothesizes that adoption of either conservation or no till practices (ConservationTillage) will be positive indicators of adoption. This BMP practice can be a 'win-win' by increasing soil productivity and decreasing time in the field (Knowler and Bradshaw 2007). Similarly, adoption of filter/riparian buffer strips is also expected to have a positive influence as a proxy for environmental awareness. For farmers using manure, a decrease in NUE adoption is predicted since 92% of corn acres from 2001 to 2010 that used manure did not meet rate, timing, and method criteria for USDA's good nitrogen management (Ribaudo *et al.* 2012). Nitrogen transformation inhibitors can be added to manure to reduce the loss of nitrogen via volatilization, as recommended by the NRCS nutrient management conservation practice standard (NRCS 2012). Two practices additional practices expected to coincide with adoption of NHibs and controlled-release fertilizers are irrigation and fall fertilizer application. Irrigation creates a heightened need for nitrogen preservation after application—therefore nitrogen inhibitor/control-release fertilizer can be beneficial (Halvorson *et al.* 2010; Chen *et al.* 2008). Fall nitrogen application can also benefit from a slowed fertilizer release since it is applied well before planting season (Schwab and Murdock 2010).

In order to reduce externalities from agriculture, the federal government has developed conservation programs that subsidize farmers to adopt environmentally friendly practices like the Environmental Quality Incentives Program (EQIP) (Ribaudo *et al.* 2011). We expect participation in federal and state programs to increase the likelihood of adoption of these practices, captured in the binary variable ConservationPayments. There may also be state or local regulations that require decreased N applications in some areas which would also increase adoption. This can occur in particular watersheds like the Chesapeake Bay and is represented by a binary variable called Nreq.

Technology-related independent variables can be indicators of willingness to adopt other technologies (Knowler and Bradshaw 2007). Included in this model are technologies with a range of cost and sophistication. Variable rate application of nitrogen can adjust application rates across a field. This technology can be expensive and benefit from economies of scale, but when used increases NUE in the farm system (Khanna 2001). Some farmers are planting pretreated seeds that are coated with pesticides, insecticides, and/or nematode treatment which reduces early aerial spraying. Using this technology is expected to positively affect adoption. The last two technology variables are GPS soil mapping and remote sensing technology. Both serve different agricultural management purposes and help represent the farmer's innovativeness. GPS soil mapping means a farmer has done soil testing on his field. Remote sensing allows in-season N variability at various growth stages (Shaver *et al.* 2007). By including a wide variety of technology variables in the model, identifiers for influential factors in NUE technology adoption can be better identified.

Table 1- Variable Names, Predicted Signs, and Definitions

Variable Categories	Variable	Predicted Sign	Definition
Education & Information Sources	Age	-	Age of principal operator
	College	+	Education variable where 1 is operator that went to college or graduated and 0 is otherwise.
	ExtensionRec	+	Extension recommended (1=yes; 0=no).
	ContractorRec	+	Contractor recommendation for nitrogen (1=yes; 0=no).
	CropConsult	+	Consultant recommendation for nitrogen. Base variable for information source (1=yes; 0=no).
	FertilizerDlr	-	Fertilizer dealer recommendation for nitrogen (1=yes; 0=no).
	NoRecommendation	-	Did not receive nitrogen recommendation from four previous sources (1=yes; 0=no).
	HighPrices	+	Planted corn because of expected high prices (1=yes; 0=no).
	CropInsurance	+	Federal Crop Insurance (1=yes; 0=no).
Location & Farm Size	Acres	+	Acres in operation.
	YldGoal	+	Yield goal in pounds per acre.
	Midwest	+	NASS Midwest region of US. Base regional dummy variable in regression.
	Plains	-	NASS Plains region of US (1=yes; 0=no).
	Atlantic	-	NASS Atlantic region of US (1=yes; 0=no).
	South	-	NASS South region of US (1=yes; 0=no).
	West	-	NASS West region of US (1=yes; 0=no).
Practices	ConservationTillage	+	Conservation till, No Till, and/or Minimum Tillage (1=yes; 0=no).
	ConservationPayment	+	Received conservation payment from government (1=yes; 0=no).
	Filter/Buffer	+	Had filter strips and/or conservation buffer, riparian buffer or field strips (1=yes; 0=no).
	Manure	-	Manure applied as fertilizer (1=yes; 0=no).
	Irrigate	+	Irrigated corn field.
	FallNapp	+	40% or more fertilizer application in the fall (1=yes; 0=no).
	ReducedNrequired	+	Reduced nitrogen application on field because of government requirement.
Technology	VariableRateN	+	Variable rate application for N. Used to spot treat areas of field with more or less fertilizer (1=yes; 0=no).
	PretreatedSeed	+	Used pretreated seed. Insecticide, fungicide, and/or nematode treatment (1=yes; 0=no).
	GPSsoilmap	+	GPS map of soil properties of field (1=yes; 0=no).
	RemoteSensing	+	Used remote sensing technology on field for early detection of crop health (1=yes; 0=no).

Chapter 5 – Summary Statistics, CART Models, and Regression Results

This results and discussion chapter begins with summary statistics along with charts that depict both variable attributes and relations. Then CART models are analyzed in an effort to segment farmers and find potential "bundles" of technologies and practices those surveyed may be using. Finally, multivariate regression results will be discussed in-depth.

5.1 Summary Statistics

Summary statistics for the 1840 observation dataset used from the 2010 ARMS Corn Survey are found in table 2. Approximately 21% of farmers conducted N tests on soil. Adoption rates of plant tissue testing and nitrogen inhibitor/controlled-release fertilizer were lower, with 3% and 10% of farmers, respectively. For the primary operators, the average age was around 55 years old, with approximately half of those operators having received some kind of college education. The four information sources listed (contractor, consultant, extension agent, fertilizer dealer) provide insight into influential entities. Almost 500 farmers said they received nitrogen recommendations from their fertilizer dealer. Over half of those surveyed said they did not receive any nitrogen fertilizer recommendations.

A majority of the corn farmers in the survey (1071) were from the Midwest region which represents the largest corn growing region. Smaller corn growing regions like the West and South make up only 4.4% of the survey while Atlantic and Plains regions make up 37%. The operating field size has a mean of 1030 acres. Ranges are not presented because the minimum and maximum number acre numbers could reveal a particular farmer's farm size, which is not allowed by researchers using ARMS data.

Field and fertilizer practices varied. Conservation, no till, or minimum tillage practices were adopted by 974 of the 1840 farmers (53%). The number of farmers receiving conservation payments and/or leaving room for field buffer strips and riparian grass filters made up 12% and 14% of the survey, respectively. Corn famers applying manure made up 36% of the dataset compared to the 2006 ARMS corn dataset that had 16% manure usage (Ribaudo *et al.* 2011). In certain areas of the country it is difficult to get fertilizer on the field in the spring due to late winters and wet springs. Fall fertilizer application is done by some farmers in these growing conditions. Approximately 19% of those surveyed applied 40% or more of their nitrogen fertilizer in the fall.

The four technology variables were adopted at different levels. Variable rate fertilizer was only used by 121 farmers out of 1840 (7%). However, farmers applying pretreated seed was widely adopted (50%). The two field mapping variables, GPS soil maps and remote sensing, were used by 11% and 6% respectively. Overall the summary statistics help to give a snapshot of agricultural practices across the nation in 2010.

Table 2- Descriptive Statistics of Variables Used in Probit Regression

Variable Categories	N=1840	Mean	Std. Error
	Dependent Variables		
NUE Innovations	NSoilTest	0.21	0.41
	PlantTishTest	0.03	0.17
	NHib	0.10	0.30
	Explanatory Variables		
Education and Information Sources	Age	54.68	12.37
	College	0.48	0.50
	ExtensionRec	0.04	0.20
	ContractorRec	0.01	0.10
	CropConsult	0.16	0.37
	FertilizerDlr	0.27	0.44
	NoRecommendation	0.52	0.49
	HighPrices	0.02	0.14
	CropInsurance	0.62	0.49
Location and Farm Size	Acres	1030.48	1832.46
	YldGoal	139.59	54.91
	Midwest	0.58	0.49
	Plains	0.22	0.42
	Atlantic	0.15	0.36
	South	0.03	0.17
	West	0.01	0.12
Practices	ConservationTillage	0.53	0.50
	ConservationPayment	0.12	0.32
	Filter/Buffer	0.14	0.35
	Manure	0.36	0.48
	Irrigate	0.08	0.27
	FallNapp	0.19	0.40
	ReducedNrequired	0.04	0.20
Technology	VariableRateN	0.07	0.25
	PretreatedSeed	0.50	0.50
	GPSsoilmap	0.11	0.31
	RemoteSensing	0.06	0.25

5.1.1 Simultaneous Adoption of Variables

Two important categorical variables in the regression are regions and nitrogen recommendation sources. Below, in table 3, these categorical variables are cross-referenced with the three dependent NUE variables. Nitrogen soil testing is the most popular of the three and has many users in both the Midwest and Plains region with the fewest in the West. Nitrogen transformation inhibitors is the second most popular with most of its users being in the Midwest region and only 5 being from the South and West NASS regions. Plant tissue testing has the least users of the three NUE dependent variables with Midwest and Plains farmers making up the large majority. For every region, the most adopted practice was nitrogen soil testing followed by nitrogen transformation inhibitors and plant tissue testing. However, in the Midwest, the numbers of farmers adopting nitrogen soil testing and nitrogen transformation inhibitors were almost equal which was not the case for any other region.

Table 3- Dependent Variables and NASS Regions

	N Soil Test	**Nitrogen Transformation Inhibitors**	**Plant Tissue Test**
Atlantic Region	74	25	7
Midwest Region	144	138	31
Plains Region	136	21	13
South Region	18	3	2
West Region	11	2	0
Total	383	189	53

In table 4, the four recommendation variables reveal adopters' information sources of nitrogen rates in relation to the three NUE innovations. The two most common sources for nitrogen rate recommendations came from consultant and fertilizer dealer recommendations. Only 18 farmers surveyed said they received contractor nitrogen recommendations—15 of these farmers adopted one of the three studied NUE innovations. It was also the only information source that was related to higher adoption of plant tissue testing than nitrogen transformation inhibitors.

Table 4- Dependent Variables and N Recommendation

	N Soil Test	Nitrogen Transformation Inhibitors	Plant Tissue Test
Consultant Rec	120	54	16
Extension Rec	24	13	5
Fertilizer Dealer Rec	118	71	16
Contractor Rec	10	1	3
Total	272	139	40

Table 5 shows a list of farm practices on the top and those same farm practices in the same order along the side. This is in a similar format to a correlation matrix. The grey boxes on the diagonal represent the number of farmers using that technology (e.g. 383 N soil test adopters adopted N soil testing). The remaining cells in the column represent the number of farmers that adopted the technology and also adopted another technology in the data (47 of those 383 N soil test adopters also used a nitrogen transformation inhibitor). Table 6 on the next page shows percentage of adoption, with the grey diagonal boxes being

100% and the remaining cells in each column representing a percentage of those adopting the technology in the column heading also adopting the technology in the row heading.

Table 5- Practice Adoption Percentage

Number of Adopters	N Soil Test	Nitrogen Inhibitors	Plant Tissue Test	No Till and/or Conservation Till	Filter or Buffer Strips	Manure	Irrigated field	Fall Fertilizer App	Reduce N Req
N Soil Test	383	47	34	237	59	122	75	68	19
Nitrogen Inhibitors	47	189	11	129	32	52	18	30	7
Plant Tissue Test	34	11	53	41	10	14	6	7	3
No Till and/or Conservation Till	237	129	41	974	143	262	91	152	44
Filter or Buffer Strips	59	32	10	143	263	113	14	57	15
Manure	122	52	14	262	113	664	30	358	77
Irrigated field	75	18	6	91	14	30	141	13	4
Fall Fertilizer App	68	30	7	152	57	358	13	358	37
Reduce N Req	19	7	3	44	15	77	4	37	77

Table 6- Practice Adoption Count

N Soil Test	100%	25%	64%	24%	22%	18%	53%	19%	25%
Nitrogen Inhibitors	12%	100%	21%	13%	12%	8%	13%	8%	9%
Plant Tissue Test	9%	6%	100%	4%	4%	2%	4%	2%	4%
No Till and/or Conservation Till	62%	68%	77%	100%	54%	39%	65%	42%	57%
Filter or Buffer Strips	15%	17%	19%	15%	100%	17%	10%	16%	19%
Manure	32%	28%	26%	27%	43%	100%	21%	100%	100%
Irrigated field	20%	10%	11%	9%	5%	5%	100%	4%	5%
Fall Fertilizer App	18%	16%	13%	16%	22%	54%	9%	100%	48%
Reduce N Req	5%	4%	6%	5%	6%	12%	3%	10%	100%

*Note: Percentages in this table were calculated by taking the cell in the corresponding column of the previous table, dividing it by the corresponding grey box in that column, and multiplying it by 100.

