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The effect of climate change on the economics of conservation tillage: A study based on field experiments in Indiana

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THE EFFECT OF CLIMATE CHANGE ON THE ECONOMICS OF CONSERVATION TILLAGE: A STUDY BASED ON FIELD EXPERIMENTS IN INDIANA

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NOMENCLATURE

SYMBOL	UNIT	DESCRIPTION
P_k	Dollars per bushel	Price of crop
$Y_{k,j}^{m}$	Bushels per acre	Yield for less intensive tillage practice for a particular crop and rotation
$Y_{k,j}^{n}$	Bushels per acre	Yield for more intensive tillage practice particular crop and rotation
O_k^m	Dollars per acre	Relative operating costs for less intensive tillage practice and crop
O_k^n	Dollars per acre	Relative operating costs for more intensive tillage practice and crop
V	Dollars per acre	Variable costs (do not differ between tillage practice)
$q_{k,j}^{m}$	Dollars per acre	Subsidy for tillage practice and crop rotation
k	Bushels/acre	Crop where c = corn s = soybeans
j		Crop rotation ($j = cc$ for continuous corn, $j = cs$ for corn/soybean rotation, and $j = ss$ for continuous soybean)
m		Less intensive tillage practice (m= NT for no till and m= ChT for chisel tillage)
n		More intensive tillage practice ($n = MP$ for moldboard plow and $n = ChT$ for chisel tillage)

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ABSTRACT

Hodde, Whitney. M.S., Purdue University, The Effect of Climate Change on the Economics of Conservation Tillage: A Study Based on Field Experiments in Indiana. Major Professor: Juan Sesmero

This study evaluates the economics of conservation tillage (chisel till and no till) and examines how climate change will likely affect it. I use data from long-term experimental plots in Indiana to estimate how corn and soybean yields respond to weather patterns under alternative tillage practices. Yield functions are coupled with random draws of weather variables to construct distributions describing the probability that conservation tillage will result in higher profits than more intensive tillage, under current and future climatic regimes. Results suggest that, in the study area, projected climate change will make conservation tillage more attractive.

CHAPTER 1: INTRODUCTION

Adoption of conservation tillage has received considerable attention in the past due to its widely promoted environmental benefits (e.g. Karlen et al., 1994a; Omonode et al., 2010; Sengupta and Dick, 2015). Concerns about soil erosion and nonpoint source pollution of water resources resulted in government support for adoption of conservation tillage. The economic performance of conservation tillage operations relative to more intensive alternatives is likely to influence farmers' decisions about which tillage practice to adopt (Stonehouse, 1991; Weersink et al., 1992a; Yiridoe et al., 2000; Kurkalova et al., 2006; Archer and Reicosky, 2009). Tillage practices influence net returns from farming through two channels: 1) differences in yields obtained under alternative tillage practices, and 2) relative costs associated with tillage operations of varying intensity.

A key feature of conservation tillage is that its effect on crop yields is influenced by weather patterns. For instance, in a given field, intensive forms of tillage have traditionally performed better (resulted in higher yields) than conservation tillage if beginning-of-season weather is cool and wet (Kovar et al., 1992). Therefore changes in weather patterns associated with climate change are likely to affect the relative performance of tillage practices. We contribute to the literature on the economics of conservation tillage by quantifying the expected effect of climate change on the economic performance of conservation tillage relative to more intensive alternatives.

To achieve our objective, we estimate expected corn and soybean yields, conditional on tillage and weather. We do so by exploiting data from field experiments to estimate yield response functions that include interaction terms between weather and tillage variables. Estimated yield functions are coupled with current and projected probability distributions of weather to characterize the expected effect of climate change on yield distributions. Randomly simulated yields are subsequently combined with prices and cost estimates to obtain probability distributions of net economic returns. These are used to examine the economic attractiveness of conservation tillage under current climatic conditions, and how such attractiveness is likely to be affected by climate change.

We consider three tillage practices, in decreasing order of intensity: moldboard plow tillage, chisel plow tillage, and no till. Moldboard plow tillage is the most soil disrupting practice, leaving less than 15% of crop residue remaining on the field between harvest and planting. Tillage using a chisel plow is a form of conservation tillage where typically at least 30% residue coverage remains between harvest and planting. No till leaves the soil completely undisturbed between harvest and planting; normally about 90% of residue cover remains under no till corn, and 75% under no till soybeans. We find that a risk neutral farmer, under current climate patterns and a corn-soybean rotation, prefers both forms of conservation tillage to a moldboard plow. However, moldboard plow dominates conservation tillage practices under continuous corn, especially in high yield (i.e. residue) systems on fine-textured soils such as the common dark prairie mollisols in the USA.

More importantly, we find that changes in weather patterns projected by mid-century improve the economics of conservation tillage relative to moldboard plow across crops and rotation systems. But these changes may or may not be large enough to warrant adoption of conservation tillage, absent public policies. We find that projected climate change at mid-century for dark prairie soils in the Corn Belt of the USA may induce a switch from chisel plow to no till among farmers growing corn in rotation. But moldboard plow is expected to continue to dominate conservation tillage practices under continuous corn. Finally, the improvement in the economics of conservation tillage (sufficient or not to warrant behavioral changes) is positively correlated with the magnitude of the change in climate. Consequently, changes in beginning-of-season weather under projected climate change enhance the alignment of private economic incentives with environmental stewardship, an issue largely overlooked by the extant literature.

CHAPTER 2: LITERATURE REVIEW

2.1 Conservation Tillage Literature

Intensive tillage has traditionally been used by farmers due to its many benefits, including weed control and seedbed preparation. However, intensive tillage disrupts and exposes the soil and leads to greater erosion, soil degradation, structural breakdown, and compaction issues (Pagliai et al., 2004). In addition there are concerns about impacts on long term soil health and productivity. More importantly, from the perspective of environmental policy, intensive tillage leads to sediment and nutrient runoff resulting in pollution of surface water.

An alternative management practice that can mitigate some of the adverse effects of intensive tillage is conservation tillage. Conservation tillage includes a number of different practices but is generally defined as any type of tillage that 1) leaves 30% or more crop residue on the soil surface after planting, or 2) maintains at least 1,000 pounds of small grain residue equivalent per acre throughout the critical wind erosion period (Natural Resources Conservation Service, 2011; Conservation Technology Information Center, 2015). This form of tillage may employ the use of chisel plows, disks, deep rippers, field cultivators, shallow vertical tillage implements, or a combination of these tools. Under no till the soil is left undisturbed from harvest to planting, except for strips of up to a third of the row width that may involve only residue disturbance or may (under strip till) include minimal soil disturbance in the intended crop row area.

Conservation tillage can alleviate soil erosion, and reduce nonpoint source pollution (from nitrogen and phosphorous) and damages to water quality (Karlen et al., 1997). Additionally, conservation tillage can offset the emission of greenhouse gases like CO_2 because it increases the amount of atmospheric carbon stored in the soil (Omonode et al., 2007; Gál et al., 2007); this is particularly true when crop productivity increases with no till (Ogle et al., 2012). Under no till, soil carbon can increase at an average annual rate of 48 +/- 13 g C m^{-2} yr^{-1} (West and Post, 2002). Reductions to losses of another major greenhouse gas, nitrous oxide (N_2O), have also received attention in the conservation tillage literature (Li, Changsheng et al., 1996; Omonode et al., 2010).

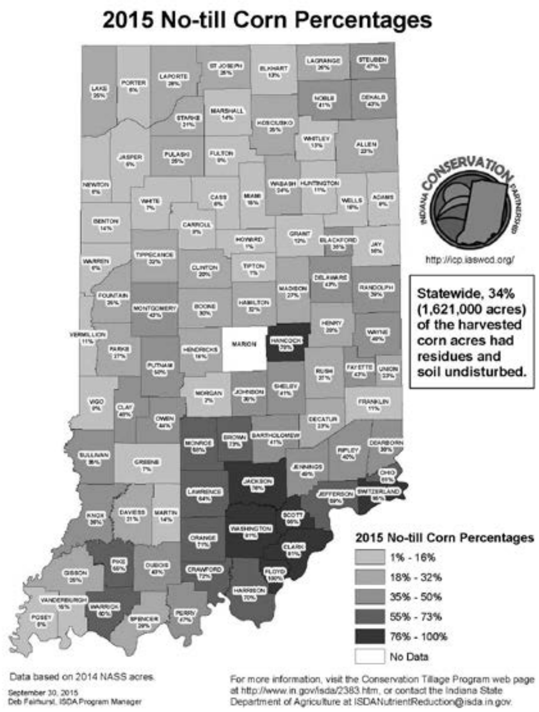
The environmental benefits from adoption of conservation tillage practices have been extensively documented. However, profitability is an important factor influencing adoption (Yiridoe et al., 2000, Cary and Wilkinson, 1997). The relative profitability of conservation tillage critically depends upon yield differentials under alternative tillage practices. It is also influenced by differences in cost of production. Costs of production vary across tillage practices due to the cost of tillage operations themselves, but also due to changes in application of chemical inputs. Other factors affecting the profitability of conservation tillage include the farmer’s planning horizon and degree of risk aversion (Epplin et al., 1982; Helms et al., 1987; Williams, 1988; Williams et al., 1990; Krause and Black, 1995). Finally, farmers’ subjective perception of the relative performance of tillage practices is also an important factor in adoption (Ding, 2009).

