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Performance of Upland Cotton Under a Hairy Vetch Regiment From a Crop Insurance Perspective

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PERFORMANCE OF UPLAND COTTON UNDER A HAIRY VETCH REGIMENT FROM A CROP INSURANCE PERSPECTIVE

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ABSTRACT

Cover crop's value from a policy perspective lies in potential environmental benefits if used en masse including waterway protection from farm runoff, reducing soil erosion, and sequestering carbon. The ultimate decision to adopt cover crops lies with farmers however and their decisions are largely driven by business performance. Because of this, economic research into cover crops has mostly revolved around factors influential to farmer's adoption decisions with direct and indirect policy effects being lesser researched. Crop insurance, a nearly ubiquitous federally administered risk management tool for farms in the United States, is often cited as a suspected negative influence for the adoption of cover crops. Little is known about how cover crops and crop insurance interact despite the suspected interference of crop insurance on adopting cover crops. This study investigates how a hairy vetch treatment on cotton yields are likely to affect crop insurance claims. We conduct our study by looking at the extensive and intensive margins of crop insurance payouts for cotton farm adopting hairy vetch. Additionally, this study investigates how insurance payouts change at various coverage levels, effectively determining the catastrophic and shallow loss changes to yield risk from cover crop adoption. Findings indicate that cover crops perform well in reducing the intensive and extensive margins of catastrophic losses, but not as well for reducing shallow losses. Hairy vetch when paired with cotton in this setting appears to be a useful tool for reducing risk when ensuring a crop at high coverage levels and provides little benefits when insuring at low coverage levels.

CHAPTER 1. INTRODUCTION

Policy Interest

Conservation in agriculture and particularly the use of cover crops has become a significant policy piece in the last few years. The growth in farm acreage, the increased risk of soil erosion, nutrient loss, and the effect these can have on neighboring environments have been at the forefront of recent policy debates. In response, the US Farm Bill, updated every five years, has seen the proportion of the farm budget increase from approximately $4 billion per year in 1996 to approximately $6 billion per year as of the most recent bill passed in 2018 with projections into 2023 holding around $6 billion per year. In light of the significant push for adoption of conservation practices on farms, the slow pace of adoption of some conservation practices, particularly cover crops, on modern farms remains of interest to both policy makers and researchers alike.

Cover crops are crops planted in the off season of the primary crop to be harvested, that serve many purposes such as reinforcing soil against erosion, adding nutrients back to the soil, and controlling certain weeds and pests. These crops will not be harvested and are usually plowed under before planting the main crops. Cover crops provide many benefits such as sequestering of soil organic carbons, reducing nutrient losses via replenishment, and protecting from erosion to name a few (Ku et al., 2017). Cover crops also provide many off-farm benefits such as providing food and shelter for beneficial insects, reducing farm runoff, and reducing the amount of chemicals that lech off farms by acting as nutrient stores. Working as nutrient stores, cover crops capture chemicals that would normally penetrate past the root zone and when they are plowed under slowly reintroduce those nutrients to the soil for the coming crop to utilize (Kladivko and Gee, 2012).

Cover crops see relatively low use around the country with the Northeastern Region seeing the highest rates of adoption at 12.54%. The Southeast region coming in at second place averages 6.11% adoption, less than half of the Northeast Region, with the Midwest region coming in at 5.44% and the Pacific West and Plains Regions trailing in at 2.57% and 2% respectively as shown in figure 1.1, a graph using averages of state data from a University of Illinois Farmdoc publication (Zulauf and Brown, 2019).

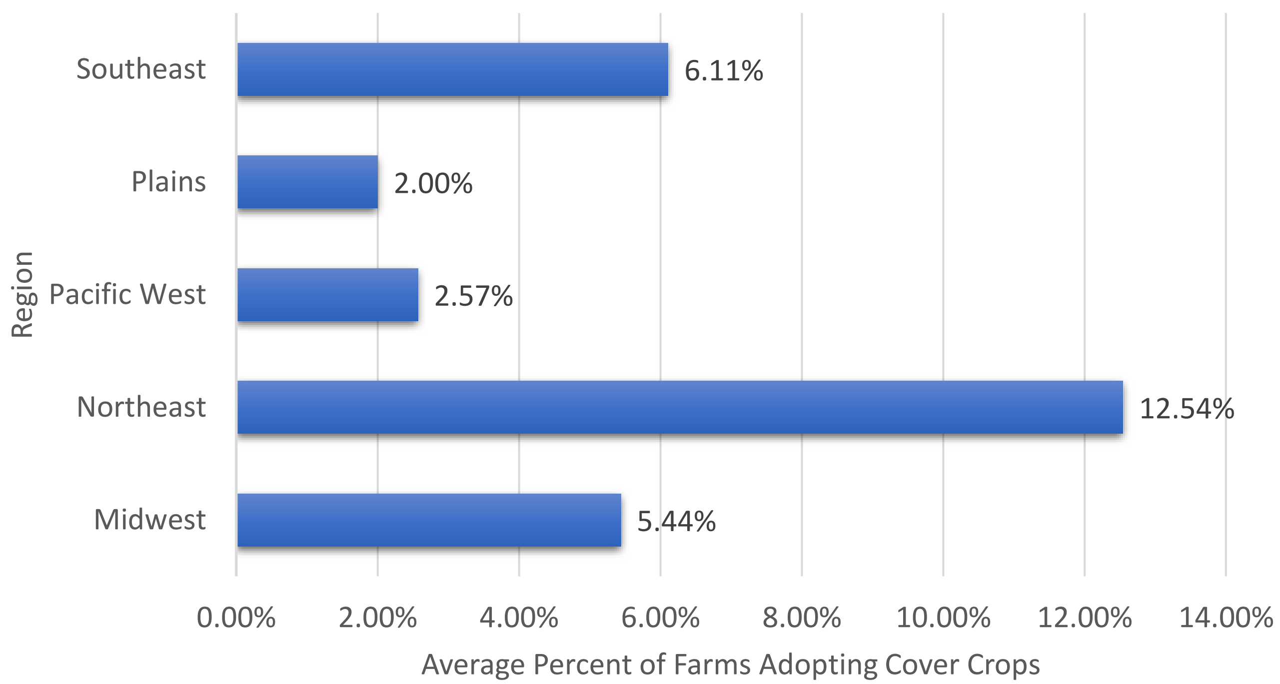

Figure 1.1. **Average Percent of Croplands that Adopt Cover Crops by USDA ARS Regions 2012-2017**

1. Regions consist of: Midwest (MN, IA, MO, WI, IL, MI, IN, OH, KY), Northeast (ME, VT, NH, NA, CT, RI, NY, PA, NJ, VA, WV, DE, MD), Pacific West (WA, OR, ID, CA, NV, UT, AZ), Plains (MT, ND, SD, WY, NE, CO, KS, NM, OK, TX), Southeast (AR, LA, MS, TN, AL, NC, SC, GA, FL)
2. Data sourced from Zulauf and Brown, 2019

A general explanation for the low rate of cover crop adoption across most of the United States is a fundamental issue with all business decisions: up-front costs and uncertainty about benefits outweigh the benefits for many farmers. This problem is especially prevalent in the establishment period where cover crops are costing money but not yet providing the previously stated benefits. Reimbursements are an obvious answer to incentivize the use of cover crops but the intricacies of how and why such a subsidy should be granted are thick.

To better understand the factors affecting cover crop adoption, several studies have been conducted that have shed light on the issue. Consistently, uncertainty of cover crop benefits, management time and the cost of adoption relative to the benefits have appeared as significant factors affecting the adoption of cover crops (McCann et al. 2019, McNally et al. 2017, Noland et al. 2018, Plastina et al. 2020, Thompson et al. 2021). Crop insurance has been named as a potential contributor, yet the literature is sparse on the contribution of crop insurance to low cover crop adoption rates and the question remains an open debate. Additionally, the role that crop insurance plays is often linked to rules for terminating cover crops set up by the NRCS that may disqualify a farmer from obtaining crop insurance coverage. The NRCS cover crop termination rules have since been adjusted for different zones as of the 2018 farm bill, and as such, many believe that issue has now been resolved, but low cover crop adoption rates remain.

In this thesis we investigate what differences in yields and by extension risk a cover crop provides over time compared to other farming. Understanding how cover crops perform in the role of improving the ensuing primary crop can potentially answer questions of why cover crop adoption rates are low. If cover crops are found to provide a great enough benefit, new policies that encourage their use could be argued for. Conversely, if cover crops are not shown to significantly improve yields, their encouragement could be framed more as an ecologically beneficial practice.

Literature Review

Crop insurance is a widely adopted protective measure for farmers in the United States and like any other cost, it has an impact on their business decisions. O’Connor (2013) notes that many farmers rely on the subsidized crop insurance as their main risk mitigation, and that the program fails to incentivize diversifying risk management. Cover crops are a particularly potent guard against low yields, erosion, and certain pests, but because of the heavy upfront cost and delayed benefits, their use is scarce in regions such as the Southern and Western United States. Many of the states with the lowest cover crop usage rates are in dry regions of the north such as the Dakotas and Montana, but other states with very wet climates such as Louisiana have similarly low usage rates (Zulauf and Brown, 2019). The exact reasons for low levels of cover crop use are difficult to pinpoint as there are many factors influencing farmers’ decisions, but there is a suspicion that crop insurance’s immediacy of risk protection has some degree of influence.

Little research has been done on the economic relations of cover crops to other land conservation practices which is problematic for those looking to promote the practice. This is detrimental as having more tools for farmers to affordably and effectively bolster their farms reduces the risk of ex ante moral hazard, choosing not to take precautions to reduce risk. Multiple questions are open on this topic but a question foundational to any potential programs to encourage the practice is: do cover crops provide risk mitigating services on farms and to what degree? The benefits cover crops provide are of high importance to answering many questions both for policy formation and extension work. Research in this area could influence conservation policy, clarify relationships between crop insurance and other farm management decisions, and improve understanding of cost benefit ratios.

Like most other types of insurance, crop insurance reduces the risk to the individual by spreading the cost of losses across a network of insured premium payers, allowing farmers to be more affordably insured. In the United States crop insurance is a Federally governed program with the national farm bills dictating the rules of the various sub programs and private companies selling and paying out the insurance. Participation in some sort of crop insurance program is high today but this is largely attributed to high government subsidization of the programs. From 1980 to 1993 participation rates were below 30% but with the 1994 farm bill introducing the subsidies, and subsequent farm bills increasing those subsides, over 80% of eligible acres are insured in some way (Glauber, 2013).

Crop insurance has many different program offerings called insurance plans, but the insurance plans can broadly be classified on whether they indemnify the losses from a yield or a revenue standpoint or whether they insure individual or area losses. Farms' acreage can be insured at many different coverage levels and based on the chosen risk loss level and county level (for individual plans) or National Agricultural Statistical Service (NASS) yield data (for area plans); a premium is calculated. The RMA crop insurance premium is intended to be actuarily fair and representative of the risk exposure of a farm. The impact of past yields on future coverage in the APH system are also thought to reduce moral hazard incentives (Mieno et al., 2018). However, the slow accumulation of (any) yield benefits for farms adopting cover crops will not be reflected in APH based rates and would fail to incentivize practices with delayed benefits such as cover crops. Such an issue has already been identified in the literature. As noted by Sherrick and Schnitkey (2011) "Because APH yields lag expected yields, guarantees will also lag" indicating a need for accommodations in some insurance cases. Their paper goes on to explain how starting in 2012, Illinoi's implementation of a Trend Adjusted-APH for its counties to allow for more accurate insurance rating. Just as yields can be underestimated by crop insurance, risk can be overestimated on a farm despite practices to reduce it.

Crop insurance's current ubiquity provides an avenue to encourage cover crop adoption by accounting for their potential risk reduction more accurately in crop insurance premium calculations via a premium discount, similarly to Illinois' program to adjust APH values to be closer to true yields. Discounts have been shown in to be effective in increasing cover crop participation for corn farms indicating promise in the idea (Noland et al., 2018). In addition to the general idea of adjusting premiums, some of the future savings could be reflected in the early months before soil improvements present to offset startup costs. Quantifying the impact of cover crops may be difficult as they happen very slowly and subsidizing a difficult to measure activity opens up a concern for moral hazard. Because of this, adverse selection should be considered for any program involving payments or discounts.

Live natural testing of cover crop efficacy would be a very imprecise process and as such a more controlled study would be preferred. Fortunately, a rather unique set of controlled data is available courtesy of the LSU AgCenter. From 1959 to 1988, the LSU AgCenter Red River Research Station in Bossier City Louisiana kept four experimental plots of upland cotton: a control, a standard nitrogen treatment, a high dose nitrogen treatment, and a hairy vetch cover cropped. The yields of these four plots were recorded for 30 years and the only modification of treatment to the plots was the implementation of an irrigation system in 1970. The plots have many differences from actual cotton farms such as a lack of crop rotation and any fertilization or pesticide use but their relatively sterile environments allow for observation of the effects cover crops have on cotton growing with more objectivity.

Using the data from the Red River Research Station's cotton plots, I will explore the effects of cover crops on risk reduction. Hairy vetch planted in companionship with upland cotton will be the stand in for cover cropping in general for the purposes of this study. The risk reduction will be investigated via comparison of the risk values and insurance rates based on the risk values. The time taken for hairy vetch to show effects on the yield will also be investigated as this will determine the length of a potential early discount to insurance rates to reflect the expected future savings. There are some limitations to the dataset this study is using, the small size and unrealistic setting of the experimental plot data. Statistical simulations will be used to add robustness to the dataset but for this study it will be assumed that statistical plot data is similar to farm data. Any results from this study should be reinvestigated using on farm data, when possible, to increase validity of findings.

CHAPTER 2. BACKGROUND AND PROCEUDRES

CROP INSURANCE BACKGROUND

Risk comes in many forms for farmers and many different tools such as futures contracts, vertical integration, and diversification are used to protect against it. Crop insurance is the main tool modern American farmers use to mitigate risk concerning their crops with 87% of acres of the major 4 crops (corn, wheat, soybeans, and cotton) being covered with crop insurance as of 2018 (Farm Bureau, 2019). Despite federal crop insurance existing in some way since 1938, participation did not reach high levels until the1994 farm bill when the modern program was developed (Glauber, 2013). The basic principle behind the modern federal crop insurance program is in the event of an agricultural loss, federally regulated and subsidized insurance plans will pay farmers the amount insured of their loss. This amount can be based on either lost yield or a direct lost revenue calculation and plans vary in their coverage; catastrophic events such as hurricanes are covered separately from below average yields due to low rainfall for example.

Branching from the broad categories of yield loss and revenue loss, the four main types of insurance policy are individual yield loss, individual revenue loss, area yield loss, and area revenue loss. The distinction between individual and area-based policies is that individual policies calculate losses for an individual farm's acreage whereas area based considers an entire county or other region that the insured farm is located in. Yield based policies are designed to protect against direct crop losses due to natural causes such as poor weather, pests, and disease by comparing an insured year to the average production of either the farm or the region. Revenue based policies provide protection to indirect losses such as market declines and some natural causes by comparing current insured prices to a held commodity price and paying the difference if a loss occurs.

Crop insurance is offered at multiple coverage levels ranging from 50% to 85 % in 5 percentage point increments. The coverage percentage is the level of production guaranteed by the policy compared to an average production history (APH) yield either of an individual farm or a region. For clarification, an 85% coverage level plan on a supposed APH of 150 bushels per acre of crop x would guarantee a policy holder 127.5 bushels per acre of crop x. If the insured farmer had a bad crop year and instead receive yields only 100 bushels per acre, his plan would pay out for the missing 27.5 bushels per acre. The different coverage levels exist to better suit the risk reduction needs of individual farmers; a farmer in a region with a moderate climate growing a stable crop may not feel the need to be as strongly insured as a farmer dealing with more divergent weather and volatile crops.

The premiums paid on a crop insurance policy is based on several factors that can be summed up as the risk evaluation. How risk is determined in rate making differs from policy to policy, but it generally revolves around historic data (USDA, 2019). Policies focusing on individual yields have rates made by comparing a historic average yield for the crop in question to the actual yields over time for the farm to be insured. Area yield rating is based on an average of historic county yields from NASS records that date back at least 30 years. Dollar based revenue models work by comparing previous insurance payouts with spans of yield data. Income protection models make their rates using a combination of factors for a more complete picture including the historic prices of the commodity, the individual's historic yields, the county's historic yields, and notional trends in that commodity's yields. Replacement coverage models make rates very similarly to dollar-based models, but an extra variability rate is included.

The premium rates are meant to reflect the risk protected against and it is possible for farmers to actively work at lowering their premium, similar to how a homeowner can do things to lower their home insurance costs. Long term use of good agricultural practices can add positively to historic yields used for crop insurance rating. Management activities that increase yields such as implementing irrigation, amending soil as needed, using herbicides and insecticides to reduce weeds and pests, and many more can help reduce crop insurance premiums. Many other tactics can be used to indirectly reduce risk, and therefore premiums, but not all practices impact insurance premiums as expected.

Crop insurance has some flaws, the main one for this discussion being how slowly crop insurance premiums adjust to changing conditions and as such, often does not accurately reflect current farming conditions. The historic yields used for rate making typically focus on a moving 10-year window known as the APH which as some weaknesses. This issue is discussed by Sherrick and Schnitkey in their 2011 publication where they acknowledge that if crops have yields that increase with time (as many do with technological improvements) the current yield will be significantly drug down in the average when rates are calculated. Because of this issue it could be considered that crop insurance rates as they currently exist in most states are not being calculated fairly. In Illinois however, there has been an effort to correct this with a trend adjusted APH (TA-APH) that compensates by adding the value of yield trend to each year in the APH multiplied by its distance from the current year (Sherrick and Schnitkey, 2011). This brings older yields in line with current rising ones to create an average that much more fairly represents production for insurance purposes.

COVER CROP BACKGROUND

The USDA defines cover crops as “a crop generally recognized by agricultural experts as agronomically sound for the area of erosion control or other purposes related to conservation or soil improvement” (USDA, 2018). Cover crops encompass a variety of plants, but most can be classified as grasses or legumes such as oats and ryegrass or crimson clover or hairy vetch respectively (Magdoff and Es, 2021). Magdoff and Es note that grasses excel in “scavenging nutrients from the previous crop” because of their wide root systems, which also help anchor soil against erosion and can choke weeds. Magdoff and Es describe Legumes as being better suited to enriching poor soils by fixing atmospheric nitrogen into the soil and by attracting pest controlling insects.

Oats can be used as a cover crop that performs well in cooler climates according to the SARE and does particularly well in colder climates where winter frost will kill the cover crop in preparation for spring planting. They can also be planted in spring as a spring weed suppressant, oats also can be killed easily by mechanical or chemical means with minimal discing required (SARE, 2018). Oats grow quickly and do a good job of choking weeds with their extensive growth while soaking up excess nitrogen for better soil balances and can also balance some phosphorus and potassium levels if planted early enough. In addition to their growth, oats’ ability to choke weeds comes from their natural herbicidal compounds in the roots which necessitates waiting approximately three weeks after terminating the cover crop to reduce negative effects on the main crop.

Ryegrass excels in quickly building soils due to its fast-growing shallow root system that reduces erosion and improves soil drainage and water infiltration. Ryegrass performs these functions even in subpar soil, rocky soil, and wet soils with moderate flooding. Ryegrass can recycle excess nitrogen in the soil and prevent it from leaching out, but does not provide the nitrogen a legume cover crop would. It does however do a decent job suppressing weeds and performs well as a mulch for corn or soybeans in no-till systems (SARE, 2012).

Crimson Clover is a popular cover crop that has many uses throughout the year for both long or short term plantings. Clover planted in the fall in warmer climes typically survives the winter and extends its usefulness into the spring as a weed suppressant. Clover is a good source of nitrogen with the SARE stating a contribution of 70-150 lbs./acre that performs typical legume nitrogen fixing and by scavenging mineralized nitrogen. Crimson clover is unfortunately a vector for pests such as the corn earworm and the cotton bollworm which can make it a liability for some farmers.

Hairy vetch, the cover crop used in the experimental cotton plots at the Red River Research Station, has properties that suit it well for accompanying a cotton crop. Firstly, hairy vetch provides a high level of nitrogen to the soil, and according to the SARE, hairy vetch alone can replace nitrogen fertilizer for cotton (SARE, 2012). Additionally, the SARE states that hairy vetch can work well for continuous no till cotton systems and "Vetch mixed with rye has provided similar or even increased yields compared with systems that include conventional tillage, winter fallow weed cover and up to 60 pounds of N fertilizer per acre.". They acknowledge that a cover crop system can incur additional costs compared to conventional fertilization practices but add that hairy vetch aids in preventing soil erosion and runoff. The root system of a hairy vetch crop provides improving water's flow through the soil which aside from the runoff and erosion benefits, allows soil to drain better which suits cotton very well.

The improvements in soil health cover crops can bring are not disputed with many papers referencing their beneficial characteristics such as Bertgold et al. (2012, 2017), Midwest Cover Crops Council (2015), Carlisle (2016), Stockwell and Moseley (2017), and Myers (2019). Despite the consensus that when used as directed by agency standards they can considerably improve a farm's health over time, usage of cover crops is not particularly widespread. Most US states plant cover crops on less than 10% of cropland, and many states plant at less than 5% (Zulauf and Brown, 2017). Speculation as to why so few farmers choose to grow cover crop suggests many possible factors ranging from lack of knowledge to concerns about complicated crop insurance rules but there is no one major cause accepted (Carlisle, 2016; Stockwell and Moseley, 2017).

Environmentally beneficial farming practices often have significant upfront costs that disincentivize their use and for that reason the USDA subsidizes them with environmental quality incentives program (EQIP) payments. These payments incentivize farmers to take up practices they may not otherwise participate in, but they are not the only way to incentivize better farming practices. Cover crops are partially supported already by EQIP payments but there is potential for another non subsidy incentive to further encourage their use. Cover crops reduce the risk on a farm; if this can be taken into account when calculating rates for crop insurance (such as the Illinois TA-APH) an effective discount could be warranted for using cover crops. Calculating the risk saved is only part of the solution however, the full benefits of cover crops are not realized until they become established over a period of a few years. Shifting some of the future cost savings to the present would be a great way to reduce the burden of the setup period costs while still accurately reflecting long term benefits in risk reduction the cover crops will provide.

COVER CROP AND CROP INSURANCE BACKGROUND

Crop insurance can be supplemented in its risk reduction in many ways and one potentially beneficial fit is cover crops. Crop insurance and cover crops can be used in tandem, but the match is not perfect at present. Crop insurance and cover crops both carry a cost and while crop insurance provides its full benefits as soon as premiums are paid, cover crops take time to add their full benefits to a field. During this startup period if a farmer were to both use crop insurance and a cover crop, they would be incurring extra expenses for no immediate additional benefit (Plastina et al., 2018). Aside from the costs of establishing a cover crop, cover crops must be terminated in time to plant the main crop, a process that costs extra labor, machine hours, and herbicide use depending on the crop (Wallander et al., 2021). Additionally, once the cover crop has come into its full benefit period there is a potential issue that is not discussed often in the relevant literature.

Costs aside, there are many rules concerning when cover crops can be planted alongside insured crops. USDA rules state that for a cash crop following a cover crop to be insurable, the cover crop must be a generally acknowledged crop used for this purpose, must have been planted in the past calendar year, and must be managed and terminated according to Natural Resources Conservation Service (NRCS) rules (USDA, 2018). Some cover crops are allowed to be harvested as hay or silage, and livestock grazing may also be permitted depending on the specific Risk Management Agency (RMA) rules surrounding the insurance policy on the main crop. Cover crops are often best kept separate from the main crop as if a cover crop and main crop inhabit the field at the same time and cannot be managed separately, the cash crop will not be insured. However, if the cash and cover crops can be managed separately while cohabitating, the cash crop can be insured as normal.

Considering all the costs of cover crops as well as the rules required to integrate them into a crop insurance plan, farmers may reasonably wonder about the hard benefits of integrating them into their risk management strategy. Even if the benefits cover crops provide to risk reduction are significant, there is a risk that they could overlap with the protection provided by crop insurance and not be accurately reflected by premium calculations. Risk redundancy is not a topic discussed in the literature, but it is a possibility that should be considered as another obstacle to combining cover cropping and crop insurance. Delayed or reduced benefit realization from an insurance perspective and general resistance to any new and costly techniques could be resolved by easing the costs to farmers or even offering increased financial incentives to adopt the practice as is done in Maryland and Delaware, but high state level incentives aren't offered in most of the United States and alternatives should be formulated (Zulauf and Brown, 2017).

Instead of a direct subsidy on crop insurance premiums, a revised premium rating plan that both accounts for the benefits accrued over time by cover crops and brings some of the savings to the future is the subject of interest for this thesis. The question is: do cover crops provide a benefit to farms in the form of risk reduction through higher, more stable yields, and is it enough of a benefit to justify discounting crop insurance premiums proportionately? Bringing some of the future savings to the present could potentially alleviate some of the financial burden of setting up a cover crop and potentially make the practice more approachable to farmers. This idea will be investigated by using the data and comparing the rates of insurance event triggers (extensive margins), and the size of insurance triggers (intensive margins) for four different fields of upland cotton from the LSU AgCenter Red River Research Station using 30 years of yield data ranging from 1959-1988.

PROJECT DATA

The dataset used for base analysis shown below in table 2.1 was collected from four different experimental plots growing upland cotton at the LSU AgCenter Red River Research station in Bossier City, Louisiana; It covers 30 years from 1959-1988 and is recorded in pounds of lint per acre. The four plots observed were subjected to three different treatments to improve the soil with one plot being held as a control. The three treated plots were treated with: a cover crop of hairy vetch, a standard nitrogen treatment of 44.8 kg/ha, and a 1.5 times standard nitrogen treatment of 67.3 kg/ha. The experimental plots were given constant treatments for the duration of the data period with the exception of irrigation being introduced unilaterally in 1970. The hairy vetch (henceforth referred to as h_vch) and the 1.5 Nitrogen (henceforth referred to as N5) treated plots from the Red River Research Station were chosen as the two plots of comparison. The increased nitrogen regiment was considered the best comparison for the hairy vetch treatment as both are intended to introduce extra nitrogen into the soil for better growth and the check was excluded as it is unrealistic for farmers not to amend their soils in any way.

Table 2.1.

RAW YEILD DATA FROM RED RIVER RESEARCH STATION 1959-1988

	Check	**Hairy Vetch**	**N 1**	**N 5**
Min	**507**	**902**	**963**	**988**
Max	**2576**	**4028**	**3566**	**3533**
Mean	**1224.43**	**2221**	**1995.9**	**2083.73**
STDEV	**522.56**	**598.81**	**602.32**	**620.74**

1.Data Recorded as Lbs./acre

2. Check represents the control plot, Hairy Vetch the hairy vetch cover crop treated plot, N1 the standard nitrogen amended plot, and N5 the 1.5 times standard nitrogen amended plot

Table 2.2.

RAW YIELD DATA PRE-IRRIGATION 1959-1969				
	Check	**Hairy Vetch**	**N 1**	**N 5**
Min	**839**	**902**	**963**	**988**
Max	**2576**	**2933**	**3260**	**3533**
Mean	**1480.55**	**1969.45**	**1918.55**	**2043.73**
STD	**577.32**	**612.21**	**713.07**	**804.30**

1.Data Recorded as Lbs./acre

2. Check represents the control plot, Hairy Vetch the hairy vetch cover crop treated plot, N1 the standard nitrogen amended plot, and N5 the 1.5 times standard nitrogen amended plot

Table 2.3.

RAW YIELD DATA POST-IRRIGATION 1970-1988				
	Check	**Hairy Vetch**	**N 1**	**N 5**
Min	**507**	**1386**	**1226**	**1290**
Max	**1869**	**4028**	**3566**	**3329**
Mean	**1076.16**	**2366.63**	**2040.68**	**2106.89**
STD	**437.59**	**555.35**	**544.27**	**509.77**

1.Data Recorded as Lbs./acre

2. Check represents the control plot, Hairy Vetch the hairy vetch cover crop treated plot, N1 the standard nitrogen amended plot, and N5 the 1.5 times standard nitrogen amended plot

Experimental data was chosen for a few reasons: the scarcity of detailed farm level data using cover crops, the consistent treatment of the observed plots, and the clear differences in the experimental plots for comparison. A disadvantage of using experimental data is that many of the interactions that take place between different productions factors are absent in the experimental setting. This lack of interactions cannot be accounted for and as such any interpretations made from research using experimental data must be considered an estimate at best for comparing to real farming data. For the purpose of investigating cover crop efficacy, the lack of live farm data is especially unfortunate as real farms perform several significant changes to their fields including soil amendments, crop rotations, and changing chemical regiments. One significant change that does place in our data however is the introduction of irrigation in 1970. This a change that does occur across many farms, which as shown in tables 2.2 and 2.3, seems to have improved yields in most cases and tightened the standard deviations. Costs of inputs make a large impact on a farmer’s decisions throughout the year and this is reality is lost when using static experimental plots. Despite the numerous disadvantages stated, experimental data was the more viable choice for this study mostly due to availability.

PROJECT PROCEDURES

DETRENDING DECISIONS AND HETEROSKEDASTICITY TEST

Before modeling decisions were made, the data was detrended and checked for heteroskedasticity as it is a common issue with agricultural data as noted by Ker and Coble (2003), Zhu, Godwin, and Ghosh (2011), and Ker and Tolhurst (2019). A major reason for detrending agricultural yield data is that in typical farming environments, vast improvements made to farming methods, technology, and seed stock over time make older yields less comparable with recent ones (Goodwin and Mahul, 2016). The experimental research plots used remained relatively static in their farming methods, but because of the irrigation introduced in 1970, this type of trend could not be discounted. A chow test was performed on the datasets and determined 1970, the year irrigation was introduced, was indeed a break year with a p value of

$7.61e^{-5}$. Concerning heteroskedasticity, in agricultural settings it usually arises from technological change over time, but with the base data being sourced from a relatively stable experimental plot this was less likely. The raw yield data for the plots of interest (Hvch and N5) was detrended by using a simple quadratic regression that can be written as $Y_{it} = T_i + I_t + Q_{it} + e_{it}$ where Y represents yield, i represents the type of plot treatment (h_vch or n5), t represents irrigation (starting from 1970), T is the variable for plot treatment (h_vch or n5), I is the irrigation variable, Q is the quadratic time trend, and e is an error term. The yield data used in this equation was transformed by taking the natural logs of each data point, a standard practice to eliminate trends. After the detrend regression was performed, another Chow test was run to determine if the influence of the irrigation was still providing a break year at 1970, but with a p value of 0.2006 it was no longer present. This suggests that heteroskedasticity is not an issue and the irrigation trend was dealt with entirely by the quadratic model. Log linear regressions and quadratic regressions among others can be utilized as part of a two stage detrend depending on the nature of the trend being compensated for.

There are many two stage detrending methods but the standard one consists of detrended time series data using a regression followed by using the detrended data to estimate yield data that will be treated as observed data (Zhu et al., 2011). Other methods were considered, mainly the spline method, but the simple quadratic regression was the best fit for this dataset. Spline detrending consists of determining points in time series data where data begins to shift towards a pattern known as knots and fitting a curve around these knots to fit the trajectory of the trend. Zero, one, and two knot splines were investigated as possible fits, but none fit as well as the simple quadratic trend. More robust methods of detrending could have been investigated but they were beyond the scope of this study.

Checking for heteroskedasticity was performed via a summary query on the linear model for each of the two plots of interest with the results displayed for hairy vetch in table 2.4 and n5 in table 2.5. This produced t values that were significant at the 5% level in all cases except for irrigation in the h_vch linear model which tested at the 10% level. Both models produced p values of above 5%, 0.05182 and 0.05831 for h_vch and N5 respectively which means we do not reject the null hypothesis that there is constant variance in the residuals and rule out heteroskedasticity. Visual analysis was also performed on Q-Q plots, scale-location plots, residuals vs. leverage plots, and residuals vs. fitted plots located in figures 2.1 and 2.2, and the plots do not indicate heteroskedasticity. This deviates from most county level farm data available and much of the literature dealing with similar yield modelling topics. A likely explanation is the lack of standard technological improvements present in farms that drive yields upward over time because of the consistent experimental methodology applied to the plots observed.

Table 2.4.

LINEAR MODEL HETEROSKEDASTICITY STATISTICS H_VCH				
Residuals				
Min	1Q	Median	3Q	Max
-1215.59	-257.96	86.17	243.61	1567.05
Coefficients				
	Estimate	t Value	Pr(>|t|)	
Intercept	1,546 (684.0)	2.260	0.0324*	
Log($\hat{y}$)	-1.564 (0.6922)	-2.260	0.0324*	
Log($\hat{y}$)*data	.0003958 (.00011751)	2.261	0.0324*	
Irrigation	.08663 (.04419)	1.960	0.0607**	

1. *=5%, **=10%

2. Coefficient estimates and standard errors in units of 10,000

Table 2.5.

LINEAR MODEL HETEROSKEDASTICITY STATISTICS N5				
Residuals				
Min	1Q	Median	3Q	Max
-1006.5	-408.6	-40.8	363.1	1241.6
Coefficients				
	Estimate	t Value	Pr(>|t|)	
Intercept	1,929	2.707	0.0118*	
	(712.6)			
Log($\hat{y}$)	-1.949	-2.703	0.0119*	
	(.7211)			
Log($\hat{y}$)*data	.0004925	2.700	0.0120*	
	(.00018241)			
Irrigation	.1058	2.297	0.0299*	
	(0.04604)			

1. Note: *=5% **=10%
2. Coefficient estimates and standard errors in units of 10,000

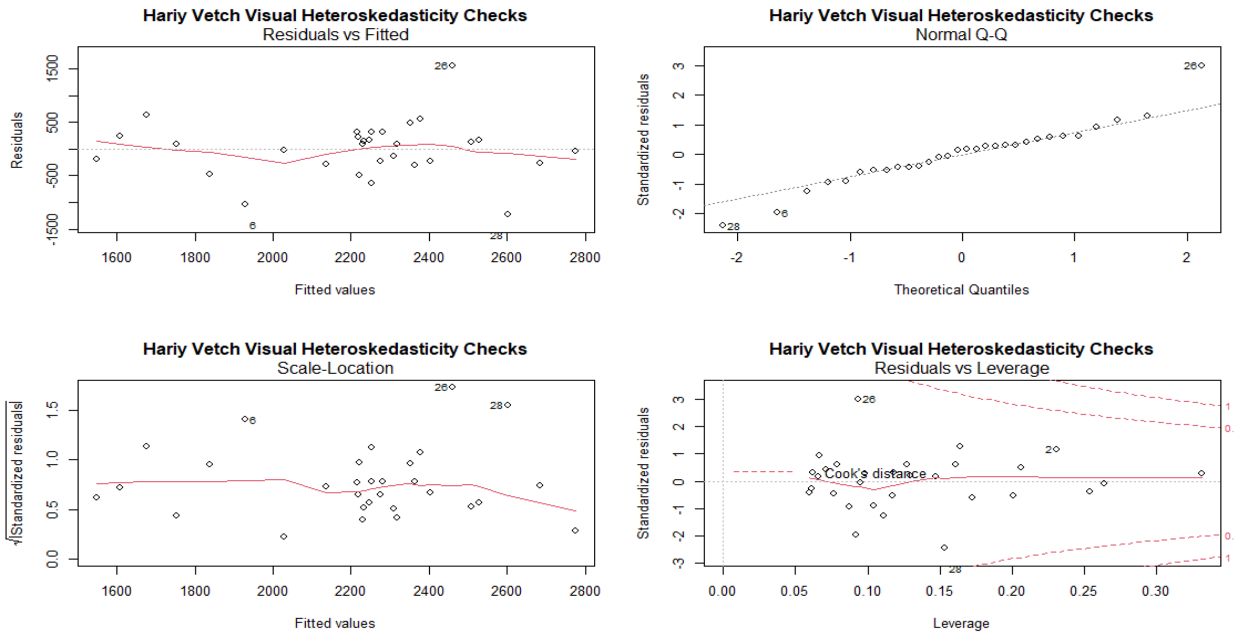

Figure 2.1. Hairy Vetch Visual Heteroskedasticity Checks H_VCH

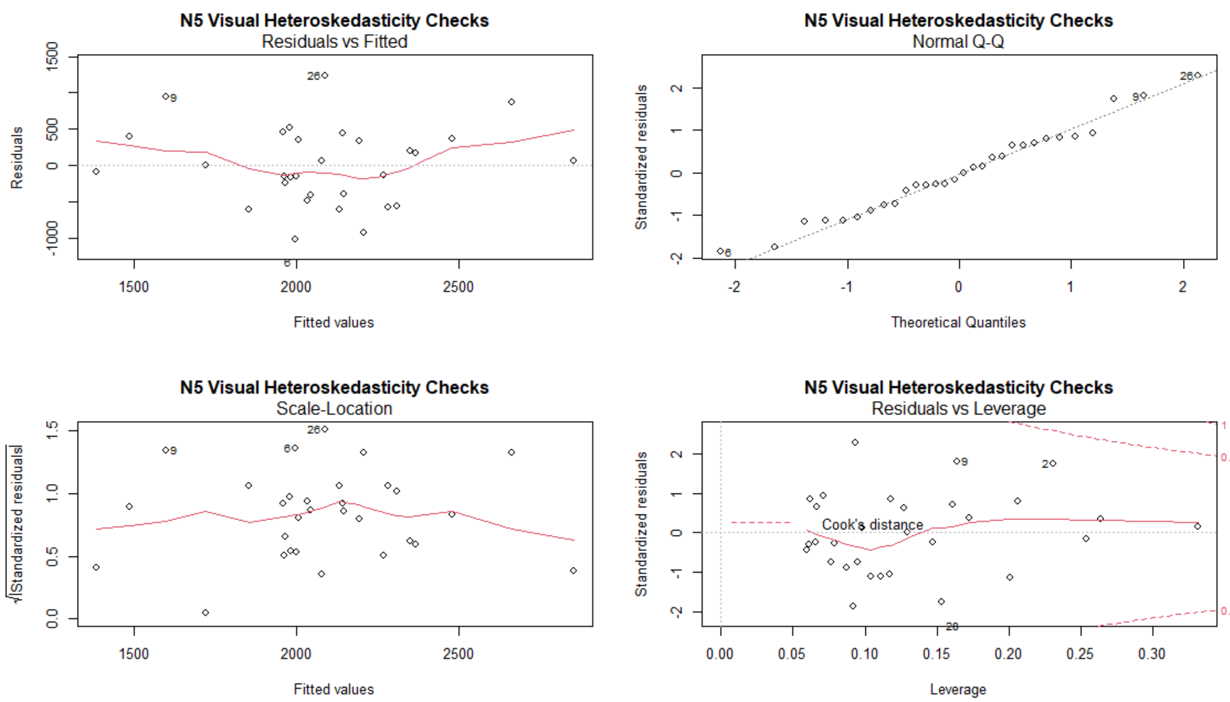

Figure 2.2. Hairy Vetch Visual Heteroskedasticity Checks N5

DISTRIBUTION FIT

The R package "fitdistrplus" was utilized to determine the distribution that best fit the data. The three major distributions considered were: Weibull, Gamma, and Log-normal; these three were chosen because Gamma distributions are commonly used in econometric applications, Weibull distributions are more generalized Gamma distributions, and Log-normal distributions are good stand ins for normal distributions that account for multiple random variables at play in a dataset. To determine how well they fit, the "gofstst" function from the package "fitdistrplus" was used. This function runs calculations for three goodness of fit statistics: the Kolmogorov-Smirnov, the Cramer-von Mises, and Anderson-Darlin, and two goodness of fit criteria: Akike's and Bayesian. Each statistic and criteria has its own specific benefits and weaknesses, but together they compensate for one another. The Anderson-Darling considers the tails and body of a distribution equally which is good for risk assessment as the extremes of a distribution are where insurance events would occur but does not compare well to itself when used for multiple distributions on the same dataset (Delignette-Muller and Dutang, 2014). The Kolmogorov-Smirnov test benefits from not requiring cumulative distribution functions being tested, but skews results towards the body of a distribution. The Cramer-von Mises test also does not consider the number of parameters involved, but as a result has bias for more complex distributions for high parameter models. Akike's criterion and Bayesian criterion pair well with these three statistics as they both penalize models that overfit and instead score on log-likelihood.

For the five goodness of fit tests used, lower scores indicate better fit for the distribution in question. For all but the Kolmogorov-Smirnov in the N5 dataset, which it was second place, the gamma distribution was the best fit across all statistics for the hairy vetch and N5 datasets solidifying the choice. In addition to the numeric tests, visual testing shown in tables 2.6 and 2.7 indicates that the gamma distribution fits better for both Q-Q and P-P plots as well as histograms and CDFs for both the hairy vetch and N5 datasets.

Table 2.6.

Hairy Vetch Goodness of Fit Statistics

GOF STATS	WEIBULL	GAMMA	LOGNORMAL
Kolmogorov-Smirnov	0.1564134	0.1334220	0.1493317
Cramer-von Mises	0.1270656	0.1202995	0.1553644
Anderson-Darling	0.8278748	0.7828064	0.9840287
GOF CRITERIA	**WEIBULL**	**GAMMA**	**LOGNORMAL**
Akaike's	465.1949	464.3093	466.2530
Bayesian	467.9973	467.1117	469.0554

Table 2.7.

N5 Goodness of Fit Statistics

GOF STATS	WEIBULL	GAMMA	LOGNORMAL
Kolmogorov-Smirnov	0.07862766	0.8519486	0.09849929
Cramer-von Mises	0.03323804	0.03149111	0.04166292
Anderson-Darling	0.25130723	0.21342135	0.27735491
GOF CRITERIA	**WEIBULL**	**GAMMA**	**LOGNORMAL**
Akaike's	466.0479	465.1699	465.8945
Bayesian	468.8503	467.9723	468.6969

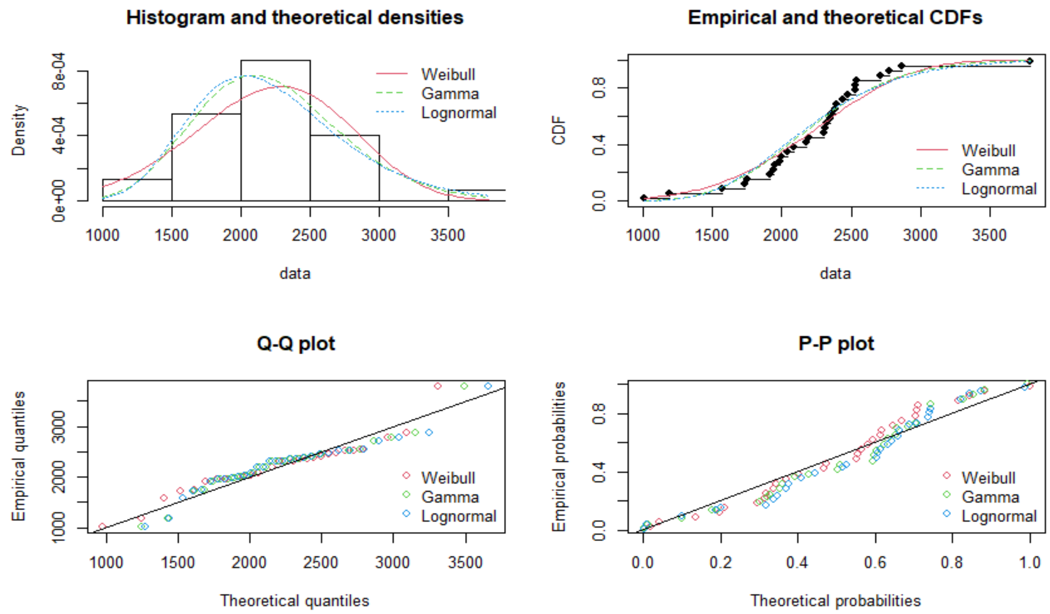

Figure 2.3. Hairy Vetch Distribution Fits

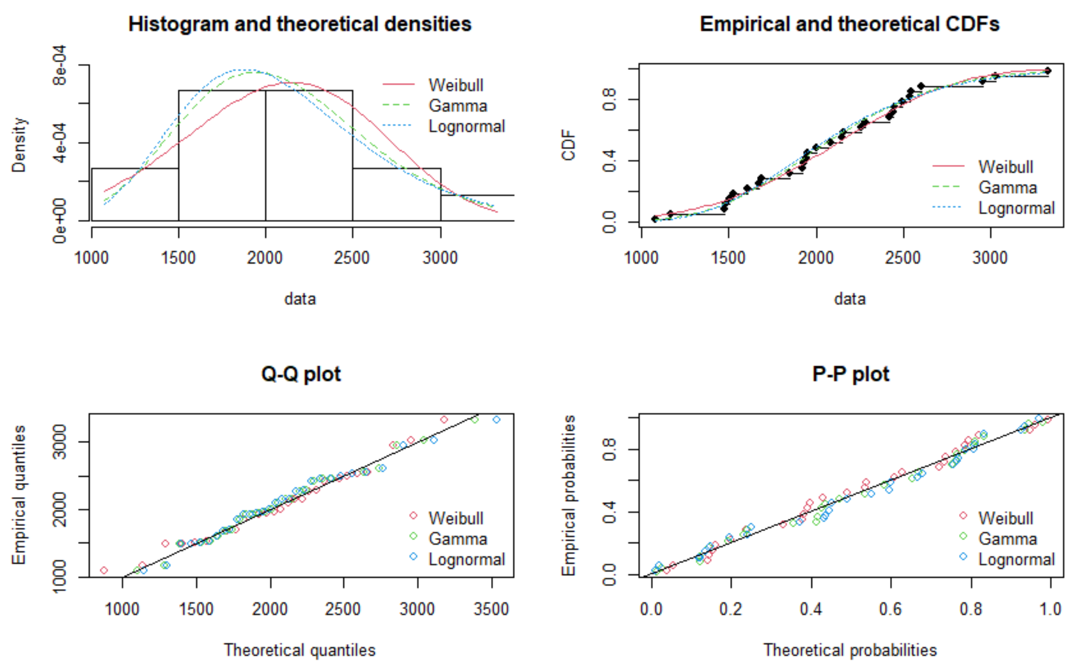

Figure 2.4. N5 Distribution Fits

With the Gamma distribution chosen, data for the hairy vetch and N5 plots were fitted to Gamma distributions for bootstrapping. Bootstrapping is known to have weaknesses when dealing with heteroskedastic data but upon finding no heteroskedasticity, it was deemed suitable. Monte-Carlo simulations, particularly bootstraps, have an established history both for predictive and bootstrapping applications making it a sound method to reinforce analytical possibility (Pouillot and Delignette-Muller, 2010). In order to ensure the validity of the bootstrapped data, the direct detrended data was not used, but instead the standard errors of the detrended data.

Monte Carlo Simulations

Once fitted to a Gamma distribution, a Monte-Carlo simulation of 100 farms with 20 years of yield data each were drawn from the distribution using both the h_vch and N5 values in a bootstrap. Monte Carlo simulations work by randomly generating data, in this case crop yields, by sampling from existing data to simulate various events over time. The simulations were made by taking random draws for values along the gamma distributed data to best serve as representative farms. The simulation is designed to mimic Tensas Parish, the predominant cotton producing Parish in Louisiana with 100 cotton producers as of the 2018 LSU AgCenter survey of agriculture. While this is more useful than comparing research station results to real farm data, it does come with a few drawbacks, namely that the research station is from Bossier Parish, a region significantly different from Tensas parish in soil and other conditions. For the purposes of this paper however it is assumed the simulated Tensas Parish farms are acceptably similar to the real parish.

Alternatives to the Monte-Carlo situation such as stratified sampling or the method of moments were considered, but ultimately passed over in favor of the Monte-Carlo. Stratified sampling involves separating a population into subpopulations before taking random samples, but this was deemed inappropriate for the data used. While it could be argued that there was a total population of cotton plants that could be broken down by their treatments and sampled together from the treatments, the goal of comparing different treatments to one another required total separation of the treatment plots with individual samplings for accurate comparison. The method of moments involves making simple calculations to predict the powers of random variables for a function that predicts output. Agricultural yields are notoriously difficult to predict with simple equations as the number of variables at play make for obtusely large equations necessary, and the more variables accounted for this way the less accurate estimates made this way will be. Because of the extensive randomness of agriculture, even in a controlled experimental setting, the method of moments was deemed a poor choice.

Twenty years of yield data were produced for each of the 100 simulated farms for a total of 2,000 simulated yields each for farms using h_vch data and N5 data for a grand total of 4,000 simulated farm yields. These 4,000 random draws simulated the variety of random factors that influence the performance of a crop, and allowed for a fair comparison of h_vch and N5 treatments by simulating how 100 farms trying the h_vch treatment and 100 farms trying the N5 treatment performed over 20 years. The randomness of the bootstrapped Monte Carlo simulated farms provides more realism than simply relying on analysis of the original experimental data. This comparison helps determine under the specific conditions observed which treatment performs better, information that can guide further study on live farms.

With the data simulated, the values are compared to an APH value made from the mean of the most recent 10 years of yields from all the farms in a treatment patch. The comparison checks whether at crop insurance coverage levels 50%-85% each simulated year's yield triggers an insurance payout. Those per farm insurance payouts are averaged for each coverage level and are averaged to produce a mean insurance trigger rate per coverage level for both h_vch and n5, known as an extensive margin. The per farm trigger rates for each coverage level for both h_vch and n5 were compared to one another in paired T tests as well as the entire spectrum of triggers for each coverage level and their standard deviations were compared in two larger paired T tests. Simulated data was also generated and analyzed for the average value of losses per farm known as an intensive margin, and the same paired T tests were run between the h_vch and n5 datasets.

CHAPTER 3. RESULTS

The simulated yields for each treatment and coverage level were compared against each other at each coverage level, as averages across all coverage levels, and as the average standard deviations across all coverage levels to test significance. Paired T Tests were used and except for the total standard deviation and 60% coverage level intensive margins all simulated values were significant at a 95% confidence interval. Tables with the T Tests of the intensive and extensive margins are listed in tables 3.1 and 3.2 respectively. The negative values of the T Tests are due to the data mostly being negative losses, or successful harvests with no insurance trigger, which is correct for most farms. With significance assured for most simulations, the margins themselves could be examined.

Table 3.1.

Extensive Margin Paired T Test Results

	T_VAL	P_VAL	LCI	UCI	MOTD
Total_Yield	-4.0854	0.004658	-0.02516	-0.00671	-0.01594
Total_SD	-4.9697	0.00162	-0.01004	-0.00357	-0.0068
50%	-0.89715	0.3718	-0.00803	0.003029	-0.0025
55%	-2.4875	0.01454	-0.01798	-0.00202	-0.01
60%	-4.401	2.72E-05	-0.0341	-0.0129	-0.0235
65%	-0.80325	0.4238	-0.02256	0.009557	-0.0065
70%	-1.5396	0.1269	-0.03548	0.004477	-0.0155
75%	-1.208	0.2299	-0.03832	0.009318	-0.0415
80%	-1.3783	0.1712	-0.04147	0.007474	-0.017
85%	-2.7719	0.006659	-0.0652	-0.0108	-0.038

Table 3.2.

Intensive Margin Paired T Test Results

COVERAGE LEVELS	HVCH YIELD	N5 YIELD	HVCH SD	N5 SD	HVCH SE	N5 SE
50%	0.70%	0.90%	0.0169	0.021766	0.000169	0.000218
55%	1.30%	2.30%	0.022891	0.031282	0.000229	0.000313
60%	2.40%	4.80%	0.033695	0.045157	0.000337	0.000452
65%	6.10%	6.80%	0.05104	0.062513	0.00051	0.000625
70%	9.90%	11.40%	0.068333	0.07285	0.000683	0.000728
75%	14.20%	15.70%	0.078083	0.080295	0.000781	0.008029
80%	20.00%	21.70%	0.089751	0.091854	0.000898	0.000919
85%	25.70%	29.50%	0.098128	0.107519	0.000981	0.001075

As shown in table 3.3, the average insurance trigger rate was lower for hairy vetch treated fields at every coverage level. This seems to indicate that hairy vetch once established can either meet or outperform the nitrogen treatment at every coverage level.

Table 3.3.

Average Extensive Margins Across Coverage Levels

	T_VAL	P_VAL	LCI	UCI	MOTD
Total_Yield	-4.1432	0.004332	-22.3754	-6.11509	-14.2452
Total_SD	-0.12015	0.9077	-13.7414	12.4125	-0.66444
50%	-1.4552	0.1488	-20.4316	3.142472	-8.64454
55%	-2.2448	0.027	-45.7404	-2.81868	-24.2796
60%	0.36275	0.7176	-23.4755	33.97919	5.251829
65%	-0.8985	0.3711	-48.9528	18.43695	-15.2579
70%	-0.68831	0.4929	-52.4842	25.44945	-13.5174
75%	-1.0716	0.2865	-51.4589	15.36741	-18.0458
80%	-1.0058	0.3169	-40.6368	13.29692	-13.6699
85%	-2.0668	0.04137	-50.5667	-1.03058	-25.7986

Similar results were found for the intensive margins (table 3.4) with the hairy vetch treated fields average loss per acre being like or significantly lower than the nitrogen treated fields at every coverage level. Lower intensive margins indicate that when a loss is sustained, that loss is lower which translates to less insurance indemnities needing paying. This is intriguing as if similar results can be found in live farm testing, it can be used quantify the long-term benefits of cover crops on a farm in a novel way.

Table 3.4.

Average Intensive Margins Across Coverage Levels

COVERAGE LEVELS	HVCH YIELD	N5 YIELD	HVCH SD	N5 SD	HVCH SE	N5 SE
50%	7.155269	15.79981	28.60968	49.9389	0.286097	0.499389
55%	25.89301	50.17256	66.78814	78.86224	0.667881	0.788622
60%	76.19694	70.94512	106.224	98.73429	1.06224	0.987343
65%	111.1313	126.3892	126.1354	117.6547	1.261354	1.176547
70%	170.2516	183.769	134.6271	158.0364	1.346217	1.580364
75%	192.4047	210.4505	122.6197	108.9036	1.226197	1.089036
80%	230.6354	244.3053	109.4662	95.9631	1.094662	0.959631
85%	256.7734	282.572	99.63721	91.3297	0.996372	0.913297

1. Intensive margins listed as Lbs./acre lost per insurance trigger

When combined, the extensive and intensive margins can calculate an average loss per acre per year. While most farms will have zero losses in a given year, this average loss can be used to explain the cost of insuring the total population of farms under a protection plan. In table 3.5, the combined margins show that hairy vetch farms tend to have less losses, and less insurance payouts, than nitrogen amended farms at every coverage level with an increasing difference as the coverage level increases.

Table 3.5.

Estimated Average Annual Insurance Payouts Per Acre in Monte Carlo Simulated Farms

COVERAGE LEVELS	HAIRY VETCH	NITROGEN ENRICHED	HAIRY VETCH SAVINGS
50%	$0.05	$0.14	$0.09
55%	$0.34	$1.15	$0.82
60%	$1.83	$3.41	$1.58
65%	$6.78	$8.59	$1.82
70%	$16.85	$20.95	$4.09
75%	$27.32	$33.04	$5.72
80%	$46.13	$53.01	$6.89
85%	$65.99	$83.36	$17.37

1.The values for the Hairy Vtech and Nitrogen Enriched payouts are calculated by multiplying the average intensive and extensive insurance margins to find an expected annual insurance cost per acre.

CHAPTER 4. SUMMARY AND CONCLUSIONS

The efficacy of cover crops has been explored before, specifically at the red River Research Station using the same dataset. Ku's, Jeong's, and Colyer's (2017) findings that hairy vetch treated plots contained sufficient nitrogen levels for crop growth comparable to a standard nitrogen regiment, but that significant amount of that nitrogen leech out. These findings support the outcomes of my simulated farms as the hvch plots perform similarly to the n5 plots for most cases. However, as shown in figures 4.1 and 4.2, the hairy vetch plots perform better from the perspective of risk reduction in more extreme situations.

Lower insurance coverage rates that cover shallow losses are not where hairy vetch simulation seems to perform well, figure 4.1 shows a nearly identical extensive margin to the nitrogen treated simulation. This can likely be explained as hairy vetch's nitrogen contributions being a possible substitution to a base nitrogen regiment as mentioned by the SARE (2012) in some farming situations. Figure 4.2 shows that in terms of intensive margins, a hairy vetch plot often has higher losses per acre than the nitrogen plots for smaller insurance events. However, the figure also shows that the majority of losses 50 lbs./acre and up were from the nitrogen plots. This could suggest some added protection provided by a vetch regiment compared to nitrogen, possibly from better water flow in the soil due to the root structures of the vetch, a benefit noted by the SARE (2012).