The three most common practices are no till and/or conservation tillage (974), manure use as fertilizer (664), and fall fertilizer application (358). Particularly for our three dependent variables, no till/conservation till was widely adopted with 77% of plant tissue testers using this practice. N soil testing was commonly adopted by farmers that irrigated fields (53%).

In table 5, 77 farmers indicated they had a reduced N requirement, all used manure as fertilizer (100%). In the estimated correlation matrix these two variables are positively correlated at the 0.6 level (anything above a 0.5 is problematic). Also every farmer that applied more than 40% of his crop fertilizer in the fall used manure (100%). Again these variables were positively correlated. If you look at these two statistics in reverse, of the 664 manure users 54% applied fertilizer in the fall and only 12% claimed they had a reduced nitrogen requirement. Ribaudo *et al.* (2012) found that most farmers using manure produced it in their farming operation. Farmers applying manure in the fall could possibly be both for fertilizing for spring crops and getting rid of excess manure due to limited storage. For this reason manure will be removed from the multivariate probit regression.

Two variables related to water quality are conservation/no tillage and riparian filter or grass buffer strips. Riparian filter strips or grass buffers help to capture nitrogen runoff, as well as other nutrients, before it can enter a water system. Both conservation and no till help prevent soil erosion and increase organic matter, preventing rapid leaching and N loss via runoff. Roughly half the farmers that had filter or buffer strips (54%) also did conservation/no till. But only 15% of farmers doing conservation/no till had filter or buffer strips on the edges of their field.

Tables 7 and 8 give technology counts and percentage of adoption by farmers from the survey. The first three technologies are the three NUE dependent variables. Several farmers adopted more than one of these technologies, indicating that a multivariate regression may be useful. Looking at the percentage table, notice that 64% of plant tissue testers did a nitrogen soil test compared to only 25% of N transformation inhibitor users. Pretreated seed was widely adopted by many of the 1840 farmers surveyed.

Two variables with under 125 adopters in the survey are variable rate technology for fertilizer application and remote sensing. A third of these high tech users also did an N soil test (33-31%). But out of the same group only 10% and 7% respectively, used plant tissue testing. Overall, technology adoption for three of the four variables was fairly low compared to non-adopters.

Table 7- Technology Adoption Count

Number of Adopters	N Soil Test	Nitrogen Inhibitors	Plant Tissue Test	VRT for N app	Pretreated Seed	GPS Soil Maps	Remote Sensing
N Soil Test	383	47	34	41	214	63	39
Nitrogen Inhibitors	47	189	11	27	126	36	24
Plant Tissue Test	34	11	53	7	33	15	12
VRT for N app	41	27	7	121	82	39	19
Pretreated Seed	214	126	33	82	915	132	72
GPS Soil Maps	63	36	15	39	132	201	48
Remote Sensing	39	24	12	19	72	48	118

Table 8- Technology Adoption Percentage

N Soil Test	100%	25%	64%	34%	23%	31%	33%
Nitrogen Inhibitors	12%	100%	21%	22%	14%	18%	20%
Plant Tissue Test	9%	6%	100%	6%	4%	7%	10%
VRT for N app	10%	13%	23%	100%	9%	19%	16%
Pretreated Seed	11%	14%	13%	68%	100%	66%	61%
GPS Soil Maps	56%	67%	62%	32%	14%	100%	41%
Remote Sensing	16%	19%	28%	16%	8%	24%	100%

*Note: Percentages in this table were calculated by taking the cell in the corresponding column of the previous table, dividing it by the corresponding grey box in the column, and multiplying it by 100.

Tables 3 through 8 show co-adopted technologies and practices U.S. corn farmers were using in 2010. These tables also give insight into the three dependent variables and the farmers who did and did not adopt them. These summary statistics and cross-tabs are valuable in establishing a baseline for the large farmer survey but are also a useful reference when analyzing CART models and regressions *post hoc*.

5.2 CART Models

The CART decision tree can be read starting at the target variable. Multiple nodes are the result of multiple splits by a particular variable creating child nodes that have one or more corresponding parent nodes creating a string of explanatory variables back to the target variable. In this paper the decision tree will be read from top to bottom.

5.2.1 How to Read a CART Model

The first CART model shown (figure 9) has nitrogen soil testing as the researcher-assigned binary dependent variable. The dependent or target variable is at the top of the chart at Node 0. Inside Node 0, the 0 represents non-adopters and 1 represents adopters. A number is directly across from the 0 or 1 which indicates the number of observations in the survey that adopted or did not adopt. For nitrogen soil testing, 1457 farmers did not use it and 383 did. Node 0 then breaks into two child nodes based on whether farmers irrigated their field, 1 meaning 'Yes' and 0 meaning 'No'. Starting on the left with Node 1, of the 383 nitrogen soil testers 308 did not irrigate—representing 18.1% of all non-irrigators in the survey sample. Of the 1457 farmers that did *not* use nitrogen soil testing, 1391 did *not* irrigate their fields. So each node shows a 1 (indicating N soil test adopters) and 0 (indicating those not using N soil tests) that follow the split criteria—in this case irrigation. Node 1 then splits into two child nodes (Nodes 3 and 4) by whether or not a farmer was in the Midwest Region. Looking at Node 3, 140 of the 308 non-irrigating nitrogen soil test farmers live in the Midwest Region making up 13.2% of all non-irrigating Midwestern farmers.

The key to not getting lost in the child node numbers is to remember that the 1's in the box indicate the number of farmers in a subgroup based on the dependent variable. The 0's indicate those farmers that did not adopt the dependent variable but still follow the splitting criteria. In each node these 1's and 0's help the researcher determine if meaningful or distinct splits are being obtained. One can now trace out farmer segments. For example, look in node 8 in Figure 9 and follow it up the tree; 38 of the 383 that used nitrogen soil testing had consultant recommendations, lived in the Midwest Region, and did not irrigate their fields.

Below are the CART models for nitrogen soil testing, nitrogen transformation inhibitors, and plant tissue testing. The model summary indicates the variables the model could select to grow the decision tree. Tables 10, 12, and 14 display the statistics for the adjacent model. Because CART statistical techniques and variance-minimizing algorithms were not discussed in-depth these risk and predictability numbers will not be highlighted. However, it is important to state that all three models were sufficient. Note that in all three models all binary and categorical variables used in the multivariate probit regression are also present but only some are included by the model based on splitting algorithm criteria.

5.2.2 Nitrogen Soil Testing CART Model

This model has 10 nodes branching from the target variable N soil testing; forming 3 levels that include 3 variables. The first split is on field irrigation, where 75 N soil test adopters irrigated making up 53.2% of all irrigators in the n=1840 survey. Of the 75, 39 farmers received a nitrogen recommendation from a consultant as seen in node 6. In comparison, a majority (53 of 66) of non-adopters of N soil testing farmers that irrigated their field did not get a consultant recommendation.

From the left, non-irrigating farmers in node 1 split by Midwest region are in nodes 3 and 4. Both these nodes split into terminal child nodes (7, 8, 9, and 10) by consultant recommendation with the majority in both terminal splits being farmers that did not receive a consultant recommendation. Not every decision tree will reveal valuable information. In this case however, farmers surveyed that did N soil testing fell into two distinct groups; irrigators (308) and non-irrigators (75). Farmers that irrigated were likely (52%) to have used a consultant recommendation. So of all the farmers in the dataset that both irrigated and used a consultant for N recommendation, 75% also performed a nitrogen soil test (node 6).This 39 person sub-group could be considered "irrigating N soil testing consultant-using" farmers.

Table 9-- N Soil Test CART Model Summary

Specifications	Growing Method	CART
	Dependent Variable	Nitrogen Soil Test
	Independent Variables	Education, Fall Fertilizer App, Fed Crop Insurance, Filter/Buffer Strips, Plant Corn bc of High Price, Irrigated Field, Manure Used, Midwest, South, Atlantic, West, Plains No Till and/or Conservation Till, Remote Sensing, Soil Types Mapped w/ GPS, Pretreated Seed, VRT N app, Reduced N Requirement, Conservation Payment, Consultant Rec, Extension Rec, Fertilizer Dealer Rec, Contractor Rec, No Recommendations for 4 Sources
	Validation	None
	Maximum Tree Depth	3
	Minimum Cases in Parent Node	100
	Minimum Cases in Child Node	20
	Independent Variables Included	Irrigated field, Midwest Region, Consultant Rec
Results	Number of Nodes	11
	Number of Terminal Nodes	6
	Depth	3

Figure 9- Nitrogen Soil Test Classification and Regression Tree

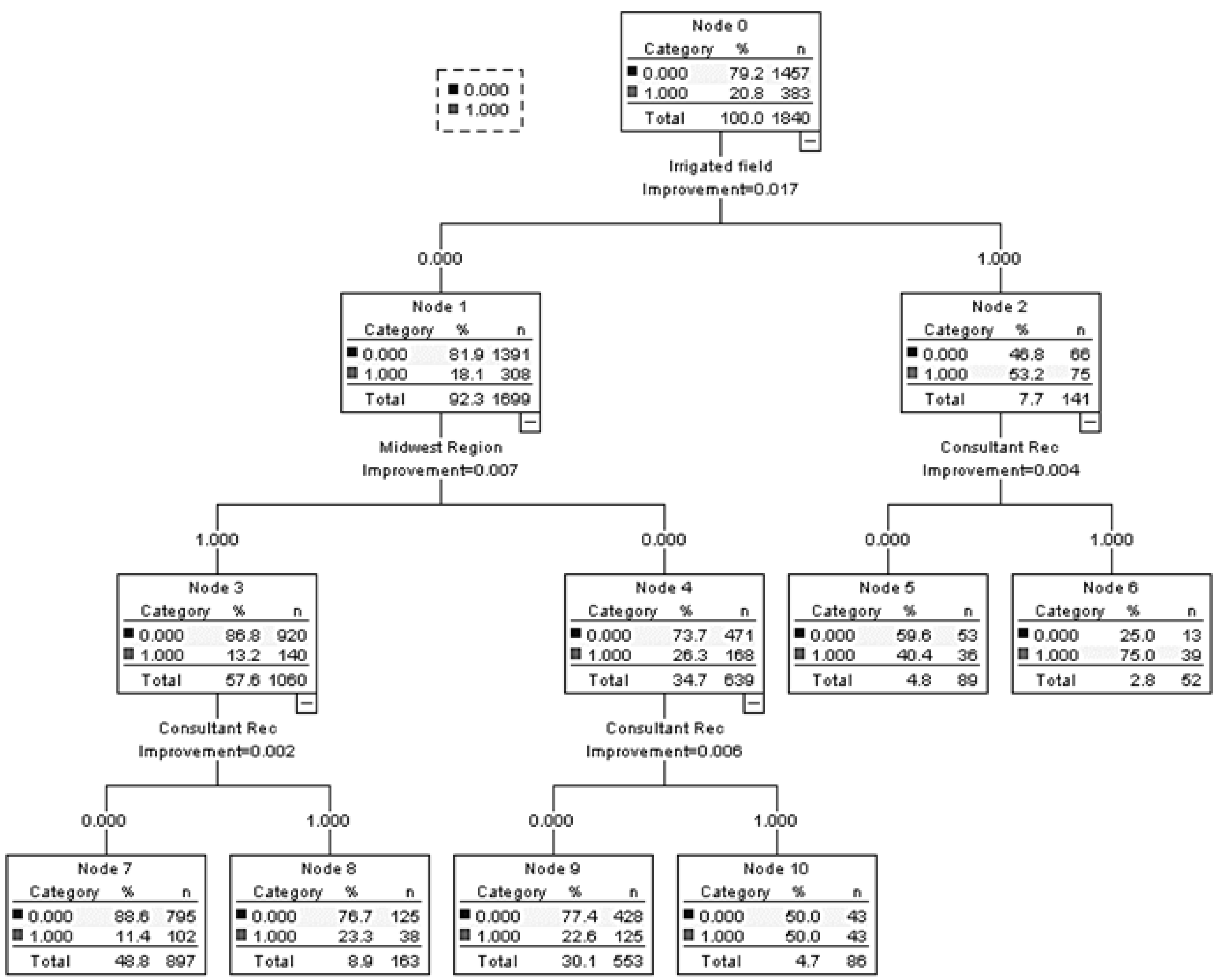


Table 10- N Soil Test Model Statistics

Nitrogen Soil Test CART	Risk		
Estimate	.194		
Std. Error	.009		
[redacted]			
Observed	Predicted		
	.00	1.00	Percent Correct
.00	1444	13	99.1%
1.00	344	39	10.2%
Overall Percentage	97.2%	2.8%	80.6%
Growing Method: CART Dependent Variable: Nitrogen Soil Test			

5.2.3 Nitrogen Transformation Inhibitor CART Model

This model has 13 nodes branching from the target variable Nitrogen Transformation Inhibitors forming 3 levels that include 5 variables. The first split is on a variable indicating no nitrogen recommendations from the four surveyed sources. For nitrogen transformation inhibitor adopters (189), node 1 shows 79 said they did not receive nitrogen recommendations for the 2010 crop year from the four surveyed sources. Node 1 then splits by pretreated seed users. Of the previous 79 farmers, 56 used pretreated seed with 39 of these 56 being from the Midwest region (node 9). Of the 79 farmers in node 1, 23 did not use pretreated seed (node 3), 16 of which did no till and/or conservation till (node 7). So 16 N transformation inhibitor adopters did not receive an N recommendation, did not use pretreated seeds, but did do no till or conservation till on their corn field.

This model splits first into two groups; those who received N recommendations and those who did not. From the right, we see that a majority (110 of 189) of our nitrogen transformation inhibitor adopters received some kind of nitrogen recommendation from one of four sources. In node 2, 731 total farmers received nitrogen recommendations from our four sources—15% of which were nitrogen transformation inhibitor adopters. Node 2 then splits by Midwest region where 84 of the 110 farmers are from. Also interesting to note, looking at the totals in node 2 and 5—731 farmers in the survey said they received N recommendations from one of our 4 sources, 450 of which were from the Midwest region. So farmers from the Midwest region made up 58% of our survey (shown in summary statistics table 2) and 62% of those receiving N recommendations. From the CART model one can infer that a sub-group of nitrogen transformation inhibitors are “Midwestern N recommendation-seeking” farmers.

Table 11- Nitrogen Transformation Inhibitor CART Model Summary

Specifications	Growing Method	CART
	Dependent Variable	Nitrogen Transformation Inhibitors
	Independent Variables	Education, Fall Fertilizer App, Fed Crop Insurance, Filter/Buffer Strips, Plant Corn bc of High Price, Irrigated Field, Manure Used, Midwest, South, Atlantic, West, Plains No Till and/or Conservation Till, Remote Sensing, Soil Types Mapped w/ GPS, Pretreated Seed, VRT N app, Reduced N Requirement, Conservation Payment, Consultant Rec, Extension Rec, Fertilizer Dealer Rec, Contractor Rec, No Recommendations for 4 Sources
	Validation	None
	Maximum Tree Depth	3
	Minimum Cases in Parent Node	100
	Minimum Cases in Child Node	20
Results	Independent Variables Included	No N Recommendations, Remote Sensing, Pretreated Seed, No Till and/or Conservation Till, Midwest Region,
	Number of Nodes	13
	Number of Terminal Nodes	7
	Depth	3

Figure 10- Nitrogen Transformation Inhibitor Classification and Regression Tree

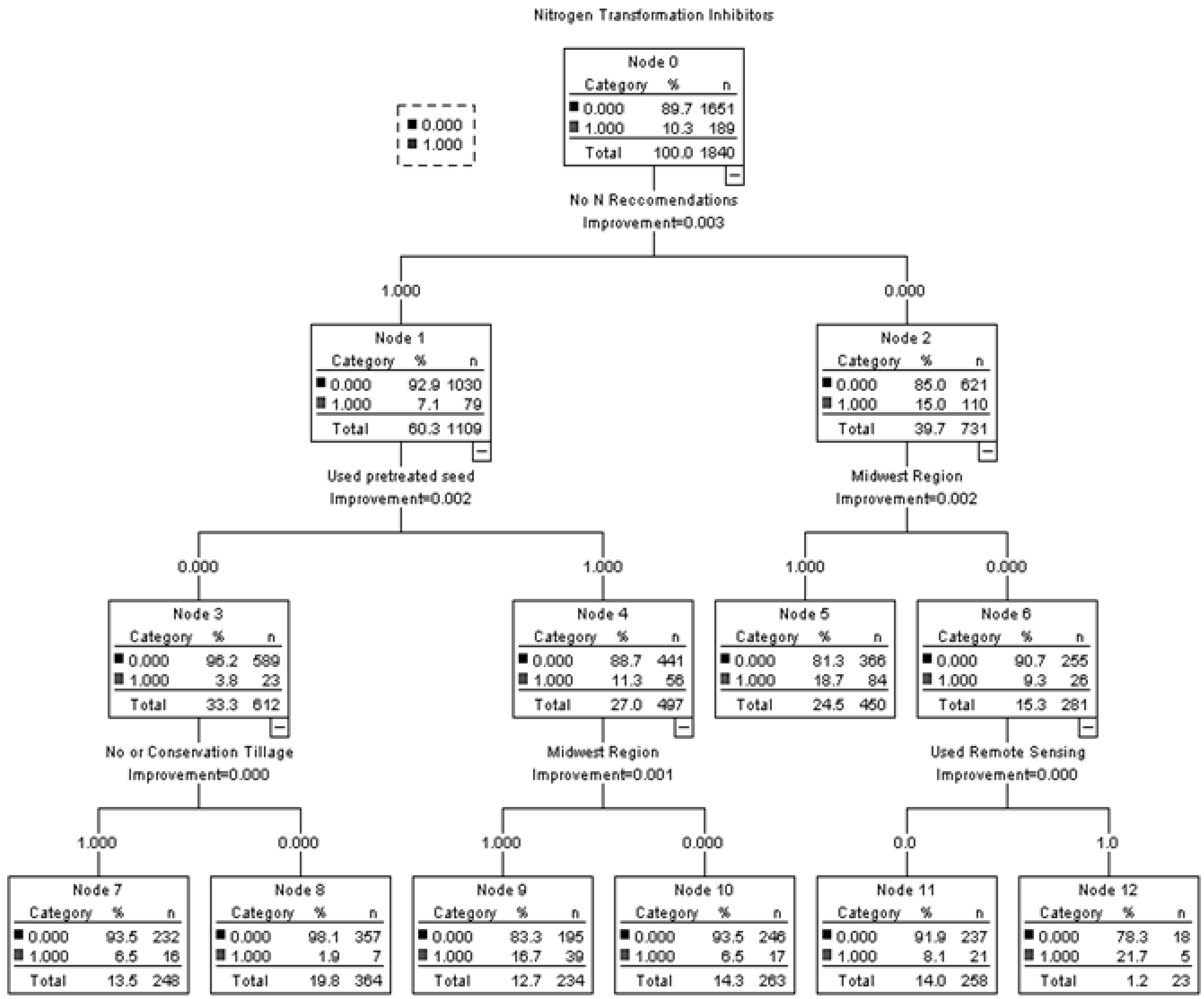


Table 12- Nitrogen Transformation Inhibitor CART Statistics

	Risk		
Estimate			.103
Std. Error			.007
[redacted]			
Observed	Predicted		
	.00	1.00	Percent Correct
.00	1651	0	100.0%
1.00	189	0	0.0%
Overall Percentage	100.0%	0.0%	89.7%
Growing Method: CART			
Dependent Variable: Nitrogen Transformation Inhibitors			

5.2.4 Plant Tissue Testing CART Model

Not surprisingly, given the relatively low number of adopters, the following plant tissue CART model is small with 7 nodes and 4 variables forming 3 levels. In node 0, there are 53 farmers using plant tissue testing and 1787 not. The first split is on whether or not the farmer used remote sensing. Node 2 has 12 of the 53 adopting remote sensing technology (22.6%), making up 10.2% of all remote sensing adopters. For non-remote sensing adopters in node 3, 41 of the 53 farmers then split on receiving conservation payments (1 = 14, 0 =179). Non-conservation payment recipients in node 3 then split by GPS soil maps with 7 plant tissue testers in node 6. This tree is relative weak compared to the previous two in that the breaks do not give us easily describable or particularly meaningful segments. Tree diagrams tend to work better with a higher number of users adopting the target variable.

Table 13- Plant Tissue CART Model Summary

Specifications	Growing Method	CART
	Dependent Variable	Plant Tissue Test
	Independent Variables	Education, Fall Fertilizer App, Fed Crop Insurance, Filter/Buffer Strips, Plant Corn bc of High Price, Irrigated Field, Manure Used, Midwest, South, Atlantic, West, Plains No Till and/or Conservation Till, Remote Sensing, Soil Types Mapped w/ GPS, Pretreated Seed, VRT N app, Reduced N Requirement, Conservation Payment, Consultant Rec, Extension Rec, Fertilizer Dealer Rec, Contractor Rec, No Recommendations for 4 Sources
	Validation	None
	Maximum Tree Depth	3
	Minimum Cases in Parent Node	100
	Minimum Cases in Child Node	20
Results	Independent Variables Included	Remote Sensing, Conservation Payment, Soil Types Mapped w/ GPS
	Number of Nodes	7
	Number of Terminal Nodes	4
	Depth	3

Figure 11- Plant Tissue Testing Classification and Regression Tree

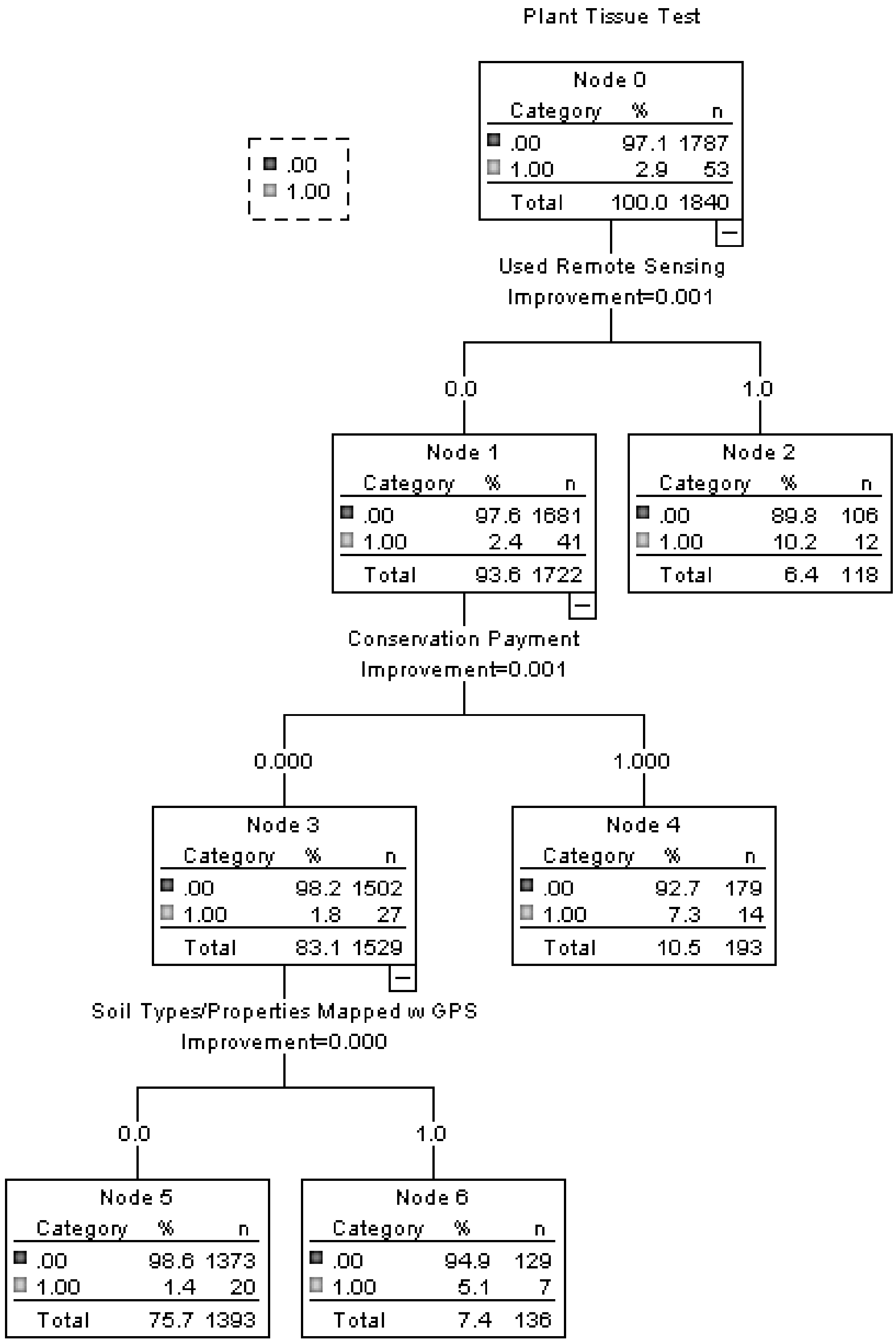


Table 14- Plant Tissue CART Statistics

Plant Tissue Testing CART	Risk		
Estimate	.029		
Std. Error	.004		
[redacted]			
Observed	Predicted		
	.00	1.00	Percent Correct
.00	1787	0	100.0%
1.00	53	0	0.0%
Overall Percentage	100.0%	0.0%	97.1%
Growing Method: CRT Dependent VariablePlant Tissue Testing			

5.2.5 CART Model Conclusions

To recap, a CART model will "recursively partition to find increasingly homogeneous subsets based on independent variable splitting criteria using variance minimizing algorithms" (Zheng *et al.* 2009:101). In all three CART models there was a different variable for the initial split from node 0; N soil testing and irrigation, N transformation inhibitors and no N recommendation sources, plant tissue testing and remote sensing. These models then broke into three levels with 7-13 nodes. The N soil testing and N transformation CART models were more robust, showing nodes with larger farmer numbers.

The N soil test CART model revealed that half of irrigating N soil testing farmers talked to a consultant about their N application quantity. For N transformation inhibitors, 110 of the 189 received N application advice from one of our four sources (consultant, contractor, extension agent, or fertilizer dealer) for the 2010 season, indicating an increased adoption rate if a farmer is contacting an outside source. The plant tissue testing model revealed that 22.6% of farmers in the survey using remote sensing also utilized plant tissue tests to check crop health and nutrient quantities.

5.3 Multivariate Probit Regression Analysis

Now that summary statistics and CART models have been examined, multivariate probit regression results will be analyzed. These results are found in table 16. This type of regression is common in adoption studies and should reveal reliable indicators for adoption of the NUE dependent variables. The beta coefficients for each independent variable should not be interpreted the same as a standard regression. For this model the coefficient values measure the conditional probability changes in adoption given the level of the independent variables, holding all other variables constant. Refer to table 1 to note the base categories for the categorical variables. The intercept includes the base categories for the variables. The discussion will focus on the significance of the variable in the regression and its positive or negative relationship to the probability of adoption.

5.3.1 Regression Results

In the adoption literature, it has been found that in some cases, technologies are adopted as part of a package, i.e. that adoption of some practices are correlated. The null hypothesis for this regression is that the three dependent variables are uncorrelated. Table 15 shows ρ estimates for adoption using a multivariate probit approach. The estimated correlation coefficient parameters show that the null hypothesis is rejected at the 1% level for plant tissue and nitrogen soil testing and at the 5% level for plant tissue testing and nitrogen inhibitors—justifying the use of a multivariate probit regression. We fail to reject the null hypothesis that ρ is zero for nitrogen soil testing and nitrogen inhibitor use. This supports the finding from the summary statistics that those who adopt plant tissue testing have also adopted a range of other practices. For the two significant cases, a positive value for ρ indicates that factors outside of the model that influence the adoption of nitrogen soil testing *increase* the likelihood of adopting plant tissue testing—likewise factors influencing the adoption of plant tissue testing also *increase* the likelihood of adopting nitrogen inhibitors or controlled-release fertilizers.

Table 15- Multivariate Regression Correlation Coefficient Results

Dependent Variable Correlation Combinations	
NSoilTest and PlantTishTest	0.499***
PlantTishTest and NHib	0.178*
NSoilTest and NHib	0.060

Given the wide variety of explanatory variables in the model, we examined correlation coefficients for pairs of variables as well as testing for multicollinearity in the regressions as a whole. The absolute values of the correlation coefficients were all less than 0.4 once manure was removed. The individual regressions found no multicollinearity problems using variance inflation factor (VIF). The VIF for all variables in the model was less than 2.7 while a VIF of 10 or greater indicates that a variable may be deemed a linear combination of other independent variables in the model (Chen *et al.* 2003).

For models with categorical dependent variables, the traditional ordinary least squares measure of fit, R^2, cannot be used. In addition, the regressions have categorical independent variables so the appropriate measure is the max-rescaled R^2 value, a likelihood-based measure that is calculated by SAS (Stokes and Davis 2009) . The measure ranges from 0 to 1 with higher values indicating better fit. Max-rescaled R^2 values for the three individual probit regressions ranged from 0.193 for nitrogen soil testing to 0.164 for the other practices, as shown in table 16.

Explanatory variables related to education and information sources had varied significance across the three dependent variables. Natural log of age was negatively associated with both nitrogen soil testing ($p<1\%$) and nitrogen inhibitors ($p<5\%$). This is in line with our hypothesis that older farmers are less likely to adopt these technologies. Higher education level and use of extension recommendations were insignificant for all three technologies. Compared to the base category of consultant recommendations, nitrogen soil testing was positively related to contractor recommendations, and negatively related to fertilizer dealer recommendations. Fertilizer dealers have an incentive to sell more not less nitrogen fertilizer. The variable for 'no nitrogen recommendation' was negative and highly significant for all three dependent variables compared to the base category. This makes sense and fits with our prediction that farmers would be less likely to adopt NUE technologies if they did not seek outside recommendations. Planting corn due to high prices was significant for all practices with plant tissue testing being positive and the other two negative. One possibility for this result is that managers are more concerned about maximizing yields when prices are high; thus, they are less worried optimizing N use. Plant tissue testing occurs during the growing season. If prices are high, farmers could be more likely to test for micro-nutrient stress in order to make sure that they maximize yield. Finally, the last variable in the first category is federal crop insurance—which is significant only for plant tissue testing. Some insurance companies require plant tissue testing if farmers are to get a discount for planting geographically appropriate GMO seed (USDA 2009).

The second variable category is location and farm size. Natural log of acres is a proxy for farm operation size and economies of scale. For nitrogen inhibitors ln(acres) was positive and significant at the 1% level. None of the coefficients for expected yield per acre were significant. The regression contained 4 regions with Midwest as the base. Warmer regions like the Plains, South, and West were negatively correlated with adoption of nitrogen inhibitors. This result aligns with the use of nitrogen inhibitors in colder climates (Chen *et al.* 2008). Nitrogen soil testing showed the four regions in the regression were positive and significant at either the 1% or 5% level compared to the Midwest. Plant tissue testing did not have any significant regional coefficients, *ceteris paribus*.

A possible indicator for likelihood of adoption can be adoption of previous innovations, both technologies and practices. Farmers' receipt of some type of state or federal money for conservation was positively associated with adoption of both nitrogen soil testing ($p<5\%$) and plant tissue testing ($p<1\%$). No NRCS funding is available for nitrogen transformation inhibitors so it is not surprising that conservation funding was not associated with adoption of this practice. This increased likelihood of adoption shows that conservation payments encourage soil and plant testing, as expected. This was also the case with conservation tillage/no till which was positively associated with plant tissue testing ($p<10\%$) and nitrogen transformation inhibitors ($p<1\%$). These results indicate that farmers who are interested in conservation and improving environmental quality are more likely to adopt these specific NUE practices.

Table 16- Multivariate Probit Regression Results for Three NUE Eco-innovations

Variable Categories	*Explanatory Variables*	Nitrogen Soil Testing	Plant Tissue Testing	Nitrogen Inhibitors
Education and Information Sources	LN(Age)	-0.494***	-0.30	-0.432**
	College	0.11	0.17	0.01
	ExtensionRec	-0.21	-0.05	-0.08
	ContractorRec	0.615**	0.50	-0.78
	CropConsult	BASE		
	FertilizerDlr	-0.242**	-0.32*	-0.05
	NoRecommendation	-0.581***	-0.35*	-0.370***
	HighPrices	-0.833***	0.62**	-1.034**
	CropInsurance	0.062	0.41**	0.06
Location and Farm Size	LN(Acres)	-0.014	-0.07	0.146***
	LN(YldGoal)	0.079	0.09	0.07
	Midwest	BASE		
	Plains	0.578***	-0.12	-0.906***
	Atlantic	0.665***	0.01	-0.15
	South	0.735***	0.19	-0.561*
	West	0.584**	-3.95	-0.939**
Practices	ConservationTillage	0.09	0.252*	0.293***
	ConservationPayment	0.239**	0.520***	-0.05
	Filter/Buffer	0.12	-0.12	0.14
	Manure	Removed		
	Irrigate	0.595***	0.09	0.400**
	FallNapp	0.065	-0.22	-0.01
	ReducedNrequired	0.195	0.31	-0.25
Technology	VariableRateN	0.20	0.04	0.372**
	PretreatedSeed	-0.01	0.05	0.327***
	GPSsoilmap	0.303***	0.28	-0.02
	RemoteSensing	0.20	0.482**	0.350**
Intercept	Intercept	0.64	-1.21	-0.84
Fit	*Individual Regression* R^2	0.193	0.164	0.164

Note: Merged Phase II and Phase III ARMS data for corn producers for 2010 were used. Estimates are statistically significant at the 0.01***, 0.05**, and 0.1* levels.

However, filter or riparian buffer strips, reduced nitrogen requirement, and fall fertilizer application were all insignificant in predicting likelihood of adoption, *ceteris* *paribus*. The non-significant results for the latter two variables are cause for concern since the potential for negative environmental impacts is heightened. Irrigation has a positive effect on N soil testing and nitrogen inhibitors at the 1% and 5% level of significance respectively. Farmers that use irrigation tend to have a high investment tied to field productivity and are concerned with N retention in soils (Robertson and Vitousek 2009), and this is reinforced in the regression results.

Four technologies were chosen as explanatory variables in the model, again acting as a proxy for farmer innovativeness. The use of variable rate fertilizer, a capital intensive technology, showed a positive effect on adoption of nitrogen inhibitors ($p<5\%$). The use of pretreated seed with insecticide, fungicide, and/or nematode coating was also positively associated with nitrogen inhibitor adoption ($p<1\%$). Both NHibs and pretreated seed are additives to traditional farm inputs. The utilization of GPS soil maps was positively associated with adoption of nitrogen soil testing at the 1% level. This means that managers with GPS soil mapping may overlay recent nitrogen soil testing data. Finally remote sensing technology increased the likelihood of adoption for plant tissue testing and nitrogen inhibitors at the 5% level. This significance shows an added concern for timing-appropriate nitrogen by farmers using this technology.

The multivariate probit analysis indicates that adoption of nitrogen soil testing is positively correlated with adoption of plant tissue testing and adoption of plant tissue testing was positively correlated with nitrogen inhibitor or controlled-release fertilizer use. As expected, older farmers were less likely to adopt the NUE eco-innovations (if the effect was significant). All three practices were less likely to be adopted by farmers receiving no nitrogen fertilizer recommendations compared to recommendations from a consultant. This result indicates decreased likelihood of NUE adoption for those farmers not actively seeking input on nitrogen management.

For the nitrogen soil testing model, all four regions were positive and significant, indicating that those regions were more likely than the Midwest, all else equal, to use this practice. Receipt of conservation payments was positive for both nitrogen soil testing and plant tissue testing, which follows the NRCS suggestions for conservation practices. This, along with indication of increased NUE practice adoption by those using conservation tillage implies that environmental concerns may be a driver for adoption of these win-win practices, although there was no significant effect of having filter/riparian buffers. Nitrogen inhibitors and controlled-release fertilizers showed a strong connection to current technology implementation, with 3 of the 4 innovations being positively associated with adoption.

This adoption model helped to reveal influential variables for three NUE dependent variables, contributing to the previous body of research reviewed in chapters 3 and 4. These findings reinforce the predictability of certain factors like age and information, as well as the complexity of the adoption process and researchers' lack of understanding of all influential factors affecting farmer adoption of eco-innovations. The regression results also revealed that there are still many factors outside the model that are influencing adoption. This research study will be further discussed in the following chapter along with concluding remarks and potential future research.

Chapter 6 — Conclusions

The main source of nitrogen non-point source pollution in the environment is caused by agriculture (Ribaudo *et al.* 2011). Further adoption of NUE innovations is important for U.S. water quality and increased sustainability of agriculture (Pretty 2008; Ribaudo *et al.* 2012). Information about the multidimensional factors associated with the adoption of NUE innovations can help shape policy design and tailor outreach by both private and government entities.

In analyzing the 2010 USDA ARMS data, this researcher tried to look at summary statistics, CART models, and multivariate probit regression results to understand drivers of adoption for three NUE innovations. Technology or practice variables like no till/conservation till and pretreated seed were widely adopted by participants evaluated in the survey. Both co-adopted table 5 and 7 indicated technologies and practices that were commonly (or uncommonly) adopted together.

The three CART models revealed three different initial variable splits for our three dependent variables; N soil testing and irrigation, N transformation inhibitors and no N recommendation sources, plant tissue testing and remote sensing. This segment information means that extension agents and consultants could target farmers that irrigate that are not using N soil testing with information on its benefits, possibly getting a move receptive audience to NUE literature than non-irrigating farmers. For farmers that are receiving information from one of the four studied sources, they may also be receptive to using a nitrogen transformation inhibitor given many current Nhib users are active information-seekers. Fertilizer dealers may be interested in this technology since, while it may reduce N applications, sales of the inhibitors are a source of revenue. This also means that consultants, extension agents, contractors, and fertilizer dealers could be a potential survey source for understanding how to better increase NUE innovation adoption in the US. All this information preceded the multivariate regression results that tested the hypotheses posed in Chapter 4.

When comparing the CART models and regression results, all first breaks in each tree were significant in the regression; N soil testing and irrigation, N transformation inhibitors and no N recommendation sources, plant tissue testing and remote sensing. For N soil testing, 75 of the 383 adopters also irrigated their fields. Irrigation was positively related to adoption in the regression (.595**). No nitrogen recommendation was negatively related to adoption of nitrogen transformation inhibitors (-0.370***), with 79 of the 189 adopters receiving no recommendation from the four surveyed sources. Finally, the plant tissue testing CART model first split on remote sensing. When comparing that to the regression results, it seems the CART model could have possibly first split by VRT or no recommendation instead of remote sensing (which the variance minimizing-algorithm selected). Considering all three influential variables, the co-adoption of other technologies or access to information seems to be related to adoption of plant tissue testing. Combined with the finding that adoption of plant tissue testing was related to both of the other NUE technologies, it seems that farmers who adopt this technology are in general very innovative farmers. They may thus fit the general category of “innovators” as described by Rogers (2003).

This study used 2010 ARMS data from the USDA, which gives an in-depth, national representation of corn farmers and their financial and field management practices. The sample was large enough (n=1840) to help validate our multivariate probit regression results. This dataset is reviewed by USDA workers and policy developers as an indicator of current farm life—which adds to both the legitimacy and applicability of the outcomes. However, there are few variables in the survey relating directly to environmental attitudes and behavioral motives. The absence of this type of information can be a weak point when analyzing farmer behavior (Prokopy *et al.* 2008). This was a weakness in the regression analysis and was one of the likely reasons for overall low statistical significance in the regression model.

Another weakness in this study was the lack of spatial details relating to geographic location and soil type. Though regional dummies and irrigation were used, this did not appropriately substitute for field fertility and soil drainage and may thus relate to the low explanatory power of the model. A better proxy would have been to use soil classification type of the surveyed field and possibly more specific locations like state. Future studies should consider adding a soil type dummy that can help to incorporate geospatial information that allows for incorporation of agroecological attributes.

According to NRCS, not applying nitrogen fertilizer in the fall for spring crops is part of good nitrogen management (NRCS 2012). Fall nitrogen application was insignificant in all three regressions and did not appear in the CART models. This is concerning since fall nitrogen application already decreases NUE and increases possibility of N loss to waterways (Ribaudo *et al.* 2012). Further research needs to be conducted on farmers that are applying fertilizer in the fall. This also needs to include manure users, all of which applied fall fertilizer in our survey sample. Policy in Europe bans spreading of manure and fertilizer in late fall and winter (van Grinsven *et al.* 2012). Some states like Wisconsin prohibit applying fertilizer on frozen ground (Vanegreen 2014). But federal policy might be a possible solution in the US if farmers applying fall fertilizer are not following other best management practices and putting water quality at risk.

Previous literature has found mixed results when analyzing predictors of agricultural eco-innovation adoption (Knowler and Bradshaw 2007; Prokopy *et al.* 2008). In this study, we examined four categories of independent variables to try and capture a breadth of possible influential factors. The results revealed that some predictors like information sources and age are associated with NUE innovation adoption. But there are still many factors outside the model which are driving the decision to use these three innovations. For example, lack of precise geospatial dummies and personality characteristics such as innovativeness may have played a role in the low R^2 values observed in this study.

The strong and contradictory effects of the variable HighPrices need to be investigated. How are farmers responding to increased prices of corn—and what are they doing in their farming system to adapt beyond increasing acreage? Further research is needed to help explain the drivers of eco-innovation adoption and what measures agribusiness and government should take to increase its use.

The reduced adoption by farmers who did not receive any nutrient recommendations implies there is a role for expanded education efforts relating to nitrogen use efficiency. Several states have implemented low level fertilizer taxes that had little impact on farmer usage (Ribaudo *et al.* 2011), but fertilizer limits have had some positive effects on water quality in Europe (van Grinsven *et al.* 2012). The national problem of agricultural nitrogen pollution highlights tradeoffs between environmental quality and profitability of agriculture. However, new, win-win technologies provide a potential way to reduce this conflict. More generally, addressing environmental and natural resource issues involves understanding the physical, biological, and institutional environment as well as its connection to technology, public choice, abatement costs, and transaction costs (McCann 2013).

Appendix 1 — USDA Corn Statistics from 2006-2013

This table contains corn data from the USDA from 2006 to 2013 (USDA 2014a). In this time frame the following all increased: planted corn acres, production in bushels, and weighted-average price per. The yield per acre went up and down from 2006-13 but remained fairly stagnate on a nationwide scale.

Table 17- U.S. Corn Production from 2006-2013

Corn: Planted acreage, harvested acreage, production, yield, and farm price								
Commodity and mkt yr 1/		Planted acreage (Million acres)	Harvested for grain (Million acres)	Production (Million bushels)	Yield per harvested acre (Bushels per acre)	Weighted-average farm price (dollars per bushel) 2/	Loan rate (dollars per bushel)
Corn	2006/07	78.33	70.64	10,531.12	149.10	3.04	1.95
	2007/08	93.53	86.52	13,037.88	150.70	4.20	1.95
	2008/09	85.98	78.57	12,091.65	153.90	4.06	1.95
	2009/10	86.38	79.49	13,091.86	164.70	3.55	1.95
	2010/11	88.19	81.45	12,446.87	152.80	5.18	1.95
	2011/12	91.94	83.99	12,359.61	147.20	6.22	1.95
	2012/13	97.16	87.38	10,780.30	123.40	6.89	1.95
	2013/14	95.37	87.67	13,925.15	158.80	4.25-4.75	1.95

1/ Corn and sorghum, September-August; barley and oats, June-May. Latest data maybe preliminary or projected.
2/ U.S. season-average price based on monthly price received by farmers weighted by monthly marketings. Prices do not include an allowance for loans outstanding and government purchases. Latest data are from World Agricultural Supply and Demand Estimates.
Source: USDA, National Agricultural Statistics Service, Crop Production and Agricultural Prices; and USDA, World Agricultural Outlook Board, World Agricultural Supply and Demand Estimates.

Data run: 3/12/2014

Appendix 2 — USDA 2010 ARMS Phase 2 Corn Survey: Selected Sections

The following sections from the USDA 2010 ARMS Corn Survey contain questions that became variables in the multivariate regression.

Project 906 - ARMS Phase II QID 072011 OMB No. 0535-0218 Approval Expires 12/31/2011

USDA

AGRICULTURAL RESOURCE MANAGEMENT SURVEY

CORN PRODUCTION PRACTICES

AND COSTS REPORT

for 2010

NATIONAL AGRICULTURAL STATISTICS SERVICE

U.S. Department of Agriculture, Rm 5030, South Building
1400 Independence Ave., S.W.
Washington, DC 20250-2000
Phone: 1-800-727-9540
Fax: 202-690-2090
Email: nass@nass.usda.gov

VERSION	ID	TRACT	SUBTRACT	T-TYPE	TABLE	LINE
2	__ __ __ __ __ __ __ __ __	01	__ __	0	000	00

ERS ECONOMIC RESEARCH SERVICE

CONTACT RECORD		
DATE	TIME	NOTES

INTRODUCTION:
[*Introduce yourself, and ask for the operator. Rephrase in your own words*.]

We are collecting information on practices and costs to produce corn and need your help to make the information as accurate as possible. Authority for collection of information on the Corn Production Practices and Costs Report is Title 7, Section 2204 of the U.S. Code. This information will be used for economic analysis and to compile and publish estimates for your region and the United States. Under Title 7 of the U.S. Code and CIPSEA (Public Law 107-347), facts about your operation are kept **confidential** and used only for statistical purposes. Response is **voluntary**.

We encourage you to refer to your farm records during the interview.

BEGINNING TIME [*MILITARY*] — H H M M: 0004 __ __ __ __

SCREENING BOX 0006

1 **LAND-USE PRACTICE**	2 **Was this practice used?** **YES = 1**	3 **What year was this practice first used?** **YEAR**	4 **Was** (*or will there be*) **an incentive or cost-share received from:** 1 Environmental Quality Incentives Program (EQIP)? 2 Conservation Security or Conservation Stewardship Programs (CSP)? 3 Conservation Reserve Program (CRP)? 4 Any other Federal, State, Local or non-government source? **CODE**
a. **Structures for soil erosion control?**.	1421		
(i) Terraces.	1420	1441 — — — —	1451
(ii) Grade stabilization structures.	1422	1442 — — — —	1452
b. **Structures for storm water runoff control/handling?**.	1423		
(i) Grassed waterways.	1438	1443 — — — —	1453
(ii) Structures for water control basins.	1424	1444 — — — —	1454
c. **Filter strips or other conservation buffers?**.	1425		
(i) Filter strips.	1426	1445 — — — —	1455
(ii) Field borders.	1427	1446 — — — —	1456
(iii) Riparian buffers (*i.e., grass buffers*).	1428	1447 — — — —	1457
d. **Other Practices?**.	1435		
(i) Contour farming and strip cropping.	1434	1448 — — — —	1458
(ii) Conservation tillage / no-till.	1437	1449 — — — —	1459
(iii) Other Practices [*Specify* __________________] . . .	1436	1450 — — — —	1460

	CODE
28. **Has the Natural Resource Conservation Service** (NRCS) **classified any part of this field as "Highly Erodible"?** . . . . **YES = 1**	1404
29. **Have you been notified by NRCS that this field contains a wetland?** . . . . **YES = 1**	1405
30. **In 2010, did you receive technical assistance for planning, installing, maintaining, or using conservation practices or systems on this field?** (***Include*** *grassed waterways and filter strips or riparian buffers, or drainage area, on or adjoining this field.* ***Include*** *assistance from any source whether paid for or free.*). . . . . **YES = 1**	1406
31. **Is this field included in an existing conservation program contract for which you or the landlord have received** (*or expect to receive*) **cost sharing payments, stewardship payments, or incentive payments?** [*Be sure to consider grassed waterways and filter strips or riparian buffers, or drainage area, on or adjoining this field. Also, be sure to consider payments that are part of this contract but were made before 2010 or payments that are anticipated for future years.*]. . . . . **YES = 1**	1407

[*If item 31 is YES, ask item 31a; else go to item 31b.*]

a. Have you received (*or will you receive*) cost sharing or incentive payments from---	1 Environmental Quality Incentives Program (EQIP) 2 Conservation Security or Conservation Stewardship Programs (CSP) 3 Conservation Reserve Program (CRP) 4 Other Federal, State, Local or non-government source	1418
b. Was this field included in a conservation program application that was rejected from---	1 Environmental Quality Incentives Program (EQIP) 2 Conservation Security or Conservation Stewardship Programs (CSP) 3 Conservation Reserve Program (CRP) 4 Other Federal, State, Local or non-government source	1419

32. **During 2010, did any written plan of the following types cover this field---**
(*A "written plan" is a plan prepared in accordance with Federal, State, or district standards.*)

1 **WRITTEN PLAN TYPE**	2 **Was this type of written plan used?** **YES = 1**	3 **What year was this plan implemented?** **YEAR**	4 **For any practice that is part of this plan, was** (*or will there be*) **an incentive or cost-share payment received from:** 1 Environmental Quality Incentives Program (EQIP)? 2 Conservation Security or Conservation Stew ardshio Programs (CSP)? 3 Conservation Reserve Program (CRP)? 4 Any other Federal, State, Local or non-government source? **CODE**
a. Conservation plan specifying practices to reduce soil erosion?.	1408	1409 __ __ __ __	1461

b. Comprehensive nutrient management plan specifying practices for applying both fertilizer and manure?.	1410	1411 ___ ___ ___ ___	1462
c. Nutrient management plan specifying practices for land application of manure only?.	1412	1413 ___ ___ ___ ___	1463
d. Pest management plan to implement Integrated Pest Management (IPM) practices to control weeds, insects, and/or plant diseases?.	1414	1415 ___ ___ ___ ___	1464
e. Irrigation water management plan specifying practices for applying or conserving irrigation water?.	1416	1417 ___ ___ ___ ___	1465

32. [*If item 32a, b, c, d, or e is YES, ask* ---]

Have you ever paid any technical service provider or consultant to develop or write any of these plans for which you or the landowner were reimbursed by the Natural Resource Conservation Service?. **YES = 1**

CODE 1352

a. [*If YES, ask* ---] **DOLLARS & CENTS**

What was the reimbursement amount for developing these plans for this field? (***Include*** *landlord's/contractor's share.* ***Exclude*** *cost of construction or materials.*). . . . .

PER ACRE **OR** **TOTAL DOLLARS**

1353 .___ ___ 1384

33. **Was the corn in this field covered by Federal Crop Insurance in 2010?**

☐ **YES** – [*Enter code 1 and continue*] ☐ **NO** – [*Go to item* 35]. . . . .

CODE 1385

a. Which coverage did you obtain?. . . . .

1 Basic catastrophic insurance (*Federal CAT*)
2 Buy-up above basic federal CAT level
3 Revenue insurance
4 Organic plan insurance
5 Other Federal Crop insurance

CODE 1386

(i) [*If item a = 3, ask* ---]

What was the level of revenue coverage you obtained for this field?. . . . .

PERCENT 1389

b. In what year did you (*the operator listed on the label*) first enroll this field in the Federal crop insurance program?. . . . .

YEAR 1387 ___ ___ ___ ___

c. What is the 2010 Approved APH (*actual production history*) yield for this field?. . . . .

BUSHELS PER ACRE 1388

d. What was the premium paid for Federal crop insurance for this field in 2010? (***Exclude*** *any sign-up fee.*). . . . .

DOLLARS & CENTS

PER ACRE **OR** **TOTAL DOLLARS**

1390 .___ ___ 1391

CODE e. Did you (*or will you*) collect an indemnity payment for this field from federal crop insurance during 2010?. . . . . **YES = 1**

35. **Was the corn in this field covered by private crop insurance in 2010** (*hail, wind, freeze, etc.*)**?** **CODE**

☐ **YES** – [*Enter code 1 and continue*] ☐ **NO** – [*Go to **Section C***]. 1393

DOLLARS & CENTS

PER ACRE **OR** **TOTAL DOLLARS**

a. What was the premium paid for private crop insurance for this field in 2010? (***Exclude** any sign-up fee.*). . . . . 1395 .__ __ 1396

YEAR

b. In what year did you (*the operator listed on this label*) first purchase private crop insurance for this field?. . . . . 1397 __ __ __ __

CODE c. Did you (*or will you*) collect an indemnity payment for this field from private crop insurance during 2010?. . . . . **YES = 1** 1394

C NUTRIENT or FERTILIZER APPLICATIONS---SELECTED FIELD C

	CODE	**EDIT TABLE**
1. **Were commercial nutrients or fertilizers applied to this field for the 2010 corn crop?**. . . . . **YES = 1**	0202	0201

2. [*If COMMERCIAL nutrient or fertilizer applied, continue; else go to item 7.*] **NUMBER**

3. **How many commercial nutrient or fertilizer applications were made to this field for the 2010 crop?** (***Include** applications made by airplanes and custom applicators*). 0203

4. **Now I need to record information for each application.**

KLIST

✓ **INCLUDE**	✓ **EXCLUDE**
Custom applied nutrients or fertilizers	☐ Micronutrients
Nutrients or fertilizers applied in the fall of 2009 and those applied earlier if this field was fallow in 2009	☐ Unprocessed manure
Commercially prepared manure or compost	☐ Nutrients or fertilizers applied to previous crops in this field
	☐ Lime and gypsum/landplaster

	T-TYPE	**TABLE**
	2	001
LINE 99	**OFFICE USE LINES IN TABLE**	0213

11. **Was a soil test for nitrogen performed on this corn field in 2009 or 2010 for the 2010 crop?** . . . . **YES = 1**

a. [*If nitrogen test done, ask* ---]

POUNDS PER ACRE

How many pounds of nitrogen (*per acre*) were recommended (*by the nitrogen test*)? 0228

CODE

12. **Was a plant tissue test or leaf analysis for nutrient deficiency performed on this field for the 2010 crop?** . . . . **YES = 1** 0229

	DOLLARS & CENTS PER ACRE	OR	TOTAL DOLLARS
13. **How much was spent for these soil and plant tissue tests on this field?** (***Include*** *operator, landlord, and contractor costs*.)	0230 .___ ___		0231

a. If tests were done at no cost, explain--- . . . .

1 Soil/plant tissue test provided free of charge by dealer, crop consultant, or extension service

2 Soil/plant tissue test costs were included in the total fertilizer costs reported in item 6

3 Some other reason

CODE 0232

14. [**ENUMERATOR ACTION***:* *Refer to the Fertilizer Table, column 2. If nitrogen (N) was applied, complete items 15, 16 and 17. If NO nitrogen applied, go to item 18.*]

15. **Was the amount of nitrogen you decided to apply to this field based on ---** **CODE**

a.	Results of a soil or plant tissue test?	**YES = 1**	0233
b.	Crop consultant recommendation?	**YES = 1**	0234
c.	Fertilizer dealer recommendation?	**YES = 1**	0235
d.	Extension Service recommendation?	**YES = 1**	0236
e.	Cost of nitrogen and/or expected commodity price?	**YES = 1**	0237
f.	Contractor recommendation?	**YES = 1**	0238
g.	Routine practice (*operator's own determination based on past experience, yield goal, etc.*)?	**YES = 1**	0239

CODE

16. **Did you purchase any commercial nitrogen fertilizer applied to this field under contract or otherwise pre-purchase the fertilizer at a pre-determined price prior to planting?** . . . . **YES = 1** 0223

a. [*If YES, ask* ---] **CODE**

What month prior to planting for the 2010 crop did you contract for the fertilizer used on this field? [*Enter code "1" for January, "2" for February, etc.*] 0224

13. **Which of the following products did you use to slow the breakdown of nitrogen on this field?** . . . . **CODE**

1 Nitrification inhibitors (*such as N-Serve*)
2 Urease inhibitors (*such as Agrotain*)
3 Chemical-coated fertilizers (*such as sulfur-coated urea and polymer-coated urea*)
4 Other inhibitors
5 None

. . . . 0241

a. [*If nitrogen inhibitors were used, continue; else go to item 18.*]

How much nitrogen inhibitor did you mix with the nitrogen applied to this field? . . . .

POUNDS PER ACRE	OR	GALLONS PER ACRE
0295 .___		0296 .___

b. What was the cost of the nitrogen inhibitors used on this field?
(***Include*** *operator, landlord, and contractor costs*.) . . . .

DOLLARS AND CENTS PER POUND	OR	DOLLARS AND CENTS PER GALLON
0297 .___ ___		0298 .___ ___

References

Anderson, Terry L. and Donald R. Leal. 2001. *Free Market Environmentalism*. Revised ed. New York, NY: Palgrave.

Antonelli, Cristiano. 2003. *The Economics of Innovation, New Technologies and Structural Change*. London: Routledge.

Arias, Esnesto, Hal Eden, Gerhard Fischer, Andrew Gorman, and Eric Scharff. 2000. "Transcending the individual human mind---creating shared understanding through collaborative design." *ACM Transactions on Computer-Human Interaction* 7(1):84-113.

Baptista, Rui. 1999. "Diffusion of Process Innovations: a selective review." *Economics of Business* 6(1):107-129.

Bardgett, Richard. 2005. *The Biology of Soil - a community approach*. Oxford: Oxford University Press.

Barnett, George A. 2011. "Mathmaticial Models of Diffusion Process." Pp. 103-122 in *The Diffusion of Innovations a Communication Science Perspective*, edited by Arum Vishwanath and George A Barnett. New York: Peter Lang Publishing.

Bass, Frank M. 1969. "A New Product Growth Model for Consumer Durables." *Management Science* (15):215-227.

Bass, Frank M., Trichy V. Krishnan, and Dipak C. Jain. 1994. "Why the Bass Model Fits without Decision Variables." *Marketing Science* 13(3):203-223.

Batie, S S. 2008. “Wicked problems and applied economics.” *American Journal of Agricultural Economics* 90(5):1176-1191.

Batte, Marvin T. and Michael W. Arnholt. 2003. “Precision farming adoption and use in Ohio: case studies of six leading-edge adopters.” *Computers and Electronics in Agriculture* 38(2):125-139.

Beckman, Jayson and Michael Livingston. 2012. “Effects of Manure Use and Use Restrictions on Variable Production Costs and Net Incomes for United States Corn Producers.” *Journal of Agricultural and Applied Economics* 44(1):83-97.

Bel, L, D Allard, J M. Laurent, R Cheddadi, and A Bar-Hen. 2009. “CART algorithm for spatial data: Application to environmental and ecological data.” *Computational Statistics & Data Analysis* 53(8):3082-93.

Billen, Gilles, Josette Garnier, and Luis Lassaletta. 2013. “The nitrogen cascade from agricultural soils to the sea : modelling nitrogen transfers at regional watershed and global scales The nitrogen cascade from agricultural soils to the sea : modelling nitrogen transfers at regional watershed and global scales.” *Philosophical Transactions of The Royal Society Biological Sciences* 268(1621):1471-2970.

Bonus, Holger. 1973. “Quasi-Engel curves, diffusion and the ownership of major consumer durables.” *Journal of Poltical Economy* 81:655-677.

Borton, C and R Porter. 2008. “Understanding Soil Nitrogen Dynamics.” 24.

Brouder, Sylvie M. and D B. Mengel. 2003. "The Presidedress Soil Nitrate Test for Improving N Management in Corn." West Lafayette.

Buckley, Cathal, Stephen Hynes, and Sarah Mechan. 2012. "Supply of an ecosystem service—Farmers' willingness to adopt riparian buffer zones in agricultural catchments." *Environmental Science & Policy* 24:101-109.

Campbell, James B. and Randolph H. Vynne. 2012. *Introduction to Remote Sensing*. 5th ed. New York: Guliford Press.

Chambers, P A., G A. Benoy, R B. Brua, and J M. Culp. 2011. "Application of nitrogen and phosphorus criteria for streams in agricultural landscapes." *Water science and technology* 64(11):2185-91.

Chang, Hung-Hao and Richard N. Boisvert. 2009. "Are farmers' decisions to work off the farm related to their decisions to participate in the conservation reserve program?" *Applied Economics* 41:71-85.

Chen, Xiao, Phil Ender, Michael Mitchell, and Christine Wells. 2003. *Regressions with SAS*. UCLA. (http://www.ats.ucla.edu/stat/sas/webbooks/reg/chapter2/sasreg2.htm).

Chen, D, Suter H, A Islam, R Edis, and J R. Freney. 2008. "Prospects of improving efficiency of fertiliser nitrogen in Australian agriculture: a review of enhanced efficiency fertilisers." *Australian Journal of Soil Research* 46:289-301.

Ciampitti, Ignacio A. and Tony J. Vyn. 2011. “A comprehensive study of plant density consequences on nitrogen uptake dynamics of maize plants from vegetative to reproductive stages.” *Field Crops Research* 121(1):2-18.

Claassen, Roger. 2012. “The Future of Environmental Compliance Incentives in U.S. Agriculture The Role of Commodity, Conservation, and Crop Insurance Programs.” Washington DC.

Clay, D, T Reardon, and J Kandasniemi. 1998. “Sustainable intensification in the highland tropics: Rwandan farmers' investments in land conservation and soil fertility.” *Economic Development and Cultural Change* 45(2):351-378.

Clearfield, Frank and Barbara T. Osgood. 1986. “Sociological Aspects of the Adoption of Conservation Practices.” Washington D.C.

Colaco, Andre F., Fabrico P. Povh, Jose P. Molin, and Thiago L. Romanelli. 2012. “Energy assessment for variable rate nitrogen application.” *Agriculture Energy International* 14(3):85-90.

Connor, David J., Robert S. Loomis, and Kenneth G. Cassman. 2011. *Crop Ecology-productivity nd management in agricultural systems*. Cambridge: Cambridge University Press.

Coombs, Rod, Paolo Saviotti, and Vivien Walsh. 1987. *Economics and Technological Change*. Hong Kong: Rowman & Littlefield.

Cooter, E J., J O. Bash, V Benson, and L Ran. 2012. "Linking agricultural crop management and air quality models for regional to national-scale nitrogen assessments." *Biogeosciences Discussions* 9(5):6095-6127.

Coussement, Kristof, Filip A. M. Van den Bossche, and Koen De Bock. 2014. "Data accuracy's impact on segmentation performance: Benchmarking RFM analysis, logistic regression, and decision trees." *Journal of Business Research* 67(1).

Daberknow, Stan G. and William D. McBride. 1998. "Socioeconomic Profiles of Early Adopters of Precision Agriculture Technologies." *Journal of Agribusiness* 16(2):151-168.

De'ath, G and K E. Fabricius. 2000. "Classification and regression trees: a pwerful yet simple technique for ecological data analysis." *Ecology* 81:3178-3192.

Dodd, Stuart C. 1955. "Diffusion is Predictable: Testing Probability Models for Laws of Interaction." *American Sociological Review* 20(4):392-401.

Dow. 2014. "Dow AgroScience." Retrieved 2014 (http://msdssearch.dow.com/PublishedLiteratureDAS/dh_0045/0901b80380045bf3.pdf?filepath=usag/pdfs/noreg/010-40478.pdf&fromPage=GetDoc).

Easingwood, E J. and S O. Lunn. 1992. "Diffusion paths in a high-tech environment; clusters and commonalities." *R & D Management* 1:69-80.

Elliot, Edward T. and C. V. Cole. 1989. "A Perspective on Agroecosystem Science." *Ecology* 70(6):1597-1602.

EPA. 2010. "ource Water Protection Practices Bulletin Managing Agricultural Fertilizer Application Fertilizer Use in Agriculture Why is it Important to Manage Fertilizer Use Near Sources of Drinking Water ?" Washington.

ERS, USDA. 2012a. "(ARMS) Documentation." Retrieved 2013 (http://www.ers.usda.gov/data-products/arms-farm-financial-and-crop-production-practices/documentation.aspx#.Ufwf8ZLEqLg).

ERS, USDA. 2012b. "What is ARMS?" Retrieved 2013 (http://www.ers.usda.gov/data-products/arms-farm-financial-and-crop-production-practices/what-is-arms.aspx#.Ufwd6ZLEqLg).

ERS, USDA. 2012c. "ARMS - Contact Us." Retrieved 2013 (http://www.ers.usda.gov/data-products/arms-farm-financial-and-crop-production-practices/contact-us.aspx#Raw).

Ervin, Christine A. and David E. Ervin. 1982. "Factors Affecting the Use of Soil Conservation Practives: Hypotheses, Evidence, and Policy Implications." *Land Economics* 58(3):277-292.

Ervin, David E. and John W. Mill. 1985. "Agricultural Land Markets and Soil Erosion: Policy Relevance and Conceptual Issues." *American Journal of Agricultural Economics* 67(2):938-942.

FAO. 2002. "World agriculture: towards 2015/2030." Rome.

FAO. 2013. “Contract Farming Resource Center.” Food and Agriculture Organization of the United Nations. Retrieved April 2014 (http://www.fao.org/ag/ags/contract-farming/faq/en/).

Feder, Gershon and Roger Slade. 1984. “The Aquisition of Information and the Adooption of New Technology.” *American Journal of Agricultural Economics* 66:312-320.

Fernandex-Cornejo, Jorge, Chad Hendricks, and Ashok Mishra. 2005. “Technology Adoption and Off-Farm Household Income: The Case of Herbicide-Tolerant Soybeans.” *Journal of Agricultural and Applied Economics* 37(3):549-563.

Field, Scott. 2004. “Global Nitrogen: Cycling Out of Control.” *Environ Health Perspectives*, July, pp. A556-A563.

Frazen, D W. 2011. “Nitrogen Extenders and Additives.” North Dakota State University, Fargo.

Fuglie, Keith O. and Darrell J. Bosch. 1995. “Economic and Environmental Implications of Soil Implications Nitrogen Testing : A Switching-Regression Analysis.” *American Journal of Agricultural Economics* 77(4):891-900.

Galloway, James N., John D. Aber , Jan W. Erisman, Sybil P. Seitzinger, Robert W. Howarth, Ellis B. Cowling, and B J. Cosby. 2003. “The Nitrogen Cascade.” *BioScience* 53(4):341-356.

Galloway, J N., F J. Dentener, D G. Capone, E W. Boyer, R W. Howarth, S P. Seitzinger, G P. Asner, C C. Cleveland, P A. Green, E A. Holland, D M. Karl, A F. Michaels, J H. Porter, A

R. Townsend, and C J. Vorosmarty. 2004. "Nitrogen Cycles: Past, Present, and Future." *Biogeochemistry* 70(2):153-225.

Gardner, Kent and Richard Barrows. 1985. "The Impact of Soil Conservation Investments on Land Prices." *American Journal Agricultural Economics* 67(5):943-947.

Gedikoglu, H and Laura M. J. McCann. 2012. "Adoption of win-win, environment-oriented, and profit-oriented practices among livestock farmers." *Journal of Soil and Water Conservation* 67(3):218-227.

Gedikoglu, Haluk, Laura McCann, and Georgeanne Artz. 2011. "Impact of Off-farm Employment Effects on Adoption of Conservation Practices." *Agricultural Resource Economic Review* 40(2):293-306.

Geroski, Paul A. 2000. "Models of technolgoy diffusion." *Research Policy* 29(4-5):603-625.

Goel, Rajeev K. 1999. *Economic Models of Technological Change: theory and application*. Westport: Quorum Books.

Gould, Brian W. and William E. Saupe. 1989. "Off-Farm Labor Market Entry and Exit." *American Journal of Agricultural and Applied Economics* 71(4):960-969.

Gould, Brian W., William E. Saupe, and Richard M. Klemme. 1989. "Conservation Tillage: The Role of Farm and Operator Characteristics and the Perception of Soil Erosion." *Land Economics* 62(2):167-182.

Greene, William H. 2003. *Econometric Analysis*. 5^{th} ed. New York: Prentice Hall.

Griliches, Zvi. 1957. “Hybrid Corn: An exploration in the economics of technological change.” *Econometrica* 92:501-522.

Hahn, Eugene D. and Refik Soyer. 2005. “Probit and Logit Models: Differences in the Multivariate Realm.” *The Journal of the Royal Statistical Society, Series B*.

Halvorson, Ardell D., Stephen J. Del Grosso, and Francesco Alluvione. 2010. “Nitrogen Source Effects on Nitrous Oxide Emissions from Irrigated No-Till Corn.” *Journal of Environmental Quality* 39:1554-62.

Herold, Nathaniel D., Gregory Koeln, and David Cunningham. 2003. “Mapping Impervious Surfaces and Forest Canopy Using Classification and Regression Tree (CART) Analysis.” Conference Presentation, Anchorage.

Horbach, Jens, Christian Rammer, and Klaus Rennings. 2012. “Determinants of eco-innovations by type of environmental impact — The role of regulatory push/pull, technology push and market pull.” *Ecological Economics* 78:112-122.

Huang, Wen-Yuan, Richard G. Heifner, Harold Taylor, and Noel D. Uri. 2000. “Timing Nitrogen Fertilizer Application to Reduce Nitrogen Losses to the Environment.” *Water Resources Management* 14:35-58.

Huber, Joseph. 2008a. “Pioneer countries and the global diffusion of environmental innovations: Theses from the viewpoint of ecological modernisation theory.” *Global Environmental Change* 18(3):360-367.

Huber, Joseph. 2008b. “Technological environmental innovations (TEIs) in a chain-analytical and life-cycle-analytical perspective.” *Journal of Cleaner Production* 16:1980-1986.

Huffman, Wallace E. 1974. “Decision Making: The Role of Education.” *American Journal of Agricultural Economics* 56(1):85-97.

IBM. 2011. “Tree Growing Process (CART algorithms).” Retrieved 2014 (http://pic.dhe.ibm.com/infocenter/spssstat/v20r0m0/index.jsp?topic=%2Fcom.ibm.spss.statistics.help%2Falg_tree-cart.htm).

Jackson, Jerry. 2012. “Product cuts nitrogen volatiziation, enhancing fertility regimes.” Retrieved 2014 (http://www.thegrower.com/issues/the-grower/Product-cuts-nitrogen-volatilization-enhancing-fertility-regimes-139995033.html).

Katz, Elihu, Martin L. Levin, and Herbert Hamilton. 1963. “Traditions of Research on the Diffusion of Innovation.” *American Sociological Review* 28(2):237-252.

Kemp, Rene and Peter Pearson. 2007. “Final report MEI project about measuring eco-innovation.” Brussels.

Kemp, Rene and Massimiliano Volpi. 2008. “The diffusion of clean technologies: a review with suggestions for future diffusion analysis.” *Journal of Cleaner Production* 16(1):514-521.

Khanna, Madhu. 2001. “Sequential Adoption of Site-Specific Technologies and Its Implications for Nitrogen Productivity : A Double Selectiveity Model.” *American Journal of Agricultural Economics* 83(1):35-51.

Khanna, Madhu, Onesime F. Epouhe, and Robert Hornbaker. 1999. "Site-Specific Crop Management: Adoption Patterns and Incentives." *Applied Economic Perspectives and Policy* 21(2):455-472.

Klerkx, Laurens, Barbra van Mierlo, and Cees Leeuwis 2012. "Evolution of systems approaches to agricultural innovation: concepts, analysis and interventions." Pp. 95-115 in *Farming Systems Research into the 21st Century: The New Dynamic*, edited by D Gibbon and B Dedieu. Dordrecht: Springer.

Knowler, Duncan and Ben Bradshaw. 2007. "Farmers' adoption of conservation agriculture: A review and synthesis of recent research." *Food Policy* 32(1):25-48.

Koch, Bradley and Rajiv Khosla. 2003. "The Role of Precision Agriculture in Cropping Systems." *Journal of Crop Production* 9(1-2):361-381.

Koundouri, Phoebe, Celine Nauges, and Vangelis Tzouvelekas. 2006. "Technology Adoptoin Under Production Uncertainity: Theory and Application." *American Journal of Agricultural Economics* 88(3):657=670.

Lach, Denise, Steve Rayner, and Helen Ingram. 2005. "Taming the waters: strategies to domesticate the wicked problems of water resource management." *International Journal of Water* 3(1):1-17.

Leite, Rui and Aurora A. Teixeira. 2011. "Innovation diffusion with heterogenous networked agents: a computational model." *Journal of Economic Interaction and Coodination* 7(2):125-144.

Lewis, Roger J. 2000. "An Introduction to Classification and Regression Tree (CART) Analysis." Conference Presentation, San Francisco.

Liu, Kui, B L. Ma, and Chaohai Li. 2011. "Nitrogen, Phosphorus, and Potassium Nutrient Effects on Grain Filling and Yield of High-Yielding Summer Corn." *Journal of Plant Nutrition* 34(10):1516-1531.

Mansfield, Edwin. 1961. "Technical Change and the Rate of Imitation." *Econometrica* 29(4):741-766.

Martin, John H., Richard P. Waldren, and David L. Stamp. 2006. *Principles of Field Crop Production*. Upper Saddle River: Pearson Education.

Ma, B L., K D. Subedi, and C Costa. 2005. "Comparison of Crop-Based Indicators with Soil Nitrate Test for Corn Nitrogen Requirement." *Agronomy Journal* 97(2):462-471.

McBrantney, Alex, Brett Whelan, and Tihomir Ancev. 2005. "Future Directions of Precision Agriculture." *Precision Agriculture* 6:7-23.

McBride, D W. and Stan G. Daberkow. 2003. "Information and the Adoption of Precision Farming Technologies." *Journal of Agribusiness* 21(1):21-38.

McCann, Laura. 2013. "Transaction costs and environmental policy design." *Ecological Economics* 88:253-262.

McCarty, John A. and Manoj Hastak. 2007. "Segmentation approaches in data-mining: A comparison of RFM, CHAID, and logistic regression." *Journal of Business Research* 60(6):656-662.

McGinnis, Michelle, Catherine Stokes, and Brenda Cleveland. 2013. “NCDA&CS Plant Tissue Analysis Guide.” Raleigh.

Meade, Nigel and Towhidul Islam 2010. “Modeling and Forecasting Diffusion.” Pp. 376-426 in *Gaining Momentum: Managing the Diffusion of Innovation*, edited by Joe Tidd. London: Imperial College Press.

Melillo, Edward D. 2012. “The First Green Revolution : Debt Peonage and the Making of the Nitrogen Fertilizer Trade , 1840 – 1930.” *American Historical Review* 117(4):1028-1060.

Menard, Scott M. 2009. *Logistic Regression: From introductory to advanced concepts and applications*. Thousand Oaks: Sage Publications.

Mengel, David B. 1986. “Agronomy Guide - Types of Nitrogen Fertilizers for Crop Production.” Purdue University Cooperative Extension Service. Retrieved 2014 (https://www.extension.purdue.edu/extmedia/AY/AY-204.html).

Metcalfe, J S. 1988. “The diffusion of innovations: an interpreative survey.” Pp. 560-589 in *Thechnical adcance and eocnomic theory*, edited by Dosi G Freeman and R R Nelson. London: Frances Pinter.

Miller, Melanie J., Matthew J. Mariola, and David O. Hansen. 2008. “EARTH to farmers: Extension and the adoption of environmental technologies in the humid tropics of Costa Rica.” *Ecological Engineering* 34(4):349-357.

Mishra, Ashok K. and Barry K. Goodwin. 1997. “Farm Income Variablility and the Supply of Off-Farm Labor.” *American Journal of Agricultural Econommics* 79:880-887.

Mitsch, William J., John W. Day, J W. Gilliam, Peter M. Groffman, Donald L. Hey, Gyles W. Randall, and Naiming Wang. 1999. “Redcuing Nutrient loads, especially Nitrate-Nitrogen, to surface water, ground water, and the Gulf of Mexico.” Decision Analysis Series No. 19.

Mosier, Arvin R., Marina A. Bleken, Pronimpol Chaiwanakupt, Erle C. Ellis, John R. Freney, Richard B. Howarth, Pamela A. Matson, Katsuyuki Minami, Roz Naylor, Kristin N. Weeks, and Zhao-Liang Zhu. 2001. “Policy Implications of human-accelerated nitrogen cycling.” *Biogeochemistry* 52:281-320.

Mosier, Arvin R., Marina A. Bleken, Pornpimol Chaiwanakupt, Erle C. Ellis, John R. Freney, Richard B. Howarth, Pamela A. Matson, Katsuyuki Minami, Roz Naylor, Kirstin N. Weeks, and Zhao-Liang Zhu. 2001. “Policy implications of human-accelerated nitrogen cycling.” *Biogeochemistry* 52(3):281-320.

Mowery, David and Nathan Rosenberg. 1979. “The influence of market demand upon innovation: a critical review of some recent empirical studies.” *Research Policy* 8:102-153.

MU-Extension. 2012. “Soil Testing and Plant Diagnostic Services.” University of Missouri Agricultural Extension. Retrieved 2014 (http://soilplantlab.missouri.edu/soil/testfees.aspx).

Mulvaney, R L., S A. Khan, and T R. Ellsworth. 2008. "Synthetic nitrogen fertilizers deplete soil nitrogen: a global dilemma for sustainable cereal production." *Journal of Environmental Quality* 38(6):2295-314.

Napier, Ted L. and Mark Tucker. 2001. "Use of Soil and Water Protection Practices Among Farmers in Three Midwest Watersheds." *Environmental Management* 27(2):269-279.

NDSU. 2013. "Variable Rate Technology - NDSU." Retrieved Oct 2013 (http://www.ag.ndsu.edu/agmachinery/precisionagriculture/variable-rate-technology).

Nelson, D W. and D Huber. 1992. "Nitrification Inhibitors for Corn Production." *National Corn Handbook* 1-6. Electronic verison July 2001.

Nelson, Richard R. and Edmund S. Phelps. 1966. "Investment in Humans, Technological Diffusion, and Economic Growth." *The American Economic Review* 56:69-75.

Nowak, P J. 1987. "The adoption of agricultural conservation technologies: economic and diffusion explanations." *Rural Sociology* 52(2):208-220.

Nowatzki, John, Robert Andres, and Karry Kyllo. 2004. "Agricultural Remote Sensing Basics." Fargo.

NRCS. 2012. "Natural Resource Conservation Service Conservation Practice Standard - Nutrient Management." Washington DC.

O'Brien, Sean M. and David B. Dunson. 2004. "Bayesian Multivariate Logistic Regression." *Biometerics* 60(3):739-746.

OECD. 2001. “Environmental Indicators for Agriculture; Methods and Results.” Paris.

Ostrom, Elinor. 1991. “Rational Choice Theory and Institutional Analysis: Toward Complementarity.” *The American Political Science Review* 85(1):237-243.

Ostrom, Elinor and Xavier Basurto. 2011. “Crafting analytical tools to study institutional change.” *Journal of Institutional Economics* 7(3):317-343.

Pannell , D J., G R. Marshall, N Barr, A Curtis, F Vanclay, and R Wilkinson. 2006. “Understanding and promoting adoption of conservation practices by rural landholders.” *Australian Journal of Experimental Agriculture* 46:1407-1424.

Peters, John B. and Carrie A. M. Laboski. 2013. “Sampling soils for testing.” Madison.

Pingali, Prabhu L. 2012. “Green revolution: impacts, limits, and the path ahead.” *Proceedings of the National Academy of Sciences of the United States of America* 109(31):12302-8.

Pollack, Mark A. 2006. “Rational Choice and EU Polititcs.” Pp. 31-55 in *The SAGE Handbook of European Politics*, edited by Knud Erik Jorgensen, Mark A Pollack, and Ben Rosamond. London: SAGE Publications.

Pretty, Jules. 2008. “Agricultural sustainability: concepts, principles and evidence.” *Philosophical transactions: Biological Sciences* 363(1491):447-465.

Pretty, Jules, William J. Sutherland, Jaqueline Ashby, Jill Auburn, David Baulcombe, Michael Bell, Jeffery Bently, Sam Bickersteth, Katrina Brown, and *et al.* 2010. “The top 100 questions of importance to the future of global agriculture.” *International Journal of Agricultural Sustainability* 8(4):219-236.

Prokopy, L S., K Floress, D Klotthor-Weinkauf, and A Baumgart-Getz. 2008. “Determinants of agricultural best management practive adoption: Evidence from the literature.” *Journal of Soil and Water Conservation* 63(5):300-311.

Qi, Jiayin, Li Zhang, Yanping Liu, Ling Li, Yongpin Zhou, Yao Shen, Liang Liang, and Huaizu Li. 2008. “ADTreesLogit model for customer churn prediction.” *Annals of Operations Research* 168(1):247-265.

Randall, Gyles W. and Jeffrey A. Vetsch. 2005. “Corn Production on a Subsurface-Drained Mollisol as Affected by Fall versus Spring Application of Nitrogen and Nitrapyrin.” *Agronomy Journal* 97:472-478.

Ribaudo, Marc, Jorge Delgado, LeRoy Hansen, Michael Livingston, Roberto Mosheim, and James Williamson. 2011. “Nitrogen in Agricultural Systems: Implications for Conservation Policy.” USDA.

Ribaudo, Marc, Michael Livingston, and James Williamson. 2012. “Nitrogen Management on U.S. Corn Acres, 2001-10.” Washington DC.

Rittel, Horst W. J. and Melvin M. Webber. 1973. “Dilemmas in a General Theory of Planning.” *Policy Sciences* 4(2):155-169.

Roberts , Roland K., Burton C. English , James A. Larson, Rebecca L. Cochran, and *et al.* 2004. “Adoption of Site-Specific Information and Variable-Rate Technologies in Cotton Precision Farming.” *Journal of Agricultural and Applied Economics* 36(1):143-158.

Roberts, Roland K., Burton C. English, James A. Larson, and Rebecca L. Cochran. 2004. "Adoption of Site-Spec Info and VT tech in cotton." *Journal of Agricultural Economics* 36(1):143-158.

Robertson, G P. and Peter M. Vitousek. 2009. "Nitrogen in Agriculture: Balancing the Cost of an Essential Resource." *Annual Review of Environment and Resources* 34(1):97-125.

Rogers, Everett M. 1962. *Diffusion of Innovation*. 1st ed. New York: Free Press.

Rogers, Everett M. 2003. *Diffusion of Innovation*. 5th ed. New York: Free Press.

Rutgers. 2014. "Services & Fees." Rutgers New Jersey Agricultural Experiment Station. Retrieved 2014 (http://njaes.rutgers.edu/soiltestinglab/services.asp).

Ruttan, Vernon W. 1997. "Induced Innovation, Evolutionary Theory and Path Dependence: Sources of Technical Change." *Economic Journal* 107:1520-1529.

Ryan, Byrce and Neal C. Gross. 1943. "The Diffusion of Hybrid SEed Corn in Two Iowa Communities." *Rural Sociology* 8:15-24.

Saha, Atanu, H. A. Love, and Robert Schwart. 1994. "Adoption of Emerging Technologies Under Output Uncertainty." *American Journal of Agricultural Economics* 76(4):836-846.

Schimmelpfennig, David and Robert Ebel. 2011. "On the Doorstep of the Information Age Recent Adoption of Precision Agriculture." Washington.

Schroder, Jaap. 2005. "Revisiting the agronomic benefits of manure: a correct assessment and exploitation of its fertilizer value spares the environment." *Bioresource technology* 96(2):253-61.

Schulte, E E. and K A. Kelling 2013. "Plant Analysis: a Diagnostic Tool." in *NCH-46*, *The Nation Corn Handbook*. Madison. (http://www.extension.purdue.edu/extmedia/NCH/NCH-46.html)

Schumpeter, Joseph A. 1934. *The Theory of Economic Development*. Cambridge: Havard University Press.

Schumpeter, Joesph A. 1934. *The Theory of Economic Development*. Cambridge: Harvard University Press.

Schwab, G J. and L W. Murdock. 2010. "Nitrogen Transformation Inhibitors and Controlled Release Urea." Madison.

Shaver, T M., D G. Westfall, and R Khosla. 2007. "Remote sensing of corn N status with active sensors." Salt Lake.

SIC, Satellite I. C. 2013. "Agricultural Introduction to Satellite Imaging." Retrieved Oct 2013 (http://www.satimagingcorp.com/svc/agriculture.html).

Silva, George. 2011. "MSU field trials indicate that ESN is just as effective and has many benefits compared to anhydrous ammonia, urea and UAN." Michigan State University - Extension. Retrieved 2014 (http://msue.anr.msu.edu/news/slow_release_nitrogen_fertilizers).

Soule, Meredith J. 2001. "Soil Management and the Farm Typology : Do Small Family Farms Manage Soil and Nutrient Resources Differently than Large Family Farms ?" *Agricultural and Resource Economics Review* 30(2):179-188.

Stokes, Maura E. and Charles S. Davis. 2009. *Categorical Data Analysis Using the SAS System*. 2nd ed. Cary, NC: SAS Institute.

Sunding, David and David Zilberman 1999. "Examples include best management practices, variable rate technology, differentiated crops for wildlife biodiversity, and lower emission farm technology." Pp. 1-47 in *Handbook of Agricultural Economics*. Berkley: UC Berkley.

Sutton, M A., J W. Erisman, J Magid, M Amann, and *et al.* 2011. "Too much of a good thing." *Nature* 472:159-61.

Tidd, Joe 2010. "From Models to the Management of Diffusion." Pp. 3-46 in *Gaining Momentum: Managing the Difusion of Innovations*, edited by Joe Tidd. London: Imperial College Press.

Tittonell, P, K D. Shepherd, B Vanlauwe, and K E. Giller. 2008. "Unravelling the effects of soil and crop management on maize productivity in smallholder agricultural systems of western Kenya—An application of classification and regression tree analysis." *Agriculture, Ecosystems & Environment* 123:137-150.

Torbett, J C., Roland K. Roberts, James A. Larson, and Burton C. English. 2008. "Perceived improvements in nitrogen fertilizer efficiency from cotton precision farming." *Computers and Electronics in Agriculture* 64:140-148.

Townsend, Alan R., Peter M. Vitousek, and Benjamin Z. Houlton. 2012. "The Climate Benefits of Better Nitrogen and Phosphorus Management." *Issues in Science & Technology* 28(2):85-91.

Trenkel, M E. 2010. "Slow- and Controlled-Release and Stablized Fertilizers: An Option for Enhancing Nutrient Use Efficiency in Agriculture." Paris.

Tscharntke, Teja, Yann Clough, Thomas C. Wanger, Louis Jackson, Iris Motzke, Ivette Perfecto, John Vandermeer, and Anthony Whitbread. 2012. "Global food security, biodiversity conservation and the future of agricultural intensification." *Biological Conservation* 151(1):53-59.

Upadhyay, R K. and S K. Tewari. 2011. "Natural nitrification inhibitors for higher nitrogen use efficiency , crop yield , and for curtailing global warming." *Journal of Tropical Agriculture* 49(1-2):19-24.

Upadhyay, Bharat M., Douglas L. Young, Holly H. Wang, and Philip Wandschneider. 2002a. "How do farmers who adopt multiple conservation practices differ from their neighbors?" Conference Presentation, Long Beach.

Upadyay, Bharat M., Douglas L. Young, Holly H. Wang, and Philip Wandschneider. 2002b. "How do farmers who adopt multiple conservation practices differ from their neighbors." Long Beach.

USDA. 2009. "Plant Biotechnology Endorsement Insurance Standards Handbook." United States Department of Agriculture, Washington DC.

USDA. 2013. "Fertilizer Use and Prices." Retrieved 2014 (http://www.ers.usda.gov/data-products/fertilizer-use-and-price.aspx#.UwBIqvldVqF).

USDA. 2014a. "Feed Grains: Yearbook Tables." Retrieved April 2014 (http://www.ers.usda.gov/data-products/feed-grains-database/feed-grains-yearbook-tables.aspx#.U0H-9fldVqF).

USDA. 2014b. "United States Deartment of Agriculture - National Agricultural Statistics Service." Retrieved 2014 (http://www.nass.usda.gov/Quick_Stats/Lite/).

USGS. 1999. "Nitrogen and Water." Retrieved 2014 (http://water.usgs.gov/edu/nitrogen.html).

van Grinsven, H J. M., H F. M. ten Berge, T Dalgaard, B Fraters, P Durand, A Hart, G Hofman, B H. Jacobsen, and *et al.* 2012. "Management, regulation and environmental impacts of nitrogen fertilization in Northwestern Europe under the Nitrates Directive; a benchmark study." *Biogeosciences Discussions* 9(6):7353-7404.

Vanegreen, Jessica. 2014. "Manure digesters seen as best hope for curbing lake pollution, but drawbacks remain." The Capital Times. Retrieved April 2014 (http://www.wiscnews.com/baraboonewsrepublic/news/state-and-regional/article_e4c6bda3-e2ab-5727-9e49-cd002b8a5c4a.html).

Vitousek, Peter M., John D. Aber, Robert W. Howarth, Gene E. Likens, Pamela A. Matson, David W. Schindler, William H. Schlesinger, and David G. Tilman. 1997. "Human Alteration of the Global Nitrogen Cycle: sources and consequences." *Ecological Applications* 7:737-750.

Warner, Keith D. 2008. "Extension Practice Agroecology as Participatory Science Emerging Alternatives to Technology Transfer Extension Practice." *Technology & Human Values* 33(6):754-777.

Weber, Alan W. 2005. *Data-Driven Business Models*. Mason: Thompson Higher Education.

Welch, Finis. 1970. "Education in Production." *Journal of Political Economy* 78:35-59.

Williamson, James M. 2011. "The Role of Information and Prices in the Nitrogen Fertilizer Management Decision : New Evidence from the Agricultural Resource Management Survey." *Journal of Agricultural and Resource Economics* 36(3):552-572.

Wozniak, Gregory D. 1986. "Human Capital, Information, and the Early Adoption of New Technology." *Journal of Human Resources* 22:102-112.

Zhang, Xiaodong, Lijian Shi, Xinhua Jia, George Seielstad, and Craig Helgason. 2010. "Zone mapping application for precision-farming: a decision support tool for variable rate technology application." *Precision Agriculture* 11:103-114.

Zheng, Haifeng, Liding Chen, Xiaozeng Han, Xingeng Zhao, and Yan Ma. 2009. "Classification and regression tree (CART) for analysis of soybean yield variability among fields in Northeast China: The importance of phosphorus application rates under drought conditions." *Agriculture, Ecosystems & Environment* 132(1-2):98-105.