This study focuses on evaluation of cost differences and yield responses in a stochastic environment. Conservation tillage can result in savings in labor, machinery, and energy costs due to a reduction in the number of field equipment passes (Weersink et al. 1992b). However, it can also result in higher cost of chemical inputs as residue cover may increase the prevalence of pests and diseases. Conservation tillage affects yields by increasing organic matter and microbial activity in upper soil horizons (Gál et al., 2007; Karlen et al., 1994b). It also gives the soil a lower bulk density and better drainage capacity. Crop residues left on the soil surface help conserve soil water by reducing evaporation and improve water infiltration (Diaz-Zorita et al., 2004). These effects may result in increased soil productivity and yields. But conservation tillage can also reduce yields by delaying warming and drying up of the soil (possibly delaying planting), and slowing plant emergence (Doster et al., 1983).

Overall, evidence suggests that yields under different tillage scenarios vary by cropping system, soil properties, land slope, and climatic conditions (e.g. Toliver, 2012). A number of studies found that adoption of no till results in decreased crop yields (Doster et al., 1983; Griffith et al., 1988; Vyn and Raimbault, 1993). Corn yield reductions with no-till are more likely in continuous corn production than in the common corn-soybean rotation (West et al., 1996). However, under favorable conditions, no till can achieve profits comparable to conventional tillage methods (Ogle et al., 2012). In some cases lower yields and reduced profits may occur in the early years of adoption, but can be overcome once soil nutrients are built up and the soil structure is improved (Grandy et al., 2006).[1]

The important role of agro-climatic conditions in shaping the response of yields to adoption of conservation tillage partly explains spatial variability in adoption patterns. For instance, in our study area (Indiana), less intensive tillage practices are widely adopted in the south where weather is warmer and where soils have a higher percentage of sand and higher slopes. This is true for both corn (Figure 1.A) and soybeans (Figure 1.B), though conservation tillage adoption is much higher throughout the state for the latter crop. Overall adoption of conservation tillage in Indiana in 2015 was 40% for corn and 80% for soybeans (Indiana State Department of Agriculture, 2015). A majority of this is no till. Estimates by the Indiana Conservation Partnership conclude that 36% of all corn acreage and about 60% of soybean acreage is under no till or strip-till (Figures 1.A and 1.A).

[1] They are also influenced by the degree to which the farmer conducts a proper implementation of conservation tillage practices. But our study abstracts away from these considerations as we use field experiments that have been implemented by specialists.



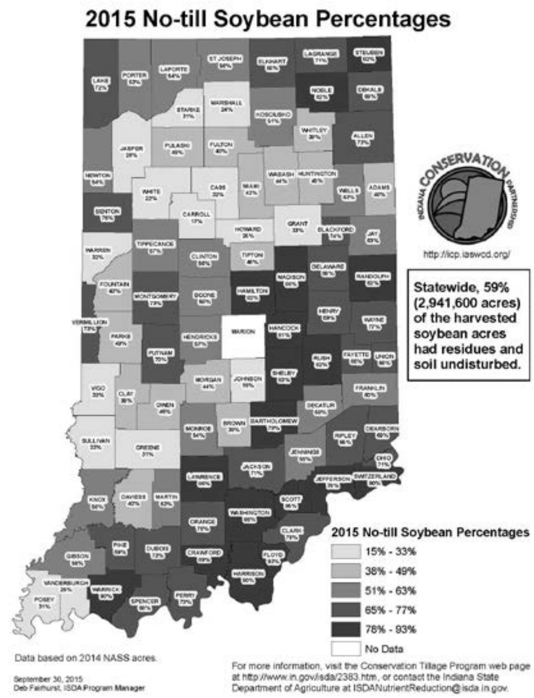


Figure 1.A. No till corn adoption in Indiana   Figure 1.B. No till soybean adoption in Indiana

As suggested above, weather is an important factor influencing yield response to tillage. Moreover, weather is random and distributed according to a pattern that can vary over time due to climate change. Therefore, the relative profitability of conservation tillage is also random and subject to temporal variation. Previous literature has used the concept of stochastic dominance to compare the economic performance of conservation tillage relative to more intensive practices (Weersink et al., 1992a; Klemme 1985; Yiridoe et al., 2000; Archer and Reicosky, 2009). These studies provide key insights into the economics (i.e. risk/return) of conservation tillage by incorporating risk through randomness of yields. However, they use unconditional distributions of yield and, thus, no systematic link to weather is estimated. This precludes examination of the effect of changes in weather patterns (e.g. due to climate change) on the economics of conservation tillage. Our study attempts to fill this gap.

2.2 Policy Background

The goal of environmental policy is to get polluters to incorporate the value of external damages caused by production processes into their private cost (Doering et al., 1999). There are many external damages associated with agricultural production, but water quality is a major area where improvement is both important and feasible. The primary source of water quality degradation in the United States (US) is soil erosion and runoff of agricultural inputs (Kling, 2011). The US government has targeted the agricultural sector for improvements by incentivizing voluntary management practices that reduce soil erosion and runoff.

The Environmental Quality Incentives Program (EQIP) and the Conservation Reserve Program (CRP), administered by the Natural Resource Conservation Service (NRCS), are perhaps the most influential programs that target non-point source pollution (Doering et al, 1999). EQIP was initiated in 1996. This program provides technical and financial assistance to help farmers implement conservation tillage and other runoff-reducing practices. The NRCS pays 75% of the cost to adopt practices such as no till or cover cropping. The federal farm bill establishes payment calculations and eligibility, and NRCS state offices make funding allocation decisions. A farmer can voluntarily apply for funding support from a given program. Payments for adoption of conservation tillage practices are done on an annual basis; a maximum of three payments is imposed over the duration of a single contract (National Resources Conservation Services, 2016a). Both no till and mulch till (in this study chisel tillage in continuous and rotation corn can be considered mulch tillage) can be covered under the program (Natural Resources Conservation Service, 2016b). The type of conservation practice covered and associated payment rates vary by state so that programs can meet local needs.

Despite these efforts, many agricultural watersheds do not meet water quality goals set forth in the Clean Water Act (Kling, 2011). A large body of literature has attempted to shed light on the causes behind the limited success of existing policies. These studies, both theoretical (Shortle and Dunn, 1986) and empirical (e.g. Rabotyagov et al. 2010), have deepened our understanding of the relative merits of competing policies addressing water quality issues. A number of studies have estimated the magnitude of subsidies required to induce adoption of conservation tillage. Some of these studies used stated preference methods (Lohr and Park, 1995; Cooper and Keim, 1996; Cooper, 1997), others have used revealed preference methods (Kurkalova et al. 2006). The present study contributes to the policy debate by examining the effect of climate change on the magnitude of the subsidy that would trigger adoption. The use of data from field experiments is a key element of our analysis, as it permits quantification of the influence of weather and tillage practices on yields.

CHAPTER 3: METHODS

We model a representative farmer that chooses a tillage practice to maximize profits, defined as revenue minus variable production cost. All other production inputs are kept constant which allows us to focus our attention on the tillage decision. A profit-maximizing farmer is likely to adopt a more intensive tillage practice n (e.g. moldboard plow tillage) if it results in higher profits relative to a less intensive practice m (e.g. chisel tillage), per unit of land:

$$P_k * \left(Y_{k,j}^m | w\right) - V - O_k^m + q_{k,j}^m \leq P_k * (Y_{k,j}^n | w) - V - O_k^n \qquad (1)$$

where P_k denotes price of crop k ($k = c$ for corn, and $k = s$ for soybean); $Y_{k,j}^m|w$ represents yield of crop k, under crop rotation j ($j = cc$ for continuous corn, $j = cs$ for corn/soybean rotation, and $j = ss$ for continuous soybean) and less intensive tillage practice m ($m = NT$ for no till, $m = ChT$ for chisel till); and $Y_{k,j}^n|w$ represents yield of crop k, under crop rotation j and more intensive tillage practice n (and $n = MP$ for moldboard plow, and $n = ChT$ for chisel till). Yields are conditional on a vector of weather variables, w. Furthermore, V represents variable costs that do not differ between tillage practices (e.g. fertilizer); O_k^m capture operating costs expected to vary by crop and tillage practice (machinery, machinery labor time, and chemical costs); and $q_{k,j}^m$ is the subsidy obtained by the farmer adopting a conservation tillage practice m which will vary by crop, rotation, and specific tillage practice. Three pair-wise economic comparisons of tillage practices can be conducted: no till vs. moldboard plow, no till vs. chisel tillage, and chisel tillage vs. moldboard plow.

The difference between yields under alternative tillage practices is determined by weather w, which is random. Therefore fulfillment of the inequality (1) is also random. All else constant, cooler and wetter weather results in higher yields under more intensive tillage practices (Toliver et al., 2012); i.e. cooler and wetter weather decreases $Y_{k,j}^{m} - Y_{k,j}^{n}$. We capture this randomness through a cumulative distribution function (CDF) describing the probability that the difference between profits under conservation practice m and those under more intensive practice n are lower or equal to some arbitrary number z; i.e. $Prob\left[X = P_k * \left(Y_{k,j}^{m} - Y_{k,j}^{n} | w\right) + (O_k^n - O_k^m) + q_{k,j}^{m} \leq z\right]$. We denote this CDF by $\Phi_{k,j}^{m-n}(z)$. Note that the CDF evaluated at $X = 0$ (i.e. $\Phi_{k,j}^{m-n}(0)$), denotes the probability that less intensive tillage practice m will result in lower profit than more intensive practice n.

Let us assume that a farmer considering adoption of a less intensive tillage practice requires at least a probability R that such practice will be more profitable ($X > 0$). Then the farmer will implement the following decision structure:

$$\begin{cases} \text{implement tillage practice } m & \text{if } \Phi_{k,j}^{m-n}[X=0] < 1 - R \\ \text{implement tillage practice } n & otherwise \end{cases} \qquad (2)$$

The function $\Phi_{k,j}^{m-n}[X]$ is composed of three parts. First, the yield differential conditional on weather, $\left(Y_{k,j}^{m} - Y_{k,j}^{n} | w\right)$. Second, deterministic parameters P_k, O_k^m, O_k^n, and $q_{k,j}^{m}$ that combine with yields to determine the profitability of less intensive relative to more intensive tillage practices. The third part is the probability distribution of weather variables in vector w. The next section discusses estimation of the yield response to seasonal weather conditions. We will subsequently discuss estimation of probability distributions of weather variables. Regarding deterministic parameters, the subsidy $q_{k,j}^{m}$ will be determined endogenously in our study; i.e. we will calculate the subsidy that makes a certain tillage practice 50% ($R = 0.5$) likely to outperform another, more intensive, practice. A detailed discussion of how parameters P_k, O_k^m, and O_k^n are calculated is included in Appendix A.

3.1 Yield Function Estimation

A long-term experiment on different tillage systems spanning 40 years (1975-2014) was conducted at the Purdue Agronomy Center for Research and Education (ACRE) in West-central Indiana (40º28'07"N, 87º00'25"W). The soil at the experiment site is Chalmers silty clay loam (4% organic matter). One year (2011) resulted in yield anomalies due to hail damage, leaving 39 years of usable experimental data. The experiment comprised a block design with 12 split-plots. The study annually tracked crop yield differences for three tillage practices (moldboard plow, chisel plow tillage, and no till) and three crop rotations (continuous corn, corn-soybean rotation, and continuous soybeans) most commonly used in Indiana. Two plots were planted to corn-soybean rotation under each tillage practice with one starting with corn and one with soybeans in 1975. This resulted in a total of 12 split-plot treatment combinations (three continuous corn plots, three continuous soybeans, and six corn-soybean rotations with three plots in each rotation crop in a given year). Therefore, in any given year, 6 plots produce corn (three continuous corn and three corn after soybeans) and 6 produce soybeans (three continuous soybeans and three soybeans after corn).

Plots in the experiment were 32-feet wide and 150-feet long. The experimental area had less than 2% slope and was systematically tile drained at 20-m intervals. All primary tillage occurred in the fall. In the spring, one disking and/or one or two field cultivation passes aided seedbed preparation. For the experimental plots analyzed, residue coverage for the moldboard plow was 5-15% following corn and 2-5% following soybeans (West, personal communication, November 16, 2015). The chisel plow experimental plots had a residue coverage of 30-40% following corn and 10-20% following soybeans (West, personal communication, November 16, 2015). The no till plots had a residue coverage of 87-95% following corn, and 70-80% following soybeans.

As part of the experiments, data on yields, weather, and management practices were collected from 1975 to 2014 (except 2011). Weather variables include growing degree days (GDD), precipitation, and stress degree days (SDD), recorded at the ACRE weather station (West Lafayette 6 NW) over the 39 year length of the experiment (Midwestern Regional Climate Center 2015). We use these data to estimate a linear regression model and quantify the expectation of yield conditional on weather and tillage practices.[2] Descriptive statistics of variables included in the regressions are reported in Table 1. Values in this table reveal a substantial variability of yields over time and across management practices. No till seems to typically result in lower yields as compared to moldboard plow and chisel. The greatest discrepancy between no till and alternative

[2] Other studies have used crop models to forecast crop yields under climate change. A growing body of literature links climate, crop and economic models together. Rosenzweig et al. (2013) reviews some of these studies and discusses how such models may be improved.

practices occurs under continuous corn. Yields under chisel and moldboard plow are similar across cropping scenarios.

Table 1. Descriptive Statistics of Regression Variables

	Mean	Median	Standard deviation	Minimum	Maximum
Yield (bushels per acre)					
Yield, corn in rotation under moldboard plow	187	185	33	131	269
Yield, corn in rotation under chisel	188	193	33	138	262
Yield, corn in rotation under no till	183	185	31	128	255
Yield, continuous corn under moldboard plow	180	180	34	120	260
Yield, continuous corn under chisel	175	178	31	122	241
Yield, continuous corn under no till	157	161	34	84	235
Yield, soybeans in rotation under moldboard plow	54	55	7	37	68
Yield, soybeans in rotation under chisel	52	52	6	39	64
Yield, soybeans in rotation under no till	52	52	9	32	71
Weather					
Precipitation April (inches)	3.6	3.5	1.9	1.1	9.1
GDD April	209	206	61	106	337
Precipitation May (inches)	4.4	4.4	2.0	0.9	9.8
GDD May	419	417	90	286	606
Precipitation June-September	15.0	14.2	4.1	7.4	23.5
GDD June-September	2,465	2,451	147	2,123	2,735
Stress degree days June-September	128	107	90	23	382

Substantial weather variability is also observed in the study period and exploited to estimate regression equations. GDD distributions in April, May, and June-September are skewed to the right. Moreover their coefficients of variation (ratio of standard deviation to mean) are 0.30, 0.21, and 0.06 respectively, revealing that growing season GDD is less variable than early season (April and May) GDD. The April precipitation distribution is skewed to the right while May and June-September distributions are less skewed following more symmetric distributions. Their coefficients of variation are 0.53, 0.45, and 0.27 respectively, also revealing less variability over the growing season than at the beginning of the season.

Two strategies are possible to estimate the effect of tillage practice on yields. First, separate regressions can be run partitioning the sample by crop and tillage practice. In this case, a total of six equations would be estimated (corn yield function under three tillage practices, and soybeans yield under three tillage practices), and each equation would be estimated based on a sample of 78 observations (2 observations per year -one for continuous cropping and one for rotation cropping- for 39 years). Second, a combined regression can be run where the sample is partitioned by crop but not by tillage practice, and the effect of tillage on yields is captured by inclusion of tillage dummies. Each function would be estimated based on a total of 234 observations (6 observations per year, for 39 years).

Estimating a combined regression with dummies results in an increase in degrees of freedom (although it may also lead to multicollinearity problems), but it assumes that the variances of the residuals from separate regressions are essentially the same (Gujarati, 2009). Its validity hinges upon fulfillment of this assumption. When the assumption does not hold, running separate regressions for each group is the best strategy. Therefore we used the following protocol to define the optimal estimation strategy. First, we run separate regressions and save the residuals. Second, we test whether variances of the two populations are statistically significantly different. For this, we use an F-test (Snedecor and Cochran, 1989). This test (available from the authors upon request) results in a failure to reject the null hypothesis of different variances. Therefore, we run a combined regression with dummies clustering observations by crop.

Two functions were estimated, one for corn and one for soybeans. Crop yield is the dependent variable in these regressions. The vector of independent variables includes dummy variables indicating tillage practices (moldboard plow is excluded as it is the baseline practice), crop rotation (a dummy for a crop grown in rotation, leaving continuous cropping as the baseline), and interactions between crop rotation and tillage dummy variables. In addition, we include variables to account for the planting date (dummies for early April, late April, late May, early June, and late June with the most common practice, early May, as the baseline), an annual time trend, and a vector of weather variables.

Generally speaking, conservation tillage tends to reduce yields relative to moldboard plow due to poorer seedbed conditions, delayed seedling emergence and crop development, and (or) more plant-to-plant variability in growth and development (Boomsma et al., 2009). Therefore we expect coefficients on standalone conservation tillage dummies to be negative. Crops grown in rotation typically attain higher yields (Hennessy, 2006), so the coefficient on the rotation dummy is expected to be positive. Moreover, conservation tillage performs better under crop rotation than in a continuous cropping system (Lund et al., 1993). This is especially true for corn. Therefore the coefficients on the interactions between conservation tillage dummies and the rotation dummy are expected to be positive, at least for corn.

The range of planting dates were divided into two week intervals. Consequently we created an early April dummy, which takes a value of one if the crop was planted in the first two weeks of April and zero otherwise, late April was equal to one if the crop was planted in the last two weeks of April, and so forth. The most commonly implemented planting dates for each crop were used as baselines—early May for corn and late May for soybeans. Planting dates were decided based on soil moisture conditions (especially in the no-till plots) at the beginning of each growing season. Planting dates for both corn and soybean were consistently the same among tillage and rotation systems in each year of the experiment. There is inter-annual variation in planting dates, but not across split-plots in a given year. Earlier planting dates are associated with longer growing seasons and higher yields. Therefore, coefficients on planting dates earlier (later) than the baseline are expected to be positive (negative).

The time trend is included to capture increases in yields due to, among other things, improvements in hybrid seeds. From 1981 to 1994, the experiment used a single corn hybrid, Becks 65X (Boomsma et al., 2009). Since 1994, superior commercial hybrids in yield and leaf disease tolerance were used to reflect then-common hybrids available to farmers. Modern hybrids have more tolerance to plant density that allows for higher plant populations and results in higher yields. Therefore the coefficient of the time trend is expected to be positive. The time trend does not interact with weather (tests rendered them insignificant), which implies that productivity gains are neutral; they do not affect yield response to weather. It is worth noting that innovations such as drought- and heat-resistant hybrids (which were not planted in this experiment) would require inclusion of year-weather interaction terms.

The vector of weather variables includes precipitation, GDD, and SDD. GDD is calculated daily as the difference between maximum daily temperature (not to be above 86° Fahrenheit) and minimum daily temperature (not to be below 50° F). These daily figures are added up to calculate monthly GDD. SDD is measured as the number of days in which temperature exceeded 86° Fahrenheit. This variable is included to capture extreme heat events that can seriously suppress plant growth, even if not affecting GDD significantly. Stress degree days capture the adverse reaction that, on average, corn plants experience to temperatures above 86 degrees Fahrenheit (Taylor, 2012). Late fall and winter rainfall and temperatures have little impact in determining corn yields (which was confirmed by preliminary regressions) and so were not used as explanatory variables.

April and May precipitation and GDD were separated from total precipitation and GDD over the June – September months that encompass the growing season. Weather occurrences in April and May were separately interacted with dummies for tillage practices to capture the fact that the effect of tillage practices on yields is conditioned by beginning-of-season weather (see for example Yamoah et al., 1998 and Vetsch and Randall, 2004).[3] Higher residue cover delays warming and drying of the soil which may

[3] April and May were chosen as early season weather variables. These were chosen because a majority of actual planting dates for the experiment occurred in April and May. Corn was planted in April or May 33 times out of the 39 years of data. Soybeans were planted in April or May 36 times. We used separate weather distributions for each April and May as opposed to combined weather distributions because we found this strategy to increase goodness of fit in addition to allowing for a more accurate picture of the beginning-of-season weather effects on yield.

affect plants' early emergence and can impact crop yields (Yamoah et al., 1998; Vetsch and Randall, 2004). This can constitute an advantage of conservation tillage in warmer weather conditions. Therefore the coefficients of the interaction between GDD in April and less intensive tillage dummies are expected to be positive. Abundant precipitation quantities in April and May are expected to have a yield-reducing effect under conservation tillage. Therefore, the derivative of yield with respect to less intensive tillage dummies is expected to become negative at high precipitation levels. However, the negative effect of abundant precipitation under conservation tillage is expected to be alleviated in our study due to the presence of systematic tile drainage.

Squared terms of the weather-tillage interactions are included to capture possible nonlinearities in the link between tillage, weather, and yields (Schlenker and Roberts, 2006). For instance, increases in moisture in April can, at first, benefit all plots. But as moisture increases beyond some critical threshold, they may negatively affect seedbed environment and hamper emergence. However the thresholds need not be the same under different tillage practices. In general, and all else constant, it is expected that plots with more intensive tillage can better handle excess moisture. Therefore coefficients of quadratic terms are expected to be negative, and to vary by conservation tillage practice. Linear and quadratic terms for April and May GDD are also included to potentially capture decreasing marginal effects of temperature on yields.

In addition to beginning-of-season weather, the estimation also includes weather information for the rest of the growing season. Specifically, GDD and precipitation from June to September were included along with quadratic terms to capture decreasing marginal effects of GDD, and negative marginal effects of excess precipitation

(Schlenker and Roberts, 2009). Therefore the coefficients on the linear terms for growing season GDD and precipitation are expected to be positive, while the coefficients on their quadratic terms are expected to be negative. Empirical evidence also suggests a negative effect of excess heat (temperatures beyond 86 degrees Fahrenheit) on yields (Schlenker and Roberts, 2009), so we expect a negative coefficient on SDD. Finally, drought stress and heat stress often occur simultaneously (Rosenzweig, 2001), so an interaction term between growing season rainfall and SDD was also included to capture the damages caused to crop yield when one is exacerbated by the other (De Boeck, 2010).

3.2 Estimation of Probability Distribution of Weather from Projected Data

The previous section described estimation of the conditional (on weather) expectation of corn and soybean yields. Yield responses to weather occurrences vary by tillage practice. Our strategy is to take random draws from beginning-of-season (i.e. April and May) probability distributions of weather variables and map those occurrences to yields, to obtain a probability distribution of yields by tillage practice. Probability distributions governing random draws of *current* weather variables can be approximated based on recent history of weather occurrences. These are displayed in Figures B.1-B.4, Appendix B. Multiple parametric approximations were fitted to the data and the best one was identified based on Akaike and Bayesian Information Criteria. April precipitation is best approximated with a Weibull distribution and May precipitation is best approximated with a normal distribution. April and May GDD are best approximated with triangular distributions. Descriptive statistics of the chosen distributions are reported in the figures in Appendix B.

These probability distributions cannot be extrapolated into the future. As anthropogenic greenhouse gases build up in the atmosphere, they are and will continue to impact probability distributions of weather variables. To quantify *future* probability distributions of the same weather variables, we take random draws of GDD and precipitation from climate models and fit parametric approximations to such observations. The World Climate Change Research Program (WCRP) houses the Working Group on Coupled Modelling (WGCM). This group established the Coupled Model Intercomparison Project (CMIP), a standard experimental protocol for studying the output of coupled atmosphere-ocean general circulation models (AOGCMs). CMIP allows for climate model validation and intercomparison. These experiments are currently in their fifth phase (CMIP5), and this model output is the basis for the Intergovernmental Panel on Climate Change (IPCC)'s Fifth Assessment Report (IPCC, 2013a).

The archived CMIP5 multi-model ensemble dataset that was used for this study is available online (Bureau of Reclamation, 2013), and contains gridded climate projections over the contiguous United States that were developed using two downscaling techniques. The data used are from the 1 degree Bias-corrected GCM projections using the Bias-Correction Constructed Analogues (BCCA) downscaling method. The specific latitude and longitude of our experimental plots were entered to the system. Using these specifications we were able to obtain daily precipitation, minimum daily temperature and maximum daily temperature output for the years 2030-2069 for 36 different model/model runs. The 2030-2069 period was selected to represent an approximation to "medium term" projected climate conditions; i.e. mid-century weather patterns. Also the length of the period is chosen to match the 39 years of observed data used to calculate “current” weather patterns. The list of CMIP5 climate models and number of runs used can be found in Table C.1 in Appendix C.

Emission scenarios available from CMIP5 include Representative Concentration Pathway (RCP) 2.6, RCP4.5, RCP6.0 and RCP8.5. These represent a range of 21st century climates (IPCC, 2013b). In this study we consider RCP2.6 and RCP8.5 greenhouse gas scenarios. The RCP2.6 represents a Greenhouse Gas (GHG) emissions mitigation scenario where atmospheric CO_2 concentrations reach 421 ppm by 2100. In this scenario, emissions peak in the middle of the century and decrease later on. Under this scenario, greenhouse gas concentrations and, therefore, temperature changes show a decrease in the second part of the 21st century (Diffenbaugh and Field, 2013). RCP2.6 is representative of a scenario that aims to keep global warming below a 2°C increase relative to pre-industrial (1850-1900) temperatures (IPCC, 2013b). RCP8.5 represents the highest projection of GHG emissions where CO_2 concentrations reach 936 ppm by 2100 and temperatures are likely to exceed a 2°C increase.

Daily outputs projected by the climate models were consolidated into monthly figures to match them to variables in the estimated yield functions. Monthly values of weather variables from all climate models (see Appendix C for a description) and all years were pooled to create the probability distributions. This means that the distributions capture heterogeneity among models, in addition to intra-model climate variability. We think this is the most appropriate approach as differences in random draws across models are themselves explained by uncertainty in geophysical parameters and, thus, in weather patterns. Probability density functions of April precipitation and GDD and May precipitation and GDD under projected climate regime (under alternative emissions scenarios) are displayed, alongside the historical distributions, in Figures B.1-B.4, Appendix B.

April and May precipitation are best approximated with gamma distributions under a low emissions scenario. A gamma distribution is also a best fit for April precipitation under a low emissions scenario, but a log-normal distribution seems more appropriate in a high emissions scenario. April GDD is best approximated with a beta distribution under a low emissions scenario and a normal distribution in a high emissions scenario. May GDD is best approximated with a normal and beta distributions under low and high emissions scenarios respectively. April and May precipitation averages and standard deviations change only slightly from current climate to alternative climate change scenarios. Changes to the April and May GDD distribution induced by climate change are more dramatic. Mean GDD increases under climate change, and higher emissions trigger a larger change. Variability of April GDD also increases under climate change.

CHAPTER 4: RESULTS

4.1 Conditional Expectation of Crop Yields

The R-squared statistics show that our yield response models explain a reasonable fraction of yield variability. The R-squared for the corn model is 0.7 (Table 2), while the R-squared for the soybean model is 0.6 (Table 3). Moreover, the signs of estimated coefficients are largely consistent with prior expectations. As is the case for famers, planting dates in the experiment were chosen depending on year-to-year conditions. Delayed planting reduces yields; all else constant, yields tend to be higher when seedbed conditions are favorable for planting early in the season. The coefficient on the time trend indicates that, on average, corn yields have increased by 1.8 bushels a year while soybean yields have done so by 0.4 bushels a year. This suggests that genetic and management improvements have resulted in higher yields over the course of the 40 years of the experiment.

Table 2. Corn Yield Function Regression Results

Variable description	Coefficient	Standard Error	P-Value
Year	1.8	0.2	0.00
No till dummy	-62.3	112.8	0.58
Chisel dummy	17.6	96.8	0.86
Rotation dummy	7.6	4.4	0.09
(No till dummy)*(Rotation dummy)	18.1	6.7	0.01
(Chisel dummy)*(Rotation dummy)	5.9	6.1	0.33
Precipitation April	15.8	5.1	0.00
(Precipitation April)*(No till dummy)	5.0	7.1	0.49
(Precipitation April)*(Chisel dummy)	1.9	5.6	0.74
Precipitation April^2	-1.0	0.5	0.03
(Precipitation April)^2*(No till dummy)	-0.7	0.7	0.34
(Precipitation April)^2*(Chisel dummy)	-0.2	0.5	0.70
GDD April	-0.6	0.3	0.05
(GDD April)*(No till dummy)	0.1	0.4	0.85
(GDD April)*(Chisel dummy)	0.1	0.4	0.84
GDD April^2	0.002	0.001	0.02
(GDD April)^2*(No till dummy)	-0.0001	0.001	0.90
(GDD April)^2*(Chisel dummy)	-0.0001	0.001	0.86
Precipitation May	-4.5	4.8	0.35
(Precipitation May)*(No till dummy)	4.9	6.3	0.44
(Precipitation May)*(Chisel dummy)	-0.5	5.3	0.92
Precipitation May^2	-0.1	0.5	0.91
(Precipitation May)^2*(No till dummy)	-0.3	0.7	0.60
(Precipitation May)^2*(Chisel dummy)	0.1	0.6	0.92
GDD May	0.1	0.3	0.68
(GDD May)*(No till dummy)	-0.01	0.4	0.98
(GDD May)*(Chisel dummy)	-0.2	0.4	0.66
GDD May^2	-0.0002	0.0004	0.56
(GDD May)^2*(No till dummy)	0.0001	0.0005	0.88
(GDD May)^2*(Chisel dummy)	0.0002	0.0004	0.65
Precipitation June-September	9.7	4.6	0.04
Precipitation June-September^2	-0.2	0.1	0.05
GDD June-September	1.2	0.3	0.00
GDD June-September^2	-0.0002	0.0001	0.00
Stress DD June-September	0.1	0.1	0.59
(Stress DD June-September)*(Precipitation June-September)	-0.02	0.01	0.00
Early April plant date	36.9	10.3	0.00
Late April plant date	7.3	4.5	0.11
Late May plant date	-12.9	5.3	0.02
Constant		YES	
R^2	0.71		
# observations	234		

The split-plot design of this experiment removes a number of confounding effects that typically emerge in observational (i.e. farm-level data) studies. By keeping agronomic conditions and other management practices constant, the block design allows us to isolate the effect of tillage practices on yields. This removes the risk of omitted variable bias, lending credence to our estimate of the effect of tillage on yields. Results reveal a concave response of yields to beginning-of-season weather variables under the baseline practice (moldboard plow). April and May weather and tillage interaction terms represent the deviation from this baseline. Corn production under less intensive tillage practices is adversely affected by abundant beginning-of-season rainfall, and favored by high temperatures as capture by increased GDD (Table 2).[4] Such relationships are much weaker for soybeans, which perform better under less intensive tillage for a wide range of weather conditions (Table 3).

Although the role of weather on the response of yields to tillage are consistent with our prior expectations, our estimates also reveal considerable imprecision. Standard deviations of coefficients are relatively large, reducing the statistical significance of individual coefficients. This may be explained by inherent noise in yields, but also by multicollinearity given the multiple ways in which beginning-of-season weather and tillage dummies enter the regression equation. Further analysis (see discussion in Appendix D) reveals a high correlation between interaction terms and their individual components, and between linear and quadratic terms. Therefore high standard deviations are likely the result of multicollinearity. Fortunately, multicollinearity does not present a

[4] This can be readily seen by taking the derivative of yield with respect to rainfall and GDD, evaluating them at the mean of the weather variables, and examining the differences across tillage practices. It can also be seen through simple plotting of the estimated yield function with respect to rainfall and GDD.

serious challenge to the analysis as we are not interested in marginal effects but the overall predictive power of the model; which is not diminished by the presence of multicollinearity. Therefore, the objective of our analysis, in combination with knowledge of agronomic relationships, warrant inclusion of the entire set of predictors.

Table 3. Soybean Yield Function Regression Results

Variable description	Coefficient	Standard Error	P-Value
Year	0.4	0.1	0.00
No till dummy	-58.0	29.3	0.05
Chisel dummy	-5.4	26.0	0.84
Rotation dummy	4.5	1.2	0.00
(No till dummy)*(Rotation dummy)	0.6	1.8	0.75
(Chisel dummy)*(Rotation dummy)	0.8	1.7	0.65
Precipitation April	1.3	1.5	0.39
(Precipitation April)*(No till dummy)	0.39	1.93	0.84
(Precipitation April)*(Chisel dummy)	-0.5	1.7	0.78
Precipitation April2	0.2	0.1	0.26
(Precipitation April)^2*(No till dummy)	-0.1	0.2	0.76
(Precipitation April)^2*(Chisel dummy)	0.05	0.17	0.78
GDD April	-0.3	0.1	0.00
(GDD April)*(No till dummy)	0.2	0.1	0.13
(GDD April)*(Chisel dummy)	0.01	0.10	0.90
GDD April^2	0.001	0.000	0.00
(GDD April)^2*(No till dummy)	-0.0003	0.0002	0.18
(GDD April)^2*(Chisel dummy)	-0.00003	0.0002	0.89
Precipitation May	1.5	1.3	0.24
(Precipitation May)*(No till dummy)	2.4	1.6	0.14
(Precipitation May)*(Chisel dummy)	1.0	1.5	0.51
Precipitation May^2	-0.1	0.1	0.29
(Precipitation May)^2*(No till dummy)	-0.2	0.2	0.19
(Precipitation May)^2*(Chisel dummy)	-0.1	0.2	0.50
GDD May	-0.2	0.1	0.00
(GDD May)*(No till dummy)	0.2	0.1	0.16
(GDD May)*(Chisel dummy)	0.004	0.09	0.96
GDD May^2	0.0003	0.00009	0.00
(GDD May)^2*(No till dummy)	-0.0002	0.0001	0.20
(GDD May)^2*(Chisel dummy)	-0.000001	0.0001	1.00
Precipitation June-September	3.4	1.1	0.00
Precipitation June-September^2	-0.1	0.03	0.00
GDD June-September	-0.1	0.1	0.29
GDD June-September^2	0.00002	0.00002	0.26
Stress DD June-September	0.02	0.02	0.49
(Stress DD June-September)* (Precipitation June-September)	-0.003	0.002	0.17
Late May plant date	2.0	3.8	0.60
Early May plant date	0.6	1.2	0.61
Early June plant date	-2.9	1.4	0.03
Late June plant date	-18.4	1.4	0.00
Constant	YES		
R^2	0.56		
# observations	234		

The inclusion of both a rotation dummy alone (as expected, rotation increases yields) and rotation-tillage interaction terms reveals that benefits of rotation are largest when corn is grown under less intensive tillage practices. This is due to the fact that continuous corn generates a substantial amount of residue that keeps the soil cool and wet in the beginning of the season, creating less favorable growing conditions. Therefore, rotating corn with soybeans reduces residue cover and generates larger yield gains under less intensive tillage. Rotating soybeans with corn increases residue coverage relative to continuous soybeans and, in combination with conservation tillage, results in lower yield gains from the conservation tillage and rotation interaction term.

4.2 Economics of Conservation Tillage

To obtain probability distributions of the relative profitability of alternative tillage practices, we proceed in three steps. First, we take random draws from probability distributions of the weather variables (April GDD, May GDD, April precipitation, and May precipitation).[5] Second, we use these random draws to estimate the difference in yields across tillage practices. Third, these predicted yield differentials are combined with prices and the respective operating cost budgets to calculate differences in profits between tillage practices. Recall that operating costs, O_k^m in equation (1), vary by tillage practice and crop introducing a difference in profitability, in addition to differences in yields. We conduct 5,000 iterations of this procedure and compute a probability

[5] Since we are modeling the *difference (across tillage practices) in profits* under the same set of prices and weather observations, all the terms of the yield functions that have the same coefficients across tillage practices for a given crop drop out of the relative profitability expression. This includes June-September weather and, thus, only random observations of beginning-of-season weather are drawn.

distribution of the relative profitability of alternative tillage practices. Three pair-wise comparisons of tillage practices are conducted: no till vs. moldboard plow, no till vs. chisel, and chisel vs. moldboard plow.

Combinations of 3 pair-wise comparisons and 4 crop scenarios (continuous corn, corn in rotation, soybean in rotation, and continuous soybean) result in 12 relative profitability distributions. We present results for all of these combinations except continuous soybeans due to low prevalence of this system in the U.S. Corn Belt in general, and Indiana in particular. The distributions are plotted in Figures 2-10. Each pair-wise comparison for each crop scenario was conducted under three climate regimes: current, mid-century low GHG emissions (RCP2.6), and mid-century high GHG emissions (RCP8.5). Therefore, each Figure displays three CDF curves comparing the effect of climate change on the profitability of conservation tillage.[6]

[6] It is worth noting that prediction of yields under future climate do not imply an out-of-sample prediction exercise. This is because most of the random draws of weather are not outside of the range of historical weather. Rather, the frequency with which weather observations occur within that range varies relative to historical occurrences.

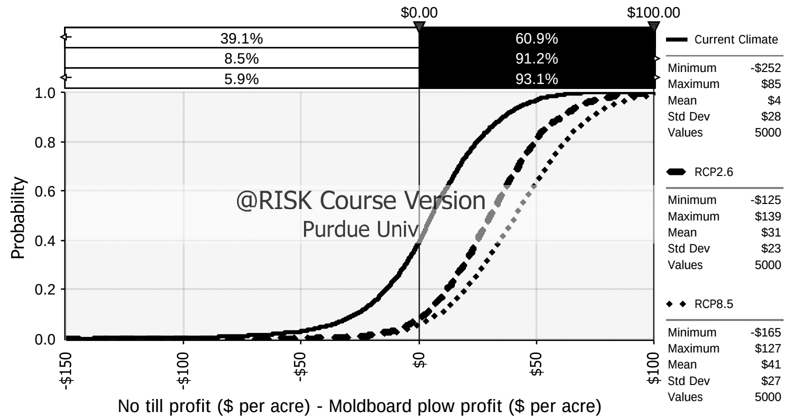


Figure A. No till returns versus moldboard plow

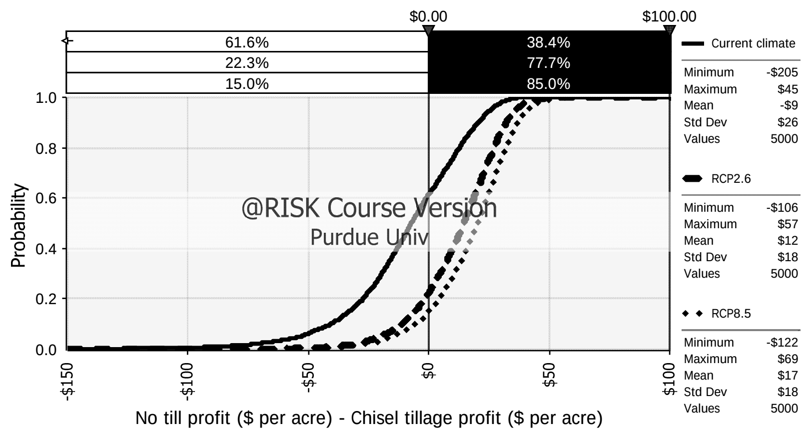


Figure B. No till returns versus chisel

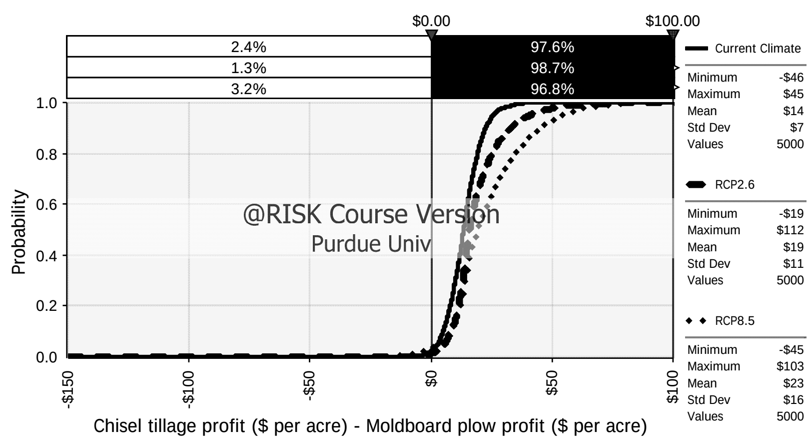


Figure C. Chisel returns versus moldboard plow

Figure 2. Comparison of Figures A, B, and C for rotation corn

Under current weather patterns a risk-neutral farmer growing corn in rotation would find chisel plowing more economically attractive than no till (chisel is nearly 62% likely to result in higher profit) and moldboard plow (chisel is 98% likely to result in higher profit), as indicated by Figures 2.B and 2.C. The farmer would also find no till more economically attractive than moldboard plow (moldboard plow is only about 40% likely to result in higher profit), as shown in Figure 2.A. Under different climate change scenarios a risk-neutral farmer growing corn in rotation will still prefer no till to moldboard plow (Figure 2.A) and chisel till to moldboard plow (Figure 2.C).

Climate change enhances the economics of no till relative to chisel till to the point of possibly inducing changes in behavior of a risk neutral farmer. Projected changes in climatic conditions reduce the probability that no till will result in lower profits than chisel by over half. Specifically, the probability that no till will result in higher profits than chisel till increases from about 38% with current climatic conditions to 78% in a climate change with low emissions scenario and nearly 85% in a high emissions scenario (Figure 2.B). These changes would likely induce a risk neutral farmer growing corn in rotation to switch from chisel till (the preferred practice under the current climate) to no till by mid-century.

Projections of future climatic patterns anticipate substantial increases in beginning-of-season GDD (Figures B.2 and B.4). In turn, our results indicate that higher GDD would favor corn yields under conservation tillage (Table 2). Therefore, the improvement in the economics of conservation tillage revealed in Figure 2.B is mostly driven by higher temperatures associated with climate change. While climate change is also expected to result in more rainfall in April (and mostly unchanged rainfall patterns in

May as revealed by Figure B.3), which would harm performance under conservation tillage, the projected change is not quantitatively large enough to offset the warming effect.

In contrast to a farmer growing corn in rotation, a risk-neutral farmer growing continuous corn would find moldboard plowing more economically attractive than no till (moldboard plowing is 100% likely to result in higher profit) and chisel till (moldboard plowing is 86% likely to result in higher profit), as revealed by Figures 3.A and 3.C respectively. She would also find chisel till more economically attractive than no till (chisel till is 100% likely to result in higher profit), as indicated by Figure 3.B. While projected changes in climatic conditions improve the economics of less intensive tillage practices relative to the current climate, none of these changes are large enough to warrant a change in behavior by a risk neutral farmer. In other words, moldboard plow is still more than 50% likely to result in higher profits than any form of conservation tillage in continuous corn systems (Figures 3.A-3.C).

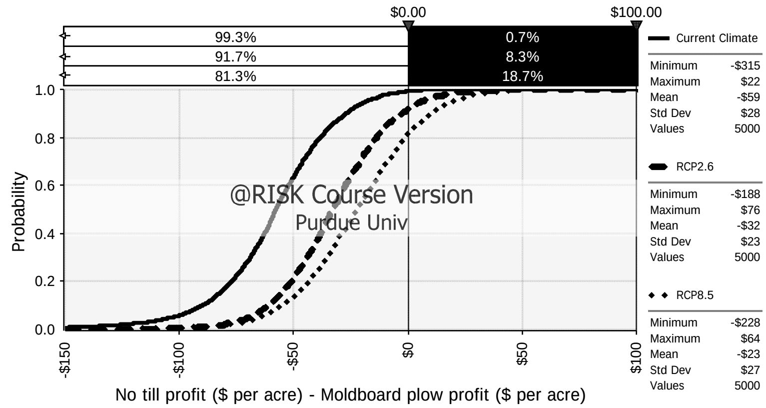


Figure A. No till returns versus moldboard plow

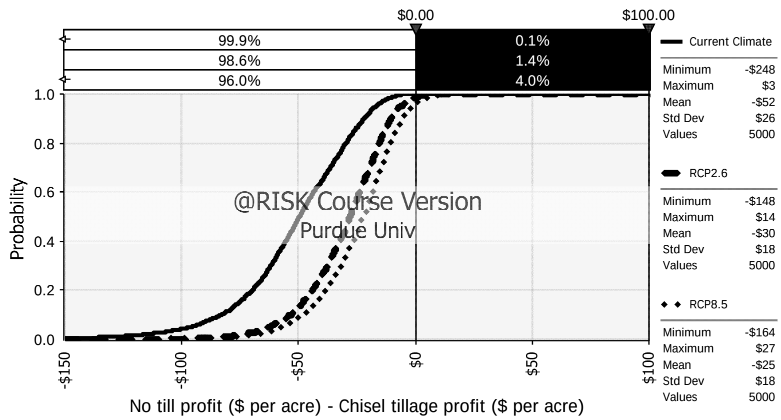


Figure B. No till returns versus chisel tillage

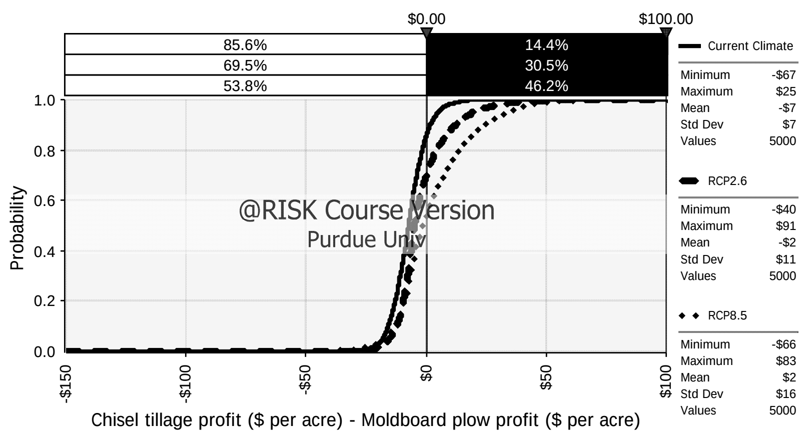


Figure C. Chisel returns versus moldboard plow

Figure 3. Comparison of Figures A,B,and C for continuous corn

Results also indicate that a farmer growing soybeans in rotation would prefer less intensive tillage practices (Figures 4.A – 4.C). In fact, no till will almost certainly result in higher profits than moldboard plow (Figure 4.A) and chisel till (Figure 4.B). Projected climate change is unlikely to change this; i.e. no till performs better than other practices under current and projected climate albeit a slight improvement in the economics of more intensive tillage practices.

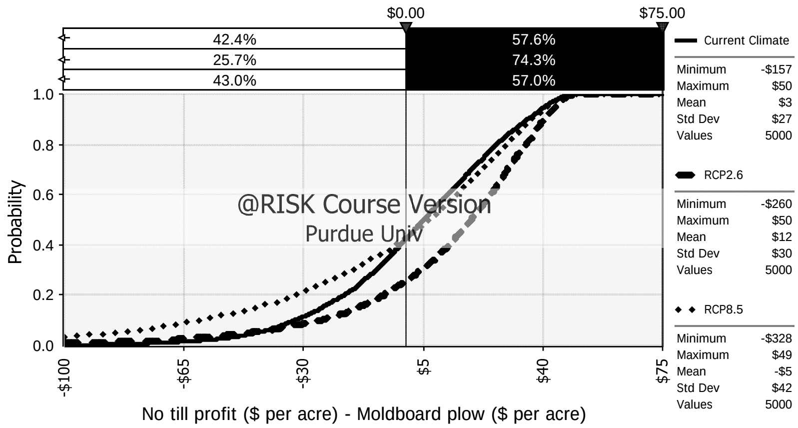


Figure A. No till returns versus moldboard plow

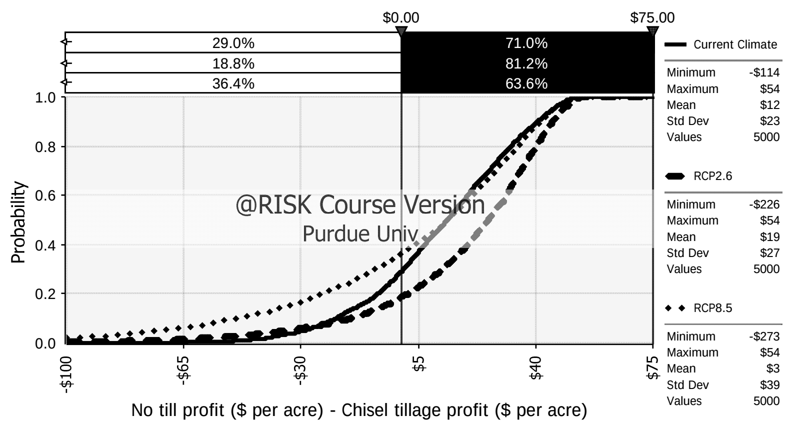


Figure B. No till returns versus chisel tillage

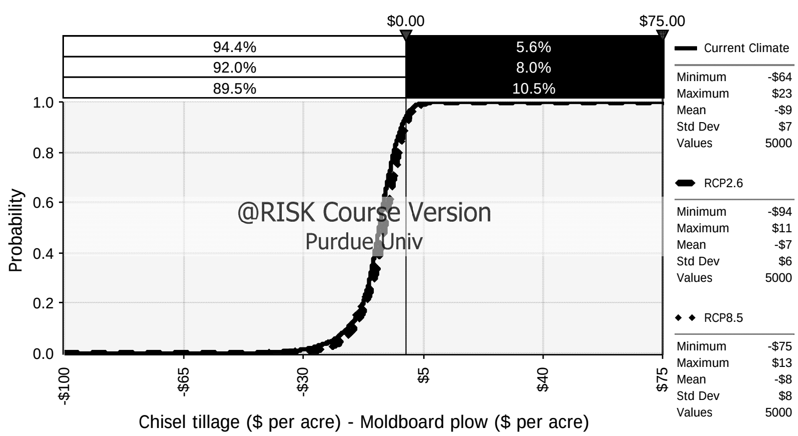


Figure C. Chisel returns versus moldboard plow

Figure 4. Comparison of Figures A,B, and C for rotation soybeans

Our results for corn under current climate are only partially consistent with those of previous studies. Klemme (1985) using data from Indiana also found that it was more profitable to produce continuous corn under intensive tillage practices, but, in contrast with our analysis, found intensive tillage to be superior when corn was grown in rotation. Yiridoe et al. (2000) found that conventional tillage dominates no till and chisel plow tillage in Ontario, while Weersink (1992a) and Archer and Reicosky (2009) found no till to be the dominant practice in a wide range of situations and assumptions. Our results differ from these in two key ways. First, although we also find that conventional tillage dominates other practices under continuous corn, our study finds that, under agro-climatic conditions in our experiment, less intensive practices are better suited for corn and soybeans grown in rotation. Second, our analysis reveals that projected changes in climate are expected to favor the less intensive practices.

4.3 Subsidies Supporting Conservation Tillage

The previous section examined the economics of alternative tillage practices in the absence of public policies supporting conservation tillage. In other words, the profitability of one form of tillage relative to another, $X = P_k\left(Y_{k,j}^m - Y_{k,j}^n | w\right) + (O_k^n - O_k^m) + q_{k,j}^m$, was evaluated when $q_{k,j}^m = 0$. Under that assumption, our results show that a risk-neutral farmer growing soybeans will prefer no till and therefore not require a subsidy to adopt conservation tillage.

Our Monte Carlo analysis revealed that a risk-neutral farmer growing corn in rotation would prefer chisel plow tillage and a risk-neutral farmer growing continuous corn would prefer moldboard plow. Therefore government intervention seems warranted in these cases if less intensive tillage practices are preferred from a social point of view (e.g. if water quality or climate regulation benefits are large enough). But the analysis also showed that climate change would favor less intensive practices, possibly reducing the subsidy required to induce socially desired behavioral changes.

We endogenize the subsidy in this section, and solve for the government payment that would make a risk neutral farmer indifferent between adopting a less intensive and a more intensive tillage practice. In particular, when corn is grown in rotation with soybeans, we calculate the subsidy that makes no till 50% likely to result in equal or higher profits than chisel till (the optimal choice without subsidy). In the case of continuous corn, we calculate the subsidy that will make chisel plow 50% likely to result in equal or higher profits than moldboard plow (the optimal choice without subsidy). We also calculate the subsidy that will make no till 50% likely to result in equal or higher profits than moldboard plow. Each of these subsidies are calculated under alternative climatic regimes.

The magnitude of subsidy payments can be contextualized by comparing them with total expected revenue per acre, as well as current EQIP payments which are geared towards incentivizing conservation tillage adoption. Using average yield data from the experimental plots and the same crop prices assumed in our analysis, we calculate that total revenue is expected to be approximately $620/acre for corn and $465/acre for soybeans. EQIP payments for Indiana are $15/acre for no till and $4/acre for mulch till[7]

[7] The EQIP program implements flat payments per acre. They are calculated to be an average of 75% of the estimated costs to implement a conservation practice across an economic region. Rates are then adjusted for differences in state labor and materials costs. Indiana is located within the Corn Belt region along with five

(National Resources Conservation Services, 2016c). Mulch tillage is a form of conservation tillage that is comparable to the chisel plow in this experiment.

We find that a $7/acre subsidy for no till corn grown in rotation will make this practice outperform chisel till 50% of the time. This reveals that payments currently offered by EQIP should go a long way in incentivizing adoption of no till. It also reveals that such payments are unlikely to affect farmers' general financial situation, as they would only amount to about 1.5% of total expected revenue. Under continuous corn, the subsidy that would make no till better than chisel plow 50% of the time is $50/acre, while the subsidy that would make chisel preferable to moldboard plow 50% of the time is $7/acre. Therefore current EQIP payments would be insufficient to trigger adoption of conservation tillage under conditions prevalent in our experiments. Our results underscore the importance of considering the cropping system when developing and evaluating policies to incentivize conservation tillage. Losses in yield with conservation tillage (and, in particular, no till) are significant in a continuous corn system, substantially increasing the subsidy required to make it breakeven with more intensive practices.

Subsidies that make conservation tillage competitive with moldboard plow will be drastically reduced by changes in weather patterns associated with climate change. These changes are demonstrated in Table 4. When corn is planted in rotation, climate change will reduce the subsidy that makes no till competitive with chisel from $7/acre to $0/acre in a moderate emissions scenario and in a higher emissions scenario. When corn is

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other States. The estimated cost to implement no till in the region is $20, which results in a payment of $15 (75% of $20).

planted continuously, the subsidy would decrease from $50/acre to $28/acre under moderate emissions, and to $22/acre under high emissions. The subsidy that would make chisel plow preferable to moldboard plow 50% of the time decreases from $7/acre to around $5/acre in the moderate and $1/acre in the high emissions scenarios.

Table 4. Per acre subsidy projections for conservation tillage under alternative climate regimes
(Current climate→ RCP2.6→ RCP8.5)

	No till over chisel	No till over moldboard plow	Chisel over moldboard plow
Rotation corn	$7→ $0→ $0	$0→ $0→ $0	$0→ $0→ $0
Continuous corn	$50→ $28→ $22	$58→ $33→ $22	$7→ $5→ $1
Rotation soybean	$0→ $0→ $0	$0→ $0→ $0	n/a*

*The moldboard plow does dominate chisel under rotation soybeans however it is assumed that a risk neutral farmer would prefer the least intensive form of tillage (no till) so no subsidy is required.

These results underscore the fact that, while current payments offered by EQIP may be insufficient to trigger adoption of conservation tillage in continuous corn systems, they may in fact induce behavioral changes as weather patterns evolve due to climate change. In other words, climate change may substantially increase the effectiveness of the EQIP program, especially in continuous corn systems. The government can then maintain current levels of payment and induce greater adoption of conservation tillage, or reduce payments and achieve past levels of adoption at a lower cost.

CHAPTER 5: CONCLUSIONS

This study uses data from long-term experimental plots on dark prairie soils to examine the relative (stochastic) profitability of alternative tillage practices. We find that, under current weather patterns and a corn-soybean rotation, a farmer would already have the incentive to adopt some form of conservation tillage. Furthermore, adoption of chisel plow would be economically preferable to no till. No till is preferred to both chisel plow tillage and moldboard plow under soybeans (grown in rotation or continuously). On the other hand, moldboard plow would be preferred by a risk-neutral profit maximizing farmer growing continuous corn.

Conservation tillage is more attractive for corn in rotation and soybeans in part due to the fact that the yield penalty to adopt conservation tillage under these crop scenarios is small, and in part because less intensive tillage implies cost savings. These results confirm the importance of considering crop rotation systems in developing conservation tillage policies. However, we note that results may only be applicable to areas with similar soil types and agro-climatic conditions, and with the appropriate data, this study could be easily replicated for other areas.

Most importantly, our results show that changes in weather patterns projected by 2030-2069 enhance the economics of conservation tillage relative to moldboard plow. Consequently, changes in weather patterns associated with climate change are expected to enhance the alignment between private incentives (i.e. profits) and social objectives (i.e. reduction of runoff). Therefore, our analysis points to an offsetting, rather than a reinforcing, relationship between market failures. In particular, all else constant, as consequences of one market failure intensify (i.e. as climate change unfolds), water pollution may be alleviated by an increase in adoption of conservation tillage. We note, however, that climate projections considered here do not take into account acute and extreme events which may occur in a single day or over a period of a few consecutive days, which may increase in frequency and harm crop development (Smith, 2011).

Our analysis faces limitations. In the long term tillage experiment, planting in all plots was performed at the same time, which was when the soil was sufficiently dry to successfully plant the conservation tillage plots. This tends to favor conservation tillage relative to moldboard plow. This is because intensive tillage allows the soil to dry up faster which typically provides an opportunity to plant earlier; an opportunity that was not exploited in these experiments.

Another limitation of our analysis is the inability to incorporate projected technical progress. There are unforeseen improvements to no till planting technologies that could enhance the performance of crops under conservation tillage. Moreover, general increases in yield due to genetic and management improvements will likely result in larger amounts of crop residue. Additional residue can have a negative impact on crop development for conservation tillage. However, this negative impact may be partially offset if decomposition of crop residue speeds up under higher temperatures which are expected in the future.

In this study it is assumed that the quantity and cost of all inputs remain constant. However fluctuations in fuel, fertilizer, and chemical costs are likely to impact our results. Climate will impact nutrient content and nitrogen leaching in the soil (Randall and Mulla, 2001), possibly affecting fertilizer application. Higher cost of fuel and chemicals in the future associated with policies curbing emissions (which are implicit in our GHG concentration scenarios) will likely favor conservation tillage. Increases in such costs are expected to be higher under more aggressive polices, such as the one underlying the RCP2.6 scenario. Finally, different tillage systems sequester carbon at different rates (Al-Kaisi and Yin, 2005; Omonode et al., 2007; West and Post, 2002) which means that climate policies that adjust subsidies/taxes to sequestration potential will likely affect the relative economics of these systems. Overcoming some of the limitations of our analysis opens promising avenues for future research.

LIST OF REFERENCES

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Al-Kaisi, M.M. and Yin, X., 2005. Tillage and crop residue effects on soil carbon and carbon dioxide emission in corn–soybean rotations. *Journal of Environmental Quality*, 34(2), pp.437-445.

Archer, D.W. and Reicosky, D.C., 2009. Economic performance of alternative tillage systems in the northern Corn Belt. *Agronomy Journal*, *101*(2), pp.296-304.

Boomsma, C.R., Santini, J.B., West, T.D., Brewer, J.C., McIntyre, L.M. and Vyn, T.J., 2010. Maize grain yield responses to plant height variability resulting from crop rotation and tillage system in a long-term experiment. *Soil and Tillage Research*, *106*(2), pp.227-240.

Bureau of Reclamation. 2013. "Downscaled CMIP3 and CMIP5 Climate Projections: Release of Downscaled CMIP5 Climate Projections, Comparison with Preceding Information, and Summary of User Needs." Climate and Hydrology Projections U.S. Department of the Interior, Bureau of Reclamation, Technical Service Center, Denver, Colorado, 116 p., Available at http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/techmemo/downscaled_climate.pdf

Cary, J.W. and Wilkinson, R.L., 1997. Perceived profitability and farmers 'conservation behaviour. *Journal of Agricultural Economics*, *48*(1-3), pp.13-21.

Conservation Technology Information Center. 2015. "Tillage Type Definitions." Conservation Technology Information Center. Available at http://www.ctic.org/resourcedisplay/322/. (accessed August 2015).

Cooper, J.C., 1997. Combining actual and contingent behavior data to model farmer adoption of water quality protection practices. *Journal of Agricultural and Resource Economics*, pp.30-43.

Cooper, J.C. and Keim, R.W., 1996. Incentive payments to encourage farmer adoption of water quality protection practices. *American Journal of Agricultural Economics*, *78*(1), pp.54-64.

De Boeck, H.J., Dreesen, F.E., Janssens, I.A. and Nijs, I., 2010. Climatic characteristics of heat waves and their simulation in plant experiments. *Global Change Biology*, *16*(7), pp.1992-2000.

Díaz-Zorita, M., Grove, J.H., Murdock, L., Herbeck, J. and Perfect, E., 2004. Soil structural disturbance effects on crop yields and soil properties in a no-till production system. *Agronomy Journal*, *96*(6), pp.1651-1659.

Diffenbaugh, N.S. and Field, C.B., 2013. Changes in ecologically critical terrestrial climate conditions. Science, 341(6145), pp.486-492.

Ding, Y., Schoengold, K. and Tadesse, T., 2009. The Impact of Weather Extremes on Agricultural Production Methods: Does drought increase adoption of conservation tillage practices? *Journal of Agricultural and Resource Economics*, pp.395-411.

Doering, O.C., Diaz-Hermelo, F., Howard, C., Heimlich, R., Hitzhusen, F., Kazmierczak, R., Lee, J., Libby, L., Milon, W., Prato, T. and Ribaudo, M., 1999. Evaluation of the economic costs and benefits of methods for reducing nutrient loads to the Gulf of Mexico: Topic 6 Report for the Integrated Assessment on Hypoxia in the Gulf of Mexico. National Oceanic and Atmospheric Administration, U.S. Department of Commerce, Silver Spring, MD.

Doster, D.H., Griffith, D.R., Mannering, J.V. and Parsons, S.D., 1983. Economic returns from alternative corn and soybean tillage systems in Indiana. *Journal of Soil and Water Conservation*, *38*(6), pp.504-508.

Epplin, F.M., Tice, T.F., Baquet, A.E. and Handke, S.J., 1982. Impacