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Farm Heterogeneity and Leveraging Federal Crop Insurance for Conservation Practice Adoption*

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December 12, 2022

Keywords: Crop insurance, conservation practices, nitrogen balance

Invited Paper prepared for presentation at the 2023 ASSA Annual Meeting, New Orleans, LA; Jan. 5-Jan. 8, 2023

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*This research was partially supported by a grant from the Environmental Defense Fund. We gratefully acknowledge Peter Woodbury for introducing us to the nitrogen balance literature and Maria Bowman for advice on data and research methodology.

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Abstract

Current and proposed policies aim to leverage the Federal Crop Insurance Program (FCIP) for adoption of conservation practices. This study use nationally representative field and farm-level data to inform the effectiveness of targeting FCIP participants. We implement an unsupervised machine learning model to assess what set of conservation practices are most common among farms that use crop insurance. Next, we introduce a novel approach to use survey data to measure nitrogen (N) balance, a yield-scaled measure of nitrogen fertilizer's environmental impact. We then test then whether crop insurance predicts more optimal N Balance. We find that farms that use crop insurance may have higher adoption rates for conservation practices that are also generally profit-maximizing.

1 Introduction

Many theoretical and empirical studies have established a link between agricultural production decisions, particularly conservation-focused ones, and use of crop insurance. The anecdotal perception is generally that crop insurance discourages conversation practices, although some new evidence suggests that farmers may not perceive crop insurance to be a barrier to conservation practice adoption (Fleckenstein et al., 2020). These linkages, as well as the near-universal use of crop insurance for row crops (Rosch, 2021), have led to increased interest in making the connection more explicit: that is, leveraging the Federal Crop Insurance Program (FCIP) to support expansion of conservation practices (National Sustainable Agriculture Coalition, 2021). The broad goal of the FCIP to promote the economic stability of the agricultural economy may be complementary with this broad push towards conservation incentives and endorsements National Sustainable Agriculture Coalition (2021). However, other policymakers and farm interest groups have raised concerns about maintaining the integrity of the FCIP as the primary tool used to manage revenue risk by many operations (Crop Insurance and Reinsurance Bureau, 2022). The effectiveness of the FCIP as a tool to leverage conservation practice adoption is central to this emerging policy debate about the propriety of doing so.

The objective of this study is to provide a framework and empirical evidence for assessing whether farm hetereogenity in production and conservation practices is relevant for the effectiveness of leveraging the FCIP to increase conservation practice adoption. Generally, leveraging existing programs rests on (often implicit) assumptions of additionality: that farms that more intensively use crop insurance are likely to respond to new incentives and that these farms have not already adopted the conservation or production practice that is being incentivized. The potential for leveraging programs should be informed by a comprehensive understanding of the already extant practices and resulting environmental impacts of producers that currently use crop insurance programs. It is also important to understand how the use of these practices changes as the intensity of FCIP use increases.[1]. In this study, we analyze the farm-level relationship between crop insurance use and (1) an extensive suite of conservation practices and (2) a measure of the environmental impact and efficiency of nitrogen fertilizer application. We use data from the Agricultural Resource Management Survey (ARMS) Phase II, a nationally representative USDA field-level survey that collects detailed data on production and conservation practices. We first use an unsupervised machine learning clustering methodology to assess the degree to which farms that use crop insurance have a common set of of production and conservation practices that have environmental impacts[2]. Next, we introduce a novel approach that uses these survey data to estimate nitrogen (N) balance, a yield-scaled measure of that captures two potential adverse environmental effects of nitrogen fertilizer: excess N use that implies run-off and insufficient use that implies leeching N from the the soil. We then test whether more intensive crop insurance use predicts more optimal N balance. We then discuss the implications of both of these results for targeting farms that use crop insurance, along with future data and research needs.

Federally supported agriculture safety-net programs, such as the FCIP or ARC/PLC (Agricultural Risk Coverage/Price Loss Coverage), are designed to trigger payments to producers when yields or prices are lower than expected. These programs can influence production decisions, as they change the incentives faced by producers and, potentially, introduce

[1]In the case of crop insurance, while most row acreage is currently covered by some form of crop insurance (Rosch, 2021), coverage levels can capture intensity of program use, and producers that select higher coverage levels may respond differently to new incentives.

[2]For brevity, this article may use ‘conservation practices’ to refer to the broad set of production and conservation practices that have explicit environmental impacts

moral hazard, thus affecting production intensity, input use, crop choice, etc. (Just et al., 1990). This study builds on and complements a large body of work on the environmental impact of farm policies in general and crop insurance in particular. Chemical inputs, such as fertilizer or pesticides, can increase or decrease both farm risk and environmental risk, with multiple financial and climate interactions that can obfuscate actual impact. Both the magnitude and the direction of the affect are in question, as the early theoretical literature has shown. Horowitz and Lichtenberg (1993) describe how crop insurance can theoretically increase chemical use and associated moral hazard. Babcock and Hennessy (1996) come to the opposite conclusion of Horowitz and Lichtenberg (1993), based on their finding that use of both chemical fertilizers and pesticides should decrease in the presence of insurance that protects against low yields. In practice, Mieno et al. (2018) find that there should be minimal moral hazard in nitrogen application once the dynamic nature of crop insurance design is accounted for.

The empirical literature is affected by a lack of access to appropriate farm-level data and findings on the environmental impact of crop insurance use are generally mixed. Most previous work has used county-level data (Goodwin and Smith (2003); Goodwin et al. (2004); Claassen et al. (2011); Schoengold et al. (2014); DeLay (2019); Ghosh et al. (2021); Connor et al. (2022); Lu et al. (2023). The environmental outcomes these papers examine are wide-ranging. For example, Ghosh et al. (2021) finds no evidence of moral hazard for crop insurance subsidies and freshwater irrigation withdraws. On the land use change side, DeLay (2019) finds an additional 1,000 insured acres leads to a 3-acre decline in the Conservation Reserve Program, while Claassen et al. (2017) uses land uses models to show that the potential impact of crop insurance on crop choice implies small pollution impacts at most. Other studies have utilized a single year of farm level data (Horowitz and Lichtenberg (1993); Smith and Goodwin (1996); Wu (1999); Chang and Mishra (2012)). These papers typically examine the static relationship between crop insurance use and outcomes related to chemical input use and crop mix as it affects chemical input use. Finally, other papers have used simulations or multiple years of data to approximate the dynamic aspects of this relationship. Walters et al. (2012) analyzed crop insurance contract data and simulated environmental impacts and found a mixed and generally small relationship. (Weber et al., 2016) used multiple years of farm survey data and finds no evidence that crop insurance causes an increase in expenditure on chemical inputs. Fleckenstein et al. (2020) used a mixed methods approach with Midwestern farmers to analyze producer perceptions of the relationship between crop insurance and conservation practices.

A related area of research that is focused more on examining potential changes to the FCIP from the supply side considers how environmental information, particularly information on soil type and quality, could be incorporated into Federal crop insurance ratings (Woodard (2016); Woodard and Verteramo-Chiu (2017); Tsiboe and Tack (2022)). In addition, there have been initial steps taken in some areas to connect insurance with conservation practices or outcomes. Some of these initiatives already in place do not involve formally developed insurance products. For example, state and national programs have incentivized cover crop use through crop insurance participation by offering additional premium subsidies (Jordan, 2019; Feldmann et al., 2019). Other policies can be developed more broadly for the FCIP under standard development and approval processes, including meeting actuarial standards[3]. The Post-Application Policy Endorsement[4] (PACE) is available to corn producers practicing split application of nitrogen, which can be both environmentally beneficial and profitable. It may, however, expose producers to risks related to excess moisture after planting. PACE makes payments when weather conditions prevent the post-planting application of nitrogen within a specified temporal window (Schnitkey and Sherrick, 2022; Schnitkey et al., 2022).

This paper makes three major contributions to this diverse literature. First, we highlight an important area of study: the effectiveness of leveraging existing programs for conservation practice adoption and how it may be influenced by the characteristics and existing practices of farms that use these programs or use them more intensely. Second, we develop a new approach to use survey data to estimate N Balance, which is an established measure

[3] For more information on this process see `https://www.rma.usda.gov/en/Federal-Crop-Insurance-Corporation/Priv`

[4] Crop insurance 'endorsements' add protection 'on top of' or in addition to an existing or underlying crop insurance policy.

of environmental impact that takes into account production needs as well McLellan et al., 2018. Third, we apply two sets of statistical techniques to characterize the conservation practices of farms that have higher crop insurance use. Many government-sponsored conservation programs, as well as private efforts, target a specific practice (i.e., cover crops). Others, such as the Conservation Stewardship Program (CSP), focus on a wider set of farm-level conservation practices. Existing conservation practices of farms that participate in the FCIP have important implications for the general effectiveness of incentivizing this group. While the environmental impact of crop insurance is a continuing debate, current conservation practice adoption levels informs whether these farms are already using many modern conservation practices and thus their potential responsiveness to new incentives for increasing these practices or adopting new ones. We thus comprehensively characterize farms by aggregate practices instead of individual practices; farms may not consistently use all of the practices deemed environmentally beneficial. Our analysis allows us to draw policy implications for efforts to improve the sustainability of U.S. crop production through existing risk management programs.

This study proceeds as follows. First, we describe out data and introduce our two primary empirical methods (N Balance estimation and CART), as well as our econometric model. This is followed by a discussion of results and conclusion.

2 Data and Methods

The foundation of our ability to examine a large set of conservation practices of farmers, as well as their level of crop insurance use, is high-quality farm-level data. Farm-level data is ideal for research on the environmental impacts of farm policy, as each farm operator makes decisions about crop insurance, crop acreage, and production expenses and practices individually, while environmental externalities are often observed in aggregate. The methods we use to assess conservation practice adoption and crop insurance were selected and developed based on their suitability for detailed farm-level data.

2.1 Data

We use the most comprehensive national farm-level data available for the United States: the ARMS (Agricultural Resource Management Survey) Phase II and Phase III data for major field crops. ARMS is a nationwide, representative farm survey that is conducted annually by the USDA. Farm or field-level ARMS data is made available to university researchers through special agreements with the USDA-Economic Research Service (ERS). ARMS Phase III is an annual survey of approximately 20,000 farms that covers production, finances and farm operator and household characteristics. Through this source, we have information on crop insurance premiums paid and, for some years, information on actual crop insurance coverage level and insurance program type (i.e., yield or revenue). We are able to use a combination of measures of crop insurance participation in our analysis: participation indicators, expenditure on premiums, actual coverage levels, and product choice. Premiums paid are a measure of crop insurance expenditure that reflects crop insurance coverage levels, as well as other factors, such as the value of the crop being insured and historic yields (APH or average production history). A higher level of crop insurance premiums will generally correspond to higher coverage levels, or a larger share of production that is protected from yield or revenue loss. Using these measures, we are able to use the variation in intensity of crop insurance use, as well as the increasingly ubiquitous decision to use crop insurance or not, to examine the impact of increasing coverage on production decisions, including various conservation practices and input uses. Summary statistics for these crop insurance measures, as well as for field-level yields, are presented below in Table 3.

While Phase III collects only limited production practices data, in some years additional farms are sampled to take part in the commodity-specific ARMS Phase II survey. A different subset of commodities is sampled every year. For this study, we have focused on corn, available for the years 1996-2001, 2005, 2010, and 2016. ARMS Phase II allows researchers to more systematically consider aggregate environmental impacts of different production practices. The survey has detailed, field-level data on various production and conservation practices, as well as expenditure on and quantities of various inputs. Table 1 contains a list of the practices that are measured with indicator variables in ARMS Phase II and that we include in our subsequent analysis. Summary statistics for these practices are available in Appendix A[5], table A1. Table A2 includes similar summary statistics for practices measured with an indicator variable and specifically related to pest management.

As the summary statistics tables show, adoption rates of these practices remain quite low, belying the policy need to incentivize adoption through mechanisms such as crop insurance policy changes or discounts. Low adoption can be explained by a variety of factors, including a lack of familiarity with the practice, the cost of implementation, and potential losses in yields. With the data we have, we can only examine the extent to which these practices constrict yields. First and foremost, the relationship between these field-level practices and yield is complicated. Yields vary widely based not only on the production practices chosen but also on location, planting date, and other farmer decisions. While we observe some of these factors in the ARMS dataset, it is difficult to neatly summarize the yield effect of a particular practice, especially one measured as as an indicator variable. The primary extenuating and unobserved factors complicating estimation are soil quality and other field-level conditions, including weather. Nonetheless, as a simple, first-order measure, we compare yields across fields that have and no not have these practices. This information is presented in table A3. Although yields tend to be higher from fields without many of these practices, these descriptive statistics do not control for location or other on-farm observable factors.

Chemical inputs, particularly fertilizer, have both strong yield effects as well as the potential for environmental externalities, especially in terms of water pollution. The Phase II survey also elicits detailed information on the use of chemical inputs at the application level, in addition to the variety of field-level practices described above. For each application of both fertilizer and pesticide, the survey collects information on the quantity, content, timing, rate, and method of application. Summary statistics for the quantities that are measured continuously and included in our analysis, by crop insurance coverage, are in Table 2. These data can be aggregated up to the field level and connected to the Phase II data in order to caclulate the amount of nitrogen applied to each field. Then, using provided weights, these

[5]We intend for Appendix A to be supplemental online material, due to typical journal space restrictions.

measures can be aggregated up further to the operation level and connected to the data on farm financial characteristics in Phase III.

2.2 N Balance model

While the relationship between conservation practices and crop insurance can inform efforts to leverage the FCIP to promote regenerative production, conservation practices are not necessarily themselves indicators of actual environmental impact. The effect of many of these practices on both yield and the environment is unclear. Further, we do not observe the intensive margin of the majority of them. We therefore rely on the input use data described above in order to make a more detailed, rigorous analysis of one practice with both a relatively straightforward relationship with yield and a with clear, quantifiable environmental impacts. We take advantages of recent advances in the agronomy literature and apply these methodologies to ARMS Phase II data. Our approach builds on previous work that used information on nitrogen application rates, timing, methods available in ARMS Phase II to analyze trends in nitrogen application in the US (Ribaudo et al., 2011, 2012). Unlike this work, our calculations of N balance take into account county-level yield goals and also consider the possibility of N application that is too low, causing production to leech this nutrient from the soil.

The importance of nitrogen fertilizer has prompted the development of yield-scaled indicators of reduction in the amount of N lost from agricultural production. One such indicator is the N *balance*, defined as the difference between the N added to an agricultural system as fertilizer and the amount of N absorbed into the crops. Using both data from field-level studies as well as a simulation model, McLellan et al. (2018) find that N balance is a "robust predictor" of the field-level amount of N lost into the environment, and that this relationship is consistent when aggregated spatially up to the watershed level and temporally across years. Their model simulations use the Adapt-N program, which is capable of deconstructing field-level N loss into the different forms of N, gaseous and solid. Using these breakdowns, the authors are able to conclude that the relationship between N balance and N loss is consistent for both kinds of major N loss: gaseous losses, such as of nitrous oxide (N_2O) and physical leaching of nitrate (NO_3^-) and ammonia (NH_3). This consistent response across different kinds of N ameliorate concerns about measurement contaminated by pollution reduction trade-offs, where, for example, practices that reduce one kind of N loss increase another.

In addition to representing the potential N lost from agricultural production at the field, farm, or even watershed level, N balance can be used to set thresholds and aid in pollution reduction targeting efforts that can be implemented at these levels. Producers, in theory, could be incentivized to meet these thresholds, which tend to be credible as N balance is responsive to individual farmer decisions. The concept of the "safe operating space," developed by the European Union Nitrogen Expert Panel (EU-NEP), is one such threshold (Panel, 2015). The safe operating space is designed to accommodate both production and environmental goals: it is defined by a minimum acceptable yield level to ensure that production levels are being maintained and by a range of acceptable N balance levels. N balances that are too low indicate risk of soil mining (depleting soil nutrients), while N balance values that are too high indicate inefficient use of chemical resources and increase the risk for potential leaching (See Figure 1).

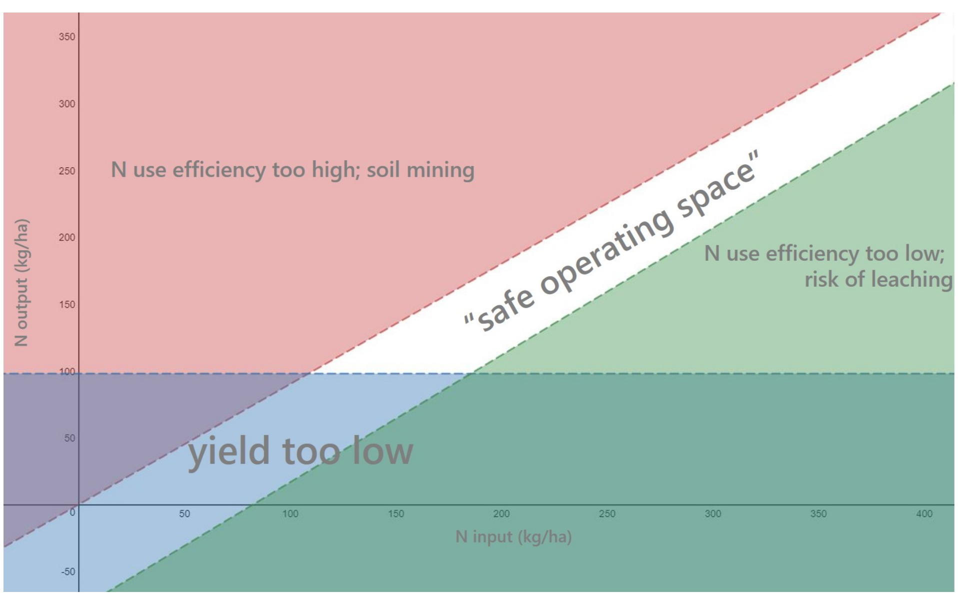

Figure 1: **The safe operating space for a generic operation.**

The safe operating space can also represent the early theoretical debate on the relationship between crop insurance and chemical input use. Horowitz and Lichtenberg (1993) argue that farmers with crop insurance increase their use of chemical inputs, which implicitly suggests they they are more likely to produce in the region where N use efficiency is too low. On the other hand, Babcock and Hennessy (1996) argues that operations with crop insurance are more likely to reduce their use of chemical inputs; which suggests moving towards the region of the graph where N use efficiency is too high and insufficient N is being applied. In this paper, we set out to determine whether use of to crop insurance, or higher crop insurance coverage levels, relates to these two potential production responses.

2.2.1 CART: Cluster analysis of conservation practices

Given the array of diverse production practices available to us through ARMS Phase II, the starting point for our analysis on the relationship between crop insurance use, conservation practices, and N balance is a classification and regression tree (CART) analysis of the production practices. CART, a data reduction and classification technique, takes the full data set and splits it into relatively more homogeneous groups. The tolerance for splitting, and the minimum of the final group size, are set by the researcher, while the CART algorithm estimates first which variables (which practices, in this case) have the most explanatory and predictive power for the variation of the outcome in question and then at what level the variable should be split. The output of the CART analysis is a tree diagram, indicating, in order of importance, which practices have the most explanatory power.

In this case, CART analysis was used to identify which of the practices $x_{1t}, x_{2t}, x_{3t}...x_{nt}$ described above and summarized in tables 1 and 2 had the most power for predicting our outcomes of interest Y_it with $i = 1, 2$ and in year t. Outcome Y_{1t} was defined to be field-level crop insurance coverage, an indicator variable for which a value of 1 indicated the field was covered by crop insurance and 0 indicating it was not. This analysis provides an understanding of which practices, and combinations of practices, explain most of the variance in crop insurance participation across the years covered in our survey.

The second outcome Y_{2t} is an indicator of whether the operation is in the safe operating space for N usage. As described above, ARMS Phase II data is used to calculate N balance for the field. This analysis continues the work of Dalgaard et al. (2014) and Blesh and Drinkwater (2013) of identifying which farm management practices, jointly and individually, contribute to optimizing N balance. All of the practices $x_{1t}, x_{2t}, x_{3t} ... x_{nt}$ used for predicting FCI coverage are used here, except for quantity of nitrogen applied, which, naturally, has overwhelming predictive power for N balance.

Next, we connect these two separate analyses with specifications that examine how extensive and intensive changes in crop insurance are associated with changes in an operation's likelihood of being in the safe operating space, as well as the distance an operation is from the optimal N balance inside that space.

2.2.2 Empirical estimation

In addition to CART analysis, we rely on standard econometric estimation to explain the likelihood of an operation's N balance being in the safe operating space. Here, we use both an indicator of the safe operating space and the calculated absolute value of the distance from the operation's N balance to the optimal N balance.[6] We are able to examine the changes in these outcomes associated with both having crop insurance, and also with increasing coverage rates. In addition, thanks to data on product type, we are able to examine the change in N balance across different insurance products, providing additional insight into the kind of insurance products that are associated with movement towards the optimal N balance. Crop insurance coverage is measured in three ways: first, an indicator of whether the field was covered by crop insurance, information solicited from the Phase II survey; second, an indicator of whether the operation purchased crop insurance, from the Phase III survey; and finally, if the operation purchased crop insurance, the amount paid by the operator for the insurance product. Premium paid is an approximation of the coverage level. Our main results are estimated using Ordinary Least Squares (OLS) and the following specification:

[6] The optimal N balance is the N balance that maximizes the Euclidean distance to all boundaries of the safe operating space.

$$Y_{it} = \beta_0 + \beta_1 FCI_{it} + \beta_{\mathbf{f}} \mathbf{X_{it}} + s_s + r_t + \epsilon_{it} \tag{1}$$

where Y_{it} is the difference between the operation i's N balance and the optimal N balance in year t; FCI_{it} is an operation's crop insurance use, measured either as an indicator variable or as the premium paid; $\mathbf{X_{it}}$ is a vector of farm production practices, both indicators and continuous quantities, as well as select farm characteristics, including operator's age, acres operated, and value of production. The estimation also includes state (s_s) and year (r_t) fixed effects.

In addition to the main specification above, equation 1 is also estimated as a logit model, with an indicator for safe operating space as the outcome (see Appendix A, table A4). The main specification is also run with the year-by-year impact of crop insurance, in order to understand how the dynamics of the relationship between FCI and N balance evolve over time, as follows:

$$Y_{it} = \beta_0 + \beta_{\mathbf{1}} \times \mathbf{FCI_i^t} + \beta_{\mathbf{f}} \mathbf{X_{it}} + s_s + \epsilon_{it} \tag{2}$$
$$t = 1996, 2000, 2001, 2005, 2010, 2016$$

with the variables defined as before, except for FCI_i, which is defined only as an indicator of the operation having crop insurance, rather than the continuous measure of coverage. The final specification uses data on the kind of crop insurance product. Changes in survey design mean that these questions were only asked of farmers in 2016, and so the data is cross-sectional rather than time series.

$$Y_{f,2016} = \beta_0 + \beta_{\mathbf{1}} \times \mathbf{FCI^k_{f,2016}} + \beta_{\mathbf{f}} \mathbf{X_{i,2016}} + s_s + \epsilon_i \tag{3}$$

where the variables are defined as before, and k indexes the 7 types of FCI insurance product (including no insurance) that covered field f in 2016. Farmers were also asked to report their actual coverage level, depending on their product, in 2016. Results of a specification where equation (1) is run with FCI_{it} equal to actual coverage level appear in Appendix A, table A5.

3 Results

3.1 CART: Cluster Analysis

Table 4 shows the results of the CART analysis: the practices with the greatest explanatory power for participation in crop insurance (1) and production in the N balance safe operating space (2) are shown, ranked in order of importance. These results summarize the CART analysis done over all of the years for which data were available; we also performed year-by-year CART analysis; those results are largely consistent with the overall analysis.[7]

The CART results predicting crop insurance coverage at the field level indicate that farmers whose fields are covered by crop insurance are more likely to undertake activities that reflect active, engaged management. The non-input practice with the most explanatory and predictive power, scouting for weeds, is especially indicative of this. Fields that were scouted for weeds were more likely to also be covered by crop insurance. Operators who scout for weeds are, at a minimum, being attentive to the overall state of their corn fields. In addition, they are less likely than the operators who are not scouting to make blanket applications of pesticides, regardless of their necessity. The other variables with substantial explanatory power for crop insurance are all chemical inputs. Together, these variables (scouting for weeds, N pounds per acre, pounds of pesticide per acre, and K pounds per acre) explain more than 80% of the variation in crop insurance coverage. Although higher rates of the application of all of these are more likely to be found on fields with crop insurance, normative statements about whether these rates are "too high" cannot be made using this CART analysis alone. In the following section, the analysis using N balance outcomes are better equipped to determine if farmers with crop insurance are using N in a more environmentally responsible way than their uninsured or less-insured counterparts.

[7]The overall CART tree outputs are available in our supplemental online materials (Figures A2-A6). The year-by-year, along with other sub-sample CART analyses, are available on request.

The results predicting whether an operation is in the safe operating space for N use show the importance of other chemical inputs in addition to active management practices. Operations with higher rates of P usage are more likely to be in the N safe operating space, but similar analysis of P use is beyond the scope of this study. One limitation of this research is that we are unable to observe field-level soil characteristics, which could help explain why operations use one type of fertilizer over another. For example, lime quantity per acre, the practice with the second most explanatory power in this analysis, typically increases with soil acidity. However, it has also been shown to increase plant uptake of all three major nutrients (N, P, K), which could help explain its predictive and explanatory power for the N balance of operations in our study (West and McBride, 2005). Supporting the idea of active and engaged management practices leading to more optimal application of N, the practice with the third most explanatory power in the CART analysis is whether the field had a nitrogen soil test. Tested fields were more likely to have an N balance in the safe operating space than those that did not, belying the importance of these tests towards informing application of fertilizer only when needed to support desired levels of production. Together, these first three variables have almost 90% of the predictive power for an operation's N balance safe operating space.

Jointly, the results of the CART analysis show that production practices are different for farms that use crop insurance than those that do that. These results suggest that while farms that use crop insurance may use a higher quantity of inputs, they use these inputs more efficiently. These findings are consistent with the 'good management practices' required for FCIP participation and are likely to not be independent of a farm's propensity to respond to conservation incentives.

3.2 FCI and N balance

The results from our main specification, described in equation (1), are found in table 5. Here, the outcome of interest is how far an operation's N balance is from the optimal N inside the safe operating space. We find a consistent relationship between nearness to the optimal

N and FCI coverage, measured three different ways. The strongest measure of field-level coverage is an indicator variable indicating that the field surveyed in Phase II is itself covered by crop insurance; this is associated with a decrease in the distance to optimal N of about 32 lbs/acre. The marginal impact of crop insurance on this difference is greater than the marginal impact of any of the continuously measured input variables.

The relationship is smaller in magnitude but remains consistently statistically significant when we use operation-level crop insurance coverage, a weaker measure of coverage at the field level. Operation coverage is associated with an operation being 24 lbs/acre closer to the optimal N. The final specification uses a continuous measure of coverage with the proxy of premium paid. An additional dollar in premium paid by the operator for crop insurance is associated with a 1.25 lb/acre move towards the optimal N. This intensive measure of crop insurance coverage exploits more variation across farmers, especially in the later years represented in our sample. By 2016, the last year for which we have data, crop insurance coverage for conventional corn was nearly universal. Premiums paid, however, were still likely to vary greatly across farmers, depending on the particular product purchased, the coverage level, and the location of the operation.

The growing ubiquity of crop insurance is reflected in our year-by-year results of the relationship between coverage and distance to the optimal N level, available in table 6. The magnitude of the relationship declines consistently through the years, especially for operation-level coverage. In 1996, when crop insurance was much less widely used and the insurance products and programs differed greatly from their modern implementation, operation-level coverage was associated with a decreased distance to optimal N of 200 lbs/acre. Two decades later, in 2016, the role of crop insurance in this relationship was half that, at about 100 lbs/acre. Nonetheless, the relationship is strong: operations with crop insurance are more likely to be producing corn with their N balance closer to the optimal N as defined by the N balance and safe operating space. This decline in the strength of the relationship is less consistent, but still present, for the field-level coverage. Although the association is significant in 1996, that is no longer the case in 2016. This declining role of crop insurance in determining optimal N use could be attributed to the almost universal use of crop insurance, as well as increasing coverage levels.

Our final set of results estimate equation (3) and use only data from 2016, the most recent year in our sample. In 2016, farmers who completed the Phase II survey were asked to report the kind of crop insurance product they used to cover that particular field. The relationship between each program on distance to ideal N, relative to the omitted category of no insurance, is consistently negative, with the exception of fields with federal CAT coverage. Catastrophic crop insurance, commonly referred to as CAT coverage, is considered the "basic level of coverage" and was initially mandatory for farmers wishing to receive deficiency payments. Because farmers paid no premium for it, operations covered by it can be thought of as minimally covered Glauber (2013). As the coverage levels and protections increases, so does the strength of the relationship with distance to ideal N. Farms with revenue protection, for example, are 82 lbs/acre closer to the ideal N than are farms with no insurance. Purchase of the supplemental coverage option (SCO) for revenue insurance reduces the distance to the ideal N by almost 20 lbs/acre over revenue protection without SCO. These results are remarkably consistent with the insights of Mieno et al. (2018), whose numerical simulations show that once production history (crop insurance design) is accounted for, there is little moral hazard in nitrogen application, especially at higher coverage levels.

Overall, these results provide strong evidence higher levels of crop insurance coverage or intensity are associated with a higher likelihood of operators producing in the safe operating N balance space. Further, this conclusion is supported by the analysis done with the actual coverage level, reported in Appendix A, table A5. Especially for the revenue insurance program, as the coverage level increases, the distance to the safe operating space decreases. The results using program type and coverage level together point to an explanation that as farm operators are more protected from financial setbacks caused by loss of crop revenue, they are more likely to apply their chemical inputs more efficiently. Use of a major chemical input (N) is not independent of crop insurance use; this relationship may extend to other practices. For policymakers interested in leveraging the FCIP for conservation practice adoption, understanding these existing relationships is an important consideration.

4 Conclusion

This study uses nationally representative field- and farm-level data to implement an unsupervised machine learning model to assess which set of conservation practices are most common among farms that use crop insurance. We also introduce a novel approach to use these data to estimate nitrogen (N) balance, a yield-scaled measure of whether on-farm under- or over-use of nitrogen fertilizer has an environmental impact. We then test whether increased crop insurance use predicts more optimal N balance, in the sense that the nitrogen used is both sufficient to supply the needs of the crops being grown without excess risk of running off the soil and entering the waterways. The methods used in this study may be useful in other studies of conservation practices, particularly those with adverse effects when under- or over-used, or those that may have deleterious effects on yield. Our results show that farms that have higher levels crop insurance use have higher adoption rates for some conservation practices, especially those that are also generally profit-maximizing or that reflect more intensive management. Further, higher levels of crop insurance coverage predicts more optimal N balance. At least to some extent, this could reflect a trade-off between the self-insuring procedure of over-applying nitrogen fertilizer and the formal insurance.

Our analysis provides strong evidence that the relationship between farmers' crop insurance use and conservation practices is policy relevant because these decisions, particularly those around "optimal" chemical input use, are not independent of each other. Nonetheless, there are limitations to this work that must be acknowledged. Our econometric analysis assesses whether crop insurance predicts or is related to optimal fertilizer application, not the casual relationship between crop insurance and N balance. While we adapt the concept of N balance for the ARMS data, thereby developing a new approach to measure environmental impact using ARMS Phase II, we do not measure any of the other possible environmental outcomes of interest, such as greenhouse gas emissions, erosion, or, indeed, chemical run-off directly. We also are not able to observe all of the external factors, agronomic or management-related, that may influence optimal production and conservation decisions. Further, while we use a comprehensive set of self-reported practices that provides detail beyond that of most available datasets, we do not observe all conservation or production practices. We also do not make any sort of value judgement between them regarding which has the most environmental impact.

While the relationships analyzed in this study are policy relevant, continued research to improve analysis of the causal relationship between conservation practices, conservation incentives, and Federal programs, including the FCIP, are important to improve policy design and evaluation. Similar analyses with other agricultural programs that are currently being leveraged (or those that could one day be used) for conservation adoption would also inform policy, as would the development of additional methodologies to use survey data to measure environmental impact in a way that acknowledges the need to maintain production targets. Our calculations of N balance in a nationally representative and time-variant way may also be useful in studies of fertilizer trends, environmental impacts, and conservation policy. Use of data on precision agriculture and soils or other physical measurements, especially combined with farm-level data, would greatly enhance future research.

Farm heterogeneity is an important consideration for leveraging the FCIP to advance the adoption of conservation practices. While farms that use crop insurance more intensely may also use inputs more intensely, we find evidence that they tend use one important input, nitrogen fertilizer, more efficiently. Farms that use crop insurance are both more likely to have an optimal N balance and use more management-intensive practices such as crop scouting, which have the potential to increase yield and decrease negative environmental externalities. This does not mean that the FCIP is *a priori* ‘good’ or ‘bad’ for targeting adoption of conservation practices: such a value judgement would ultimately depend on policy objectives. For some practices, our analysis indicates that policymakers may want to consider the additionality of incentives attached to the FCIP. However, our analysis also suggests that farms that more intensively use crop insurance may be more responsive to financial incentives, which could accelerate adoption. Generally, a better understanding of the characteristics of farms using programs that are being leveraged has the potential to improve stewardship of public and private resources and support achievement of conservation objectives while maintaining a stable farm economy.

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Tables

Table 1: **Practices observed in ARMS Phase II**

Field practices:	Pest resistant seed, No till, Terraces, Grassed waterways, Contour farming, Strip cropping, Underground channels, Drainage channels, Filter strips, Erosion control plan, Fertilizer & manure mgmt plan, Manure mgmt plan, Pesticide mgmt plan, Water mgmt plan, Lime applied, Sulfur applied, Gypsum applied, Micronutrients applied, Zinc applied, Pre emergence herbicides applied, Fertilizer variable rate technology, Pesticide variable rate technology, Soil or plant test, Nitrogen test, Scouted for weeds, Scouted for insects, Scouted for disease, Kept scouting records, Use N inhibitor, Phosphorus soil test
Pest control practices:	Adjust row spacing, Adjust planting dates, Alternate pesticides, Till/chop/mow, Water management, Clean equipment, Soil analysis, Consider beneficials, Use treated seeds, ID pests in a lab, Apply beneficial organisms, Pheremone lures, Wireworm traps, Cultivated field, Times cultivated, Use resistant varieties, Rotate crops, Pest mgmt training, Restricted use license

Table 2: **Input quantities, by field-level crop insurance coverage**

	n	**mean**	**sd**	**n**	**mean**	**sd**	
	No FCI			**FCI**			
N (lbs/acre)	3,757	91.19	67.97	10,244	106.21	67.34	***
P (lbs/acre)	3,757	37.34	41.11	10,244	33.45	37.81	***
K (lbs/acre)	3,757	47.35	55.00	10,244	37.78	52.00	***
Liquid pesticide (Gal/acre)	3,757	0.42	0.34	10,244	0.38	0.33	***
Solid pesticide (lbs/acre)	3,757	1.16	2.40	10,244	1.59	2.59	***
Lime (tons/acre)	3,730	1.32	1.29	10,126	1.02	1.56	***
Sulfur (lbs/acre)	1,813	1.54	5.89	5,138	2.44	6.85	***
Manure (tons/acre)	2,477	1.92	5.24	6,276	1.02	3.73	***

***,**,*Indicates significant difference between means at 1%, 5%, and 10%, respectively

Table 3: **Yields and crop insurance**

	n	**mean**	**sd**
Yield, grain (bu/acre)	19,855	270.65	329.63
Yield, silage (ton/acre)	19,857	1.91	5.49
Premium paid ($)	6,734	$ 9,661.87	$ 30,444.19
Premium paid per acre*	6,734	$ 5.63	$ 7.73
Acres operated	6,734	1429.04	2075.29
Operation had FCI*	6,734	68.5%	46.5%
Field covered by crop insurance**	14,001	73.2%	44.3%

*From Phase III survey (1996, 2001, 2005, 2010, 2016)

**From Phase II survey (1996, 2000, 2001, 2005, 2010, 2016)

Table 4: **Summary of CART Results**

(1) FCI	**(2) SOS**
Solid pesticides (lbs/acre)	P (lbs/acres)
N (lbs/acre)	Lime (ton/acre)
Scout weeds	Nitrogen test
K (lbs/acre)	Resistant seed
Lime	K (lbs/acre)
Grassed waterways	Solid pesticides (lbs/acre)
Resistant seed	

Results of CART analysis across all years for each outcome variable

These practices explain over 90% of the variation in the outcome variables

Table 5: **Results: Relationship of FCI participation with distance to ideal *N* balance**

	(1) Distance to SOS	(2) Distance to SOS	(3) Distance to SOS
Field covered by FCI	-31.71***		
	(10.40)		
Operation has FCI		-23.77**	
		(8.829)	
Premium paid ($)			-1.248*
			(0.700)
N (lbs/acre)	-0.768***	-0.769***	-0.767***
	(0.113)	(0.112)	(0.111)
P (lbs/acre)	-0.178	-0.173	-0.164
	(0.107)	(0.104)	(0.105)
K (lbs/acre)	-0.164**	-0.162**	-0.164**
	(0.0643)	(0.0654)	(0.0641)
Liquid pesticide (gal/acre)	-11.24	-11.18	-13.04
	(10.78)	(10.62)	(10.88)
Solid pesticide (lbs/acre)	-1.064	-1.181	-1.174
	(2.342)	(2.387)	(2.442)
Production practice controls	YES	YES	YES
Year FE	YES	YES	YES
State FE	YES	YES	YES
Constant	267.6***	285.1***	279.7***
	(16.21)	(28.14)	(28.62)
Observations	6,566	6,567	6,567
R-squared	0.229	0.228	0.227

Standard errors robust to correlation at the state level in parentheses
*** p¡0.01, ** p¡0.05, * p¡0.1

Table 6: **Results: Year-by-year relationship of FCI participation with distance to ideal N balance**

	(1) Distance to SOS	(2) Distance to SOS
Field covered by FCI, 1996	-83.15***	
	(17.73)	
Field covered by FCI, 2001	-10.61	
	(13.81)	
Field covered by FCI, 2005	-25.65**	
	(11.70)	
Field covered by FCI, 2010	-28.57**	
	(12.28)	
Field covered by FCI, 2016	-21.74	
	(13.79)	
Operation has FCI, 1996		-200.1***
		(19.81)
Operation has FCI, 2001		-165.7***
		(15.10)
Operation has FCI, 2005		-113.7***
		(17.13)
Operation has FCI, 2010		-107.5***
		(12.52)
Operation has FCI, 2016		-102.4***
		(8.690)
N (lbs/acre)	-0.767***	-0.633***
	(0.114)	(0.0867)
P (lbs/acre)	-0.179	-0.104
	(0.109)	(0.110)
K (lbs/acre)	-0.167**	-0.0757
	(0.0643)	(0.0949)
Liquid pesticide (gal/acre)	-5.908	74.23***
	(11.59)	(10.54)
Solid pesticide (lbs/acre)	-1.289	3.116
	(2.328)	(2.534)
Production practice controls	YES	YES
Year FE	YES	YES
State FE	YES	YES
Constant	234.7***	178.7***
	(15.71)	(22.83)
Observations	6,566	19,677
R-squared	0.220	0.203

Standard errors robust to correlation at the state level in parentheses
*** p¡0.01, ** p¡0.05, * p¡0.1

Table 7: **Results: Relationship of type of insurance product to distance to ideal N balance**

	(1) Distance to SOS
Federal CAT	-26.54
	(39.03)
Yield protection	-71.59***
	(22.48)
Yield plus SCO	-72.29*
	(35.04)
Revenue protection	-82.23***
	(13.71)
Revenue plus SCO	-101.3***
	(18.52)
Other program	-108.4***
	(17.82)
N (lbs/acre)	-0.843***
	(0.123)
P (lbs/acre)	0.0663
	(0.174)
K (lbs/acre)	-0.308*
	(0.152)
Liquid pesticide (gal/acre)	-30.12
	(19.21)
Solid pesticide (lbs/acre)	-0.535
	(2.291)
Production practice controls	YES
State FE	YES
Constant	407.2***
	(46.47)
Observations	1,091
R-squared	0.375

Robust standard errors in parentheses
*** p¡0.01, ** p¡0.05, * p¡0.1

5 Appendix A: Supplemental Online Appendix

Table A1: **Field practices, by field-level crop insurance participation**

	n	mean	sd	n	mean	sd	
Percent of corn fields with:		**No FCI**			**FCI**		
Pest resistant seed	3,756	42.0%	49.4%	10,242	51.4%	50.0%	***
No till	2,325	35.0%	47.7%	6,672	40.6%	49.1%	***
Terraces	3,757	8.2%	27.4%	10,244	13.8%	34.5%	***
Grassed waterways	3,757	22.2%	41.5%	10,244	26.8%	44.3%	***
Contour farming	3,757	12.7%	33.3%	10,244	16.2%	36.9%	***
Strip cropping	3,376	8.6%	28.0%	8,678	5.1%	22.0%	***
Underground channels	3,116	30.6%	46.1%	8,860	35.7%	47.9%	***
Drainage channels	2,735	7.3%	26.1%	7,294	9.4%	29.2%	***
Filter strips	2,606	5.4%	22.6%	6,369	6.0%	23.8%	
Erosion control plan	2,985	22.0%	41.5%	7,928	27.7%	44.8%	***
Fertilizer & manure mgmt plan	2,987	11.5%	31.9%	7,935	13.2%	33.9%	**
Manure mgmt plan	2,606	5.4%	22.6%	6,369	5.1%	21.9%	
Pesticide mgmt plan	2,987	6.3%	24.3%	7,935	10.0%	30.0%	***
Water mgmt plan	2,987	2.4%	15.2%	7,935	4.0%	19.5%	***
Lime applied	3,756	64.0%	48.0%	10,240	49.6%	50.0%	***
Sulfur applied	1,518	15.9%	36.6%	4,025	27.0%	44.4%	***
Gypsum applied	2,987	0.9%	9.5%	7,933	0.8%	8.7%	
Micronutrients applied	688	0.0%	0.0%	1,621	0.0%	0.0%	
Zinc applied	688	9.0%	28.7%	1,621	16.1%	36.8%	***
Pre emergence herbicide applied	3,751	61.6%	48.6%	10,234	63.6%	48.1%	**
Post emergence herbicide applied	3,750	54.6%	49.8%	10,231	67.5%	46.8%	***
Fertilizer v.r.t.	2,985	4.2%	20.1%	7,935	11.3%	31.7%	***
Pesticide v.r.t.	2,985	1.8%	13.2%	7,935	3.7%	19.0%	***
Soil or plan test	3,757	7.2%	25.8%	10,235	12.4%	32.9%	***
Nitrogen test	3,755	17.4%	37.9%	10,241	27.1%	44.5%	***
Scouted for weeds	3,757	67.0%	47.0%	10,238	79.1%	40.6%	***
Scouted for insects	3,757	46.4%	49.9%	10,244	61.7%	48.6%	***
Scouted for disease	3,756	36.3%	48.1%	10,241	45.9%	49.8%	***
Kept scouting records	2,985	12.2%	32.7%	7,927	20.0%	40.0%	***
Use N inhibitor	3,757	73.3%	163.5%	10,243	63.0%	146.3%	***
Phosphorus soil test	2,986	24.7%	43.1%	7,933	35.9%	48.0%	***

***,**,*Indicates significant difference between means at 1%, 5%, and 10%, respectively

Table A2: **Pest control practices, by field-level crop insurance participation**

Pest control measures:	**n**	**mean** No FCI	**sd**	**n**	**mean** FCI	**sd**	
Adjust row spacing	3,756	6.5%	24.7%	10,243	8.9%	28.5%	***
Adjust planting dates	3,756	6.3%	24.3%	10,242	8.7%	28.1%	***
Alternate pesticides	3,757	15.3%	36.0%	10,244	21.5%	41.1%	***
Till, chop, mow	3,756	31.3%	46.4%	10,242	38.3%	48.6%	***
Water management	3,757	2.9%	16.9%	10,241	3.8%	19.2%	***
Clean equipment	3,756	25.9%	43.8%	10,241	31.5%	46.4%	***
Soil analysis	2,202	1.4%	11.8%	5,881	2.9%	16.9%	***
Consider beneficials	3,757	8.4%	27.8%	10,244	10.6%	30.8%	***
Use treated seeds	3,223	21.8%	41.3%	8,828	19.7%	39.8%	**
ID pests in a lad	2,324	2.6%	15.9%	6,670	3.8%	19.2%	***
Apply beneficial organisms	3,224	0.3%	5.3%	8,828	0.3%	5.4%	
Pheremone lures	1,792	0.3%	5.3%	5,256	0.3%	5.2%	
Wireworm traps	770	0.1%	3.6%	2,309	0.4%	6.2%	
Cultivated field	3,757	15.5%	36.2%	10,244	16.7%	37.3%	
Times cultivated	2,987	0.25	0.58	7,935	0.27	0.57	
Use resistant varieties	2,986	31.9%	46.6%	7,933	47.1%	49.9%	***
Rotate crops	2,986	63.1%	48.3%	7,934	76.6%	42.4%	***
Pest mgmt training	3,752	33.1%	172.9%	10,224	46.2%	279.8%	***
Restricted use license	770	69.5%	46.1%	2,309	80.8%	39.4%	***

***,**,*Indicates significant difference between means at 1%, 5%, and 10%, respectively

Table A3: **Yield, by binary field practice**

Practice:	**mean**	**sd**	**n**	**mean**	**sd**	**n**	**Difference significant at:**
	Yield for fields without practice:			**Yield for fields with practice:**			
Pest resistant seed	378.8	497.7	11250	246.6	364.3	8602	***
No till	317.5	435.2	6709	197.1	266.1	3727	***
Terraces	326.4	455.7	17601	282.7	396.9	2254	***
Grassed waterways	338.5	464.3	15145	266.8	394.0	4710	***
Contour farming	325.5	453.6	16926	298.3	425.2	2929	***
Strip cropping	344.5	471.8	16928	253.9	404.6	1001	***
Underground channels	313.1	443.1	11602	397.6	506.4	6250	***
Drainage channels	365.8	490.6	14561	361.9	479.0	1365	
Filter strips	127.5	129.4	10309	123.1	62.8	674	
Erosion control plan	133.5	130.3	7983	131.1	108.6	2831	***
Fertilizer & manure mgmt plan	133.8	125.8	9448	126.3	118.6	1375	**
Manure mgmt plan	130.1	132.0	8440	94.4	102.6	457	***
Pesticide mgmt plan	131.7	122.8	9857	144.7	144.9	966	***
Water mgmt plan	131.4	119.0	10445	174.6	232.1	378	***
Lime applied	316.4	444.5	9061	325.8	454.0	10789	
Sulfur applied	119.8	110.8	5975	154.4	171.4	1599	***
Gypsum applied	131.3	122.3	12811	126.2	68.8	96	
Micronutrients applied	125.0	125.8	4075	140.0	92.3	299	***
Zinc applied	122.9	117.7	3770	145.3	155.8	604	***
Pre emergence herbicide applied	251.0	375.2	6692	357.5	479.4	13147	***
Post emergence herbicide applied	340.8	470.3	7621	309.6	436.1	12214	***
Fertilizer v.r.t.	364.5	487.2	15531	246.6	368.3	1243	***
Pesticide v.r.t.	361.1	482.8	16373	231.9	322.5	401	***
Soil or plan test	245.2	367.0	15567	599.3	591.3	4279	***
Nitrogen test	330.3	457.7	15426	291.0	419.1	4424	***
Scouted for weeds	291.8	429.5	4596	330.5	455.2	15253	***
Scouted for insects	304.6	440.7	8300	333.6	455.6	11555	***
Scouted for disease	305.2	437.6	10862	341.2	463.1	8989	***
Kept scouting records	352.6	474.8	13765	383.5	502.8	3001	***
Phosphorus soil test	127.6	123.3	7266	13.7	127.7	3554	***

***,**,*Indicates significant difference between means at 1%, 5%, and 10%, respectively

Table A4: **Logit: Effect of insurance participation and premium paid on safe operating space**

	(1) Safe operating space	(2) Safe operating space	(3) Safe operating space
Field covered by FCI	0.414***		
	(0.0673)		
Operation has FCI		0.339***	
		(0.0755)	
Premium paid ($)			0.00265
			(0.00588)
N (lbs/acre)	0.0317***	0.0317***	0.0318***
	(0.00315)	(0.00315)	(0.00315)
P (lbs/acre)	0.000257	0.000296	0.000214
	(0.00196)	(0.00195)	(0.00198)
K (lbs/acre)	0.000319	0.000224	0.000158
	(0.00104)	(0.00104)	(0.00106)
Liquid pesticide (gal/acre)	0.211*	0.209*	0.202*
	(0.121)	(0.119)	(0.114)
Solid pesticide (lbs/acre)	0.0185	0.0188	0.0198
	(0.0149)	(0.0150)	(0.0157)
Production practice controls	YES	YES	YES
Year FE	YES	YES	YES
State FE	YES	YES	YES
Constant	-6.365***	-6.327***	-6.126***
	(0.487)	(0.487)	(0.500)
Observations	6,615	6,616	6,616

Standard errors robust to correlation at the state level in parentheses
*** p¡0.01, ** p¡0.05, * p¡0.1

Table A5: **Results: Effect of coverage level on distance to ideal N balance**

	(1) Distance to SOS	(2) Distance to SOS	(3) Distance to SOS
Yield coverage level	-0.00700		
	(0.00464)		
Price coverage level		-0.132*	
		(0.0656)	
Revenue coverage level			-0.559***
			(0.107)
N (lbs/acre)	-0.817***	-0.812***	-0.823***
	(0.122)	(0.0984)	(0.0935)
P (lbs/acre)	-0.210*	-0.0996	-0.0994
	(0.120)	(0.100)	(0.0968)
K (lbs/acre)	-0.164*	-0.341***	-0.310***
	(0.0871)	(0.0999)	(0.0863)
Liquid pesticide (gal/acre)	-15.72	-33.59***	-21.61**
	(10.42)	(10.20)	(9.412)
Solid pesticide (lbs/acre)	-3.935	-6.552***	-4.449***
	(3.025)	(2.000)	(1.527)
Production practice controls	YES	YES	YES
State FE	YES	YES	YES
Constant	256.7***	233.3***	251.9***
	(15.05)	(20.94)	(18.50)
Observations	3,929	2,299	2,531
R-squared	0.239	0.291	0.296

Standard errors robust to correlation at the state level in parentheses
*** p¡0.01, ** p¡0.05, * p¡0.1

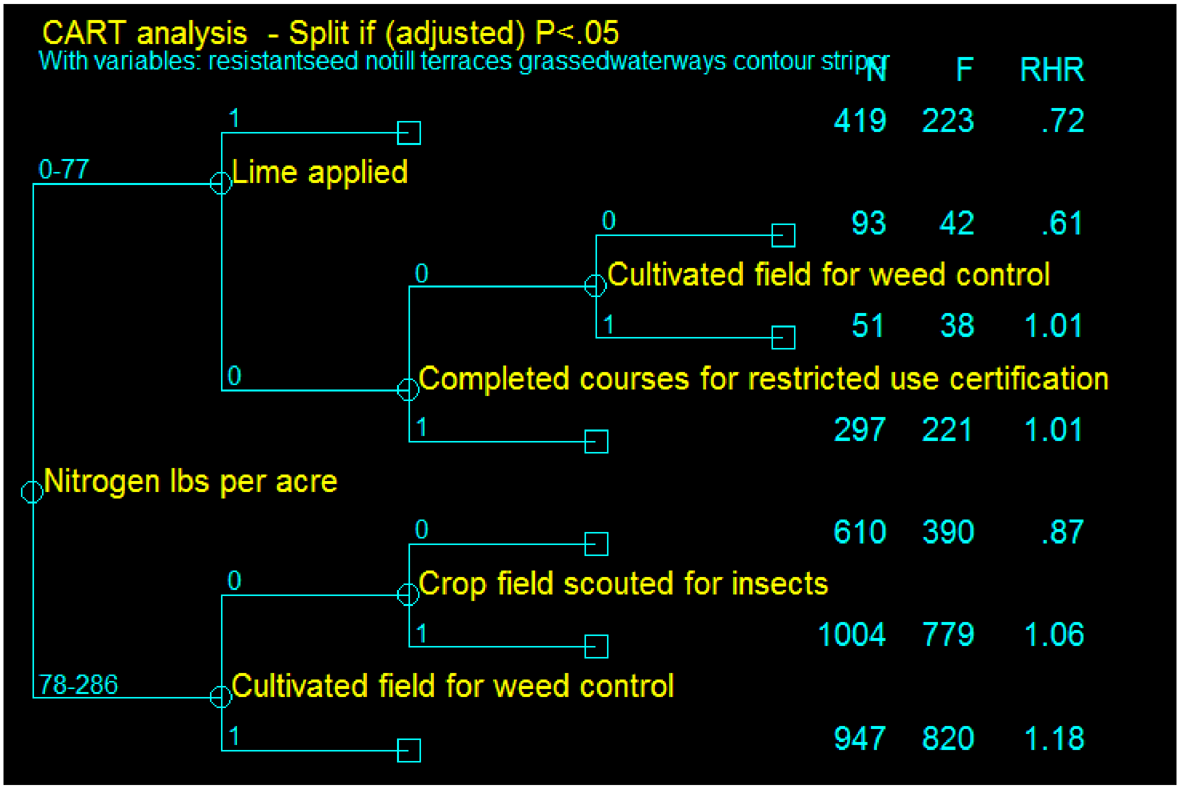

Figure A2: **CART: 1996**

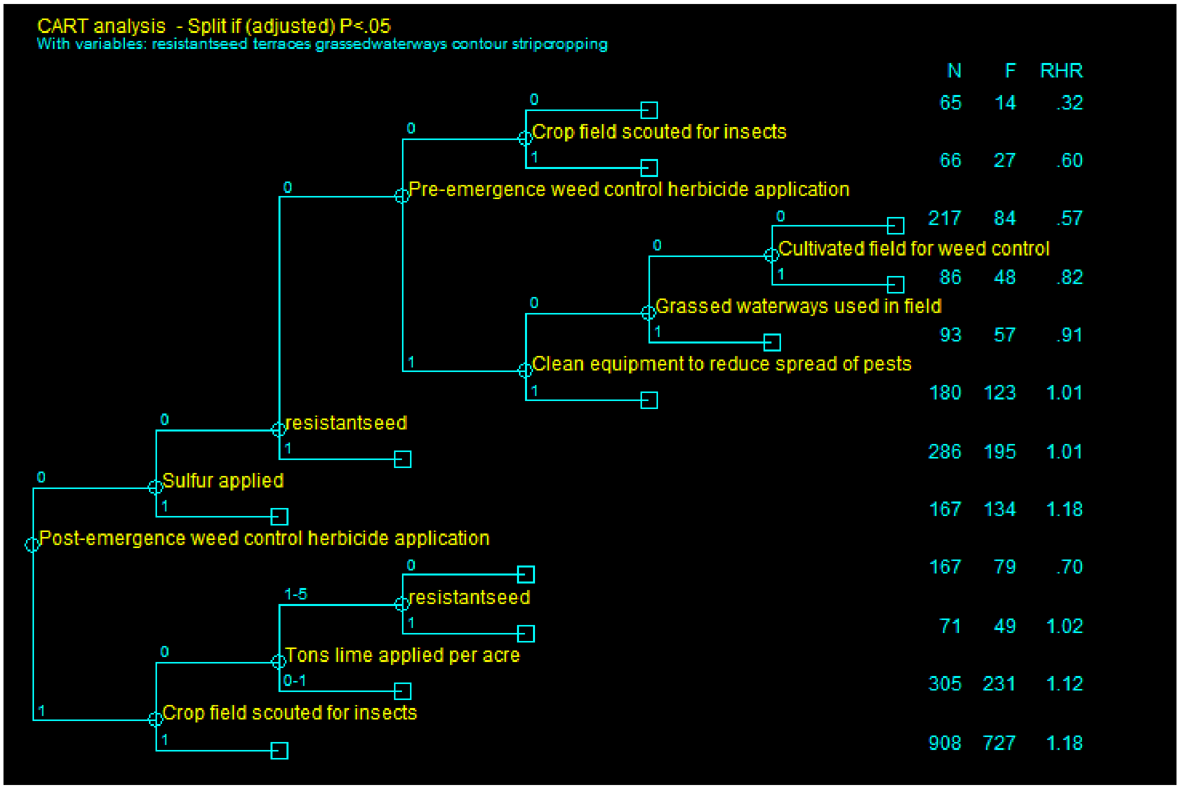

Figure A3: **CART: 2000**

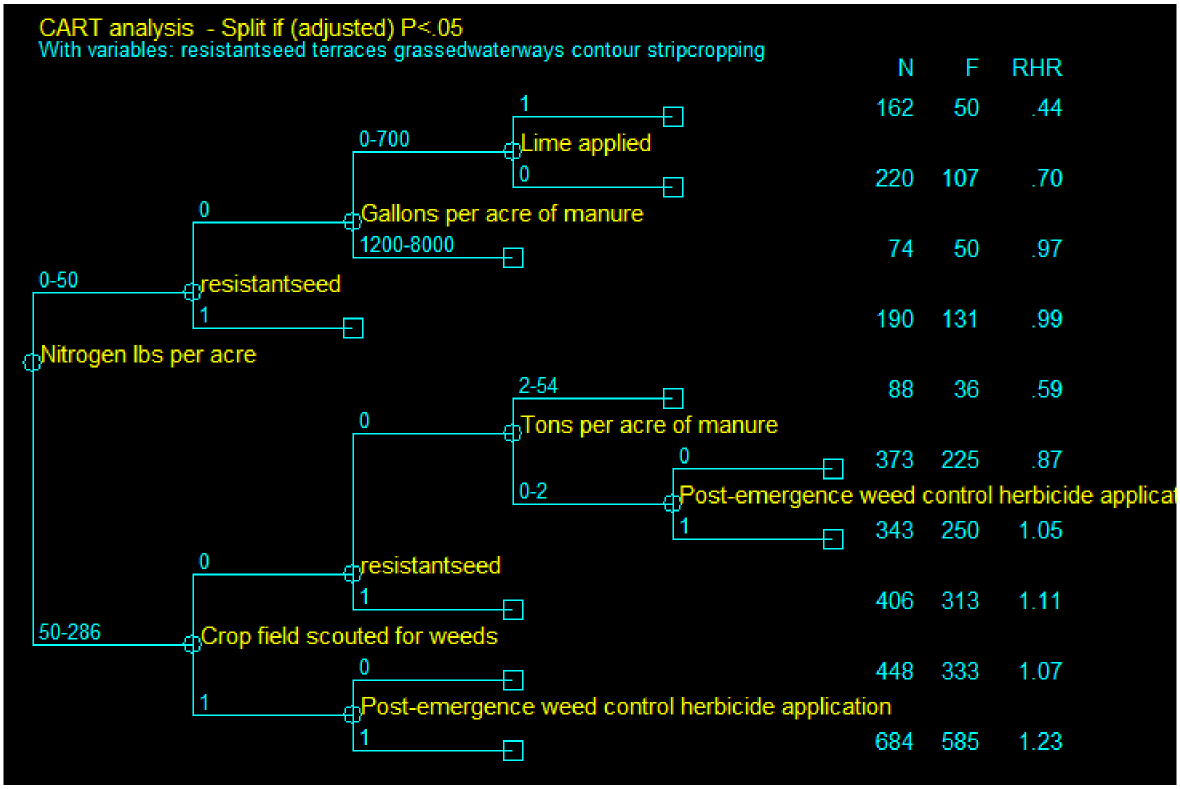

Figure A4: **CART: 2001**

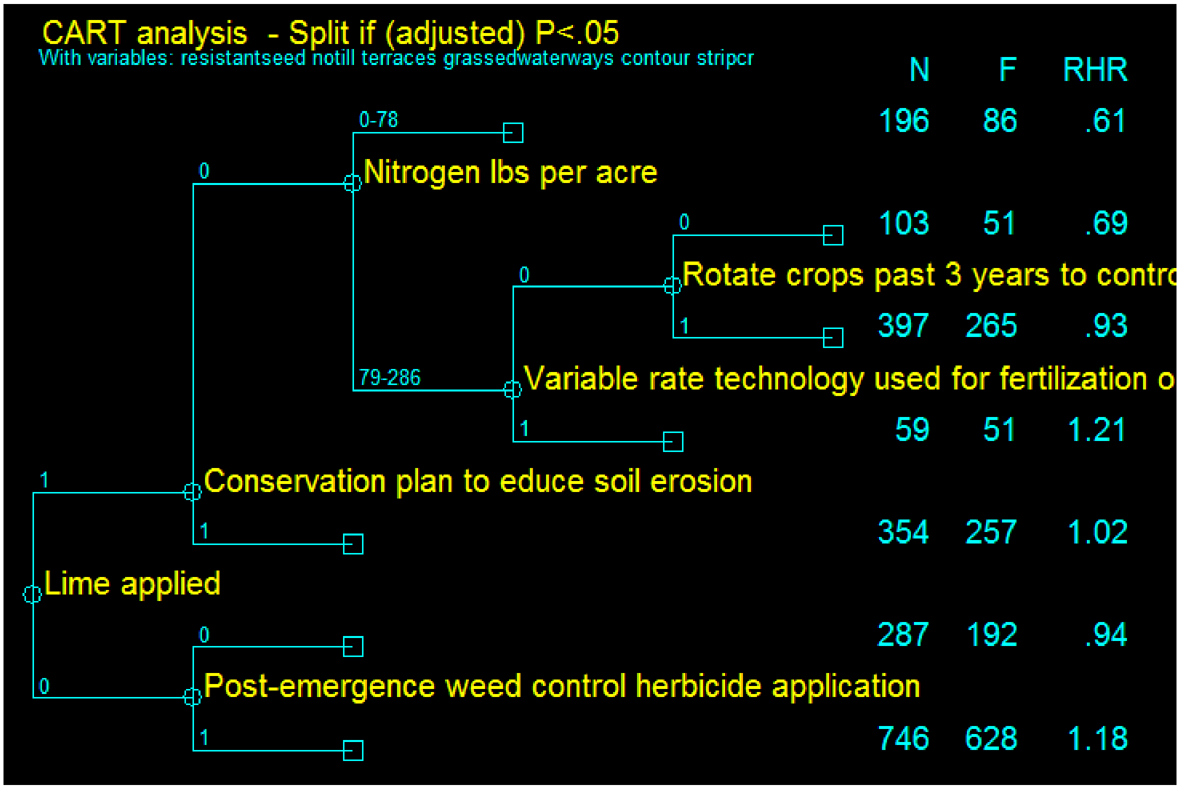

Figure A5: **CART: 2005**

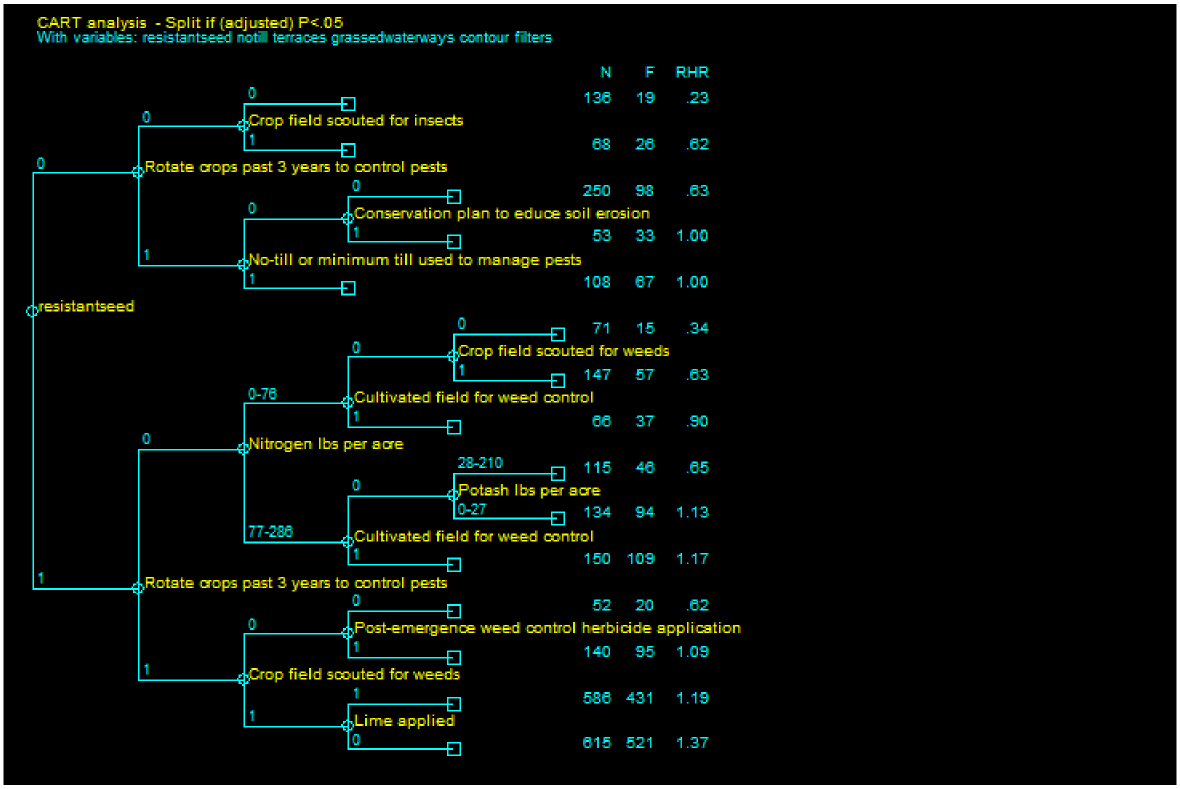

Figure A6: **CART: 2010**