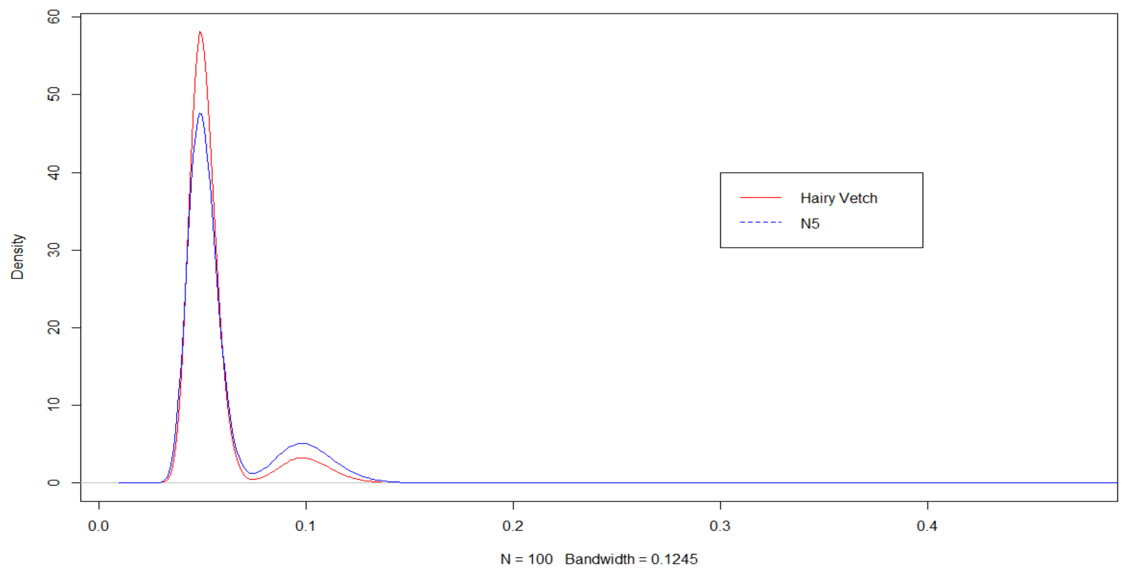

Figure 4.1. Density of Hairy Vetch and N5 Extensive Margins For 100 Simulated Farms at 50% Coverage

1. X axis values represent percent of farms that trigger an insurance event at the 50% coverage level

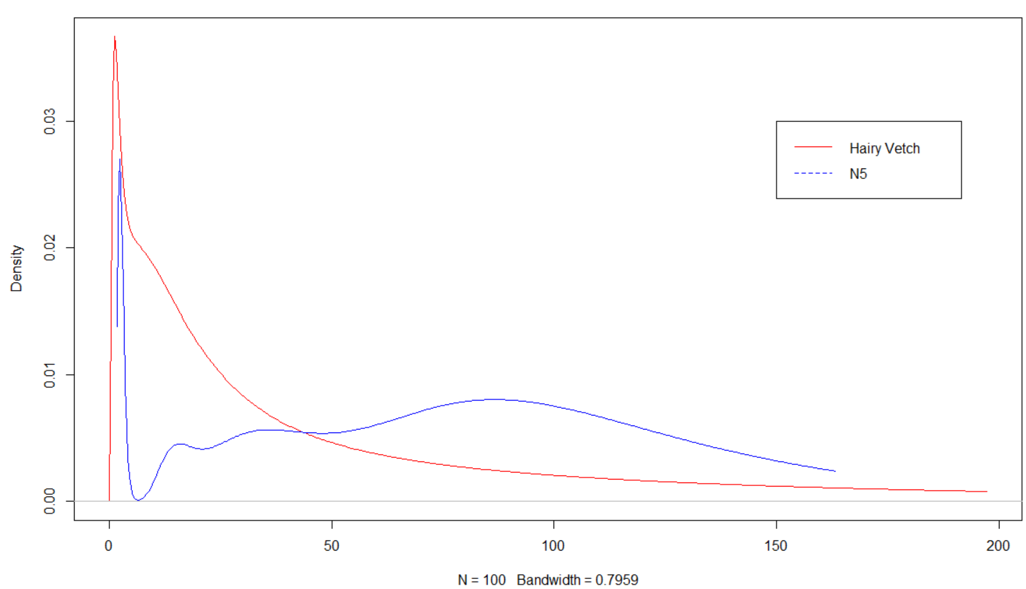

Figure 4.2. Density of Hairy Vetch and N5 Intensive Margins For 100 Simulated Farms at 50% Coverage

1. X axis values represent lbs./acre loss when an insurance event is triggered at the 50% coverage level

Interestingly, at higher coverage levels the hairy vetch plots outperform the nitrogen plots both for intensive and extensive margins. Despite the findings from Chen et al. (2020) suggesting that cover crop adoption should not be adopted at this time due to insufficient benefits, hairy vetch treated plot simulations had less catastrophic insurance events, and those events that did occur had lesser losses per acre as shown in figures 4.3 and 4.4. These results seem to indicate that hairy vetch cover crops can provide some protection against catastrophic losses. A potential explanation for this is that the root systems of cover crops can help to aerate the soil better and improve drainage which could ease flooding, a common issue for Louisiana Agriculture (Kaspar and Singer, 2011, Plastina et al., 2018). Additional data from more regions will be needed to confirm this finding further as well as how various cover crops perform in different conditions. Further research could be done testing cover crop efficacy in a variety of climates with crops other than cotton and how they affect risk, not just raw yields.

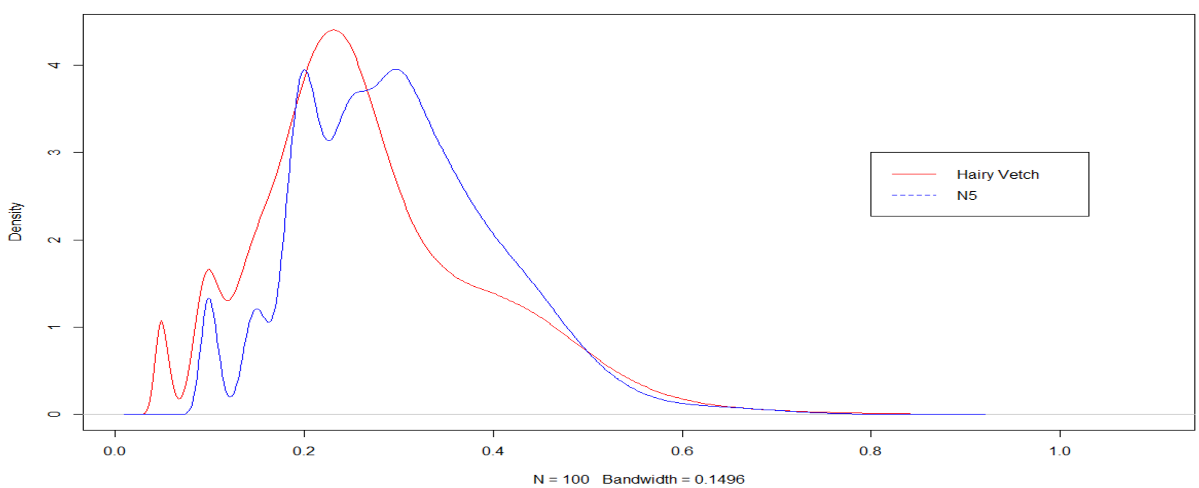

Figure 4.3. Density of Hairy Vetch and N5 Extensive Margins For 100 Simulated Farms at 85% Coverage

1. X axis values represent percent of farms that trigger an insurance event at the 85% coverage level

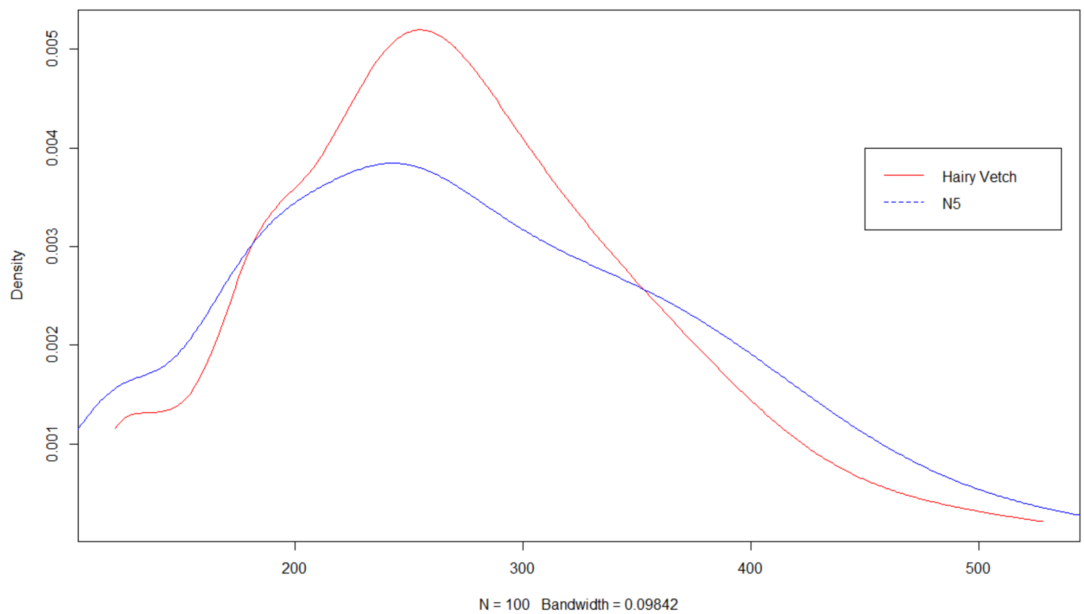

Figure 4.4. Density of Hairy Vetch and N5 Intensive Margins For 100 Simulated Farms at 85% Coverage

1. X axis values represent lbs./acre loss when an insurance event is triggered at the 85% coverage level

Seeing how the hairy vetch cover crop performed in both the raw data and the Monte-Carlo simulations, I believe there is validity into further investigating a discount for cover crops in crop insurance plans. While the general risk reduction provided by the hairy vetch is negligible compared to nitrogen amendments, the reduction of high-level loss events could provide enough of a savings to justify the discount. Future research into the risk reduction could branch in several directions ranging from the data used, the analysis performed, and the crops and cover crops examined.

Experimental plot data has some advantages, but much more accurate analysis could be drawn if data from farms using hairy vetch as a long-term cover for their crops could pe procured. Ideally, several farms growing the same or crops using hairy vetch in the same geographic area could be observed for data. A more realistic improved dataset would be finding a series of farms that all use hairy vetch as a cover crop for a similar group of crops in a similar series of geographic areas. The relatively low number of farmers that use cover crops would make finding a large sample size of farmers with similar crops and weather conditions difficult. Farm collected data could still be used to create a Monte Carlo simulation like the one used here to make a larger dataset and compensate for small sample size. Another challenge to this approach would be the fact that farmers change their techniques, pesticides, and even seed stock over time. Much of this could be compensated for with detrending but if these realities could be included in the analysis more realistic results could be achieved.

Concerning the statistical analysis, alternatives and additions to the simple linear model used could provide new insight to both the experimental dataset used and any similar datasets used in the future. A major factor not directly incorporated into this simple model was weather. The effects were indirectly captured through the changes in yield but a more complex model accounting for weather patterns would make a much more accurate base for a similar Monte Carlo simulation in the future. Tillage practices, if multiple farms are observed, could be another model inclusion as while the soil nutrient benefits of cover crops are often achieved by plowing the terminated cover crop under, reduced tillage systems could also make use of cover crops. The impact of full versus reduced tillage systems could allow for better comparison of cover crop efficacy across a variety of farming systems.

Hairy vetch paired with upland cotton is only one of multiple crop and cover crop combinations available and all perform differently. Similar linear model analysis could be conducted on experimental plot data or farm data using hairy vetch with different cover crops could paint a much more complete picture of how hairy vetch performs. Data from a variety of crop systems could be used to greatly strengthen an argument in favor of a crop insurance discounts if results corroborate the findings of this paper. This idea could be further expanded to other cover crops as well for additional comparison of potential risk reductions.

Appendix

Supplemental Data

Table A.1.

RAW YIELD DATA FROM RED RIVER RESEARCH STATION

YEARS	**CHECK**	**HVCH**	**N1**	**N5**
1959	2019	2634	2711	2918
1960	2576	2933	3260	3533
1961	2095	2562	2547	2843
1962	1343	1862	1812	1750
1963	1611	2002	1798	1748
1964	870	902	963	988
1965	968	1368	1065	1246
1966	959	1853	1623	1722
1967	1737	2321	2243	2539
1968	1269	1861	1783	1893
1969	839	1366	1299	1301
1970*	1869	2058	2547	2547
1971	1690	2407	2134	2134
1972	1581	2593	2531	2531

(table cont'd.)

YEARS	CHECK	HVCH	N1	N5
1974	1338	2373	2069	2147
1975	654	1729	1340	1558
1976	794	2531	1737	1846
1977	1495	2438	2266	2492
1978	1168	2313	2002	1822
1979	950	2422	2430	2422
1980	1005	2048	1698	1729
1981	748	2173	1893	1822
1982	954	2847	2307	2367
1983	558	2168	1611	1630
1984	1766	4028	3566	3329
1985	1253	2696	2100	2593
1986	616	1386	1226	1290
1987	507	2418	1481	1705
1988	683	2734	2309	2541

*Irrigation was added to the Red River Research Station

1.Data Recorded as Lbs./acre

TABLE A.2.

DETRENDED YIELDS

YEARS	HVCH DETRENDED	N5 DETRENDED
1959	2347	2150
1960	2777	2956
1961	2530	2448
1962	1945	1526
1963	2193	1686
1964	1193	1077
1965	1751	1477
1966	2320	2085
1967	2864	3024
1968	2473	2490
1969	2038	2001
1970*	1916	2282
1971	2309	1952
1972	2532	2421
1973	1572	1479
1974	2361	2154
1975	1730	1608
1976	2537	1929
1977	2441	2599
1978	2305	1943
1979	2395	2547
1980	1994	1848
1981	2085	1925
1982	2716	2444
1983	1986	1672
1984	3788	3325
1985	2390	2534
1986	1005	1166

(table cont'd.)

YEARS	HVCH DETRENDED	N5 DETRENDED
1987	1955	1506
1988	2181	2257

*Irrigation was added to the Red River Research Station

1.Data Recorded as Lbs./acre

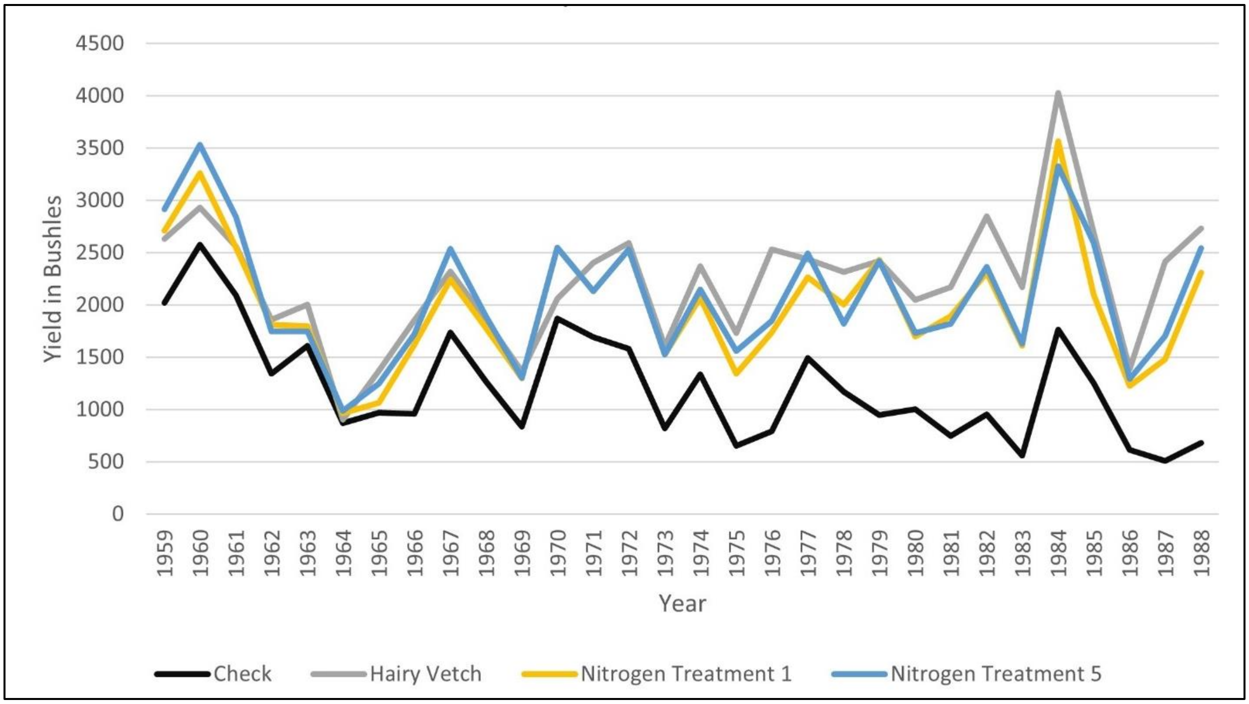

Figure A.3. Cotton Yields by Treatment 1959-1988

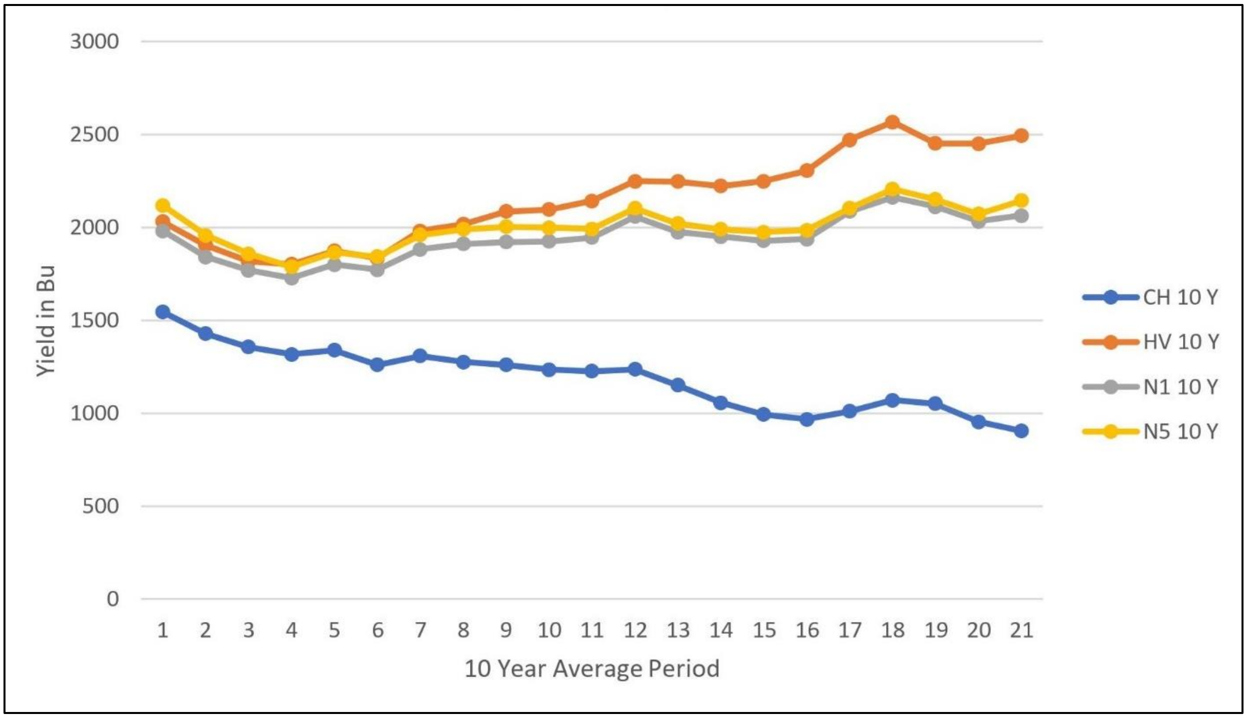

Figure A.4. Ten Year Yield Averages for 30 years of Cotton Plot Data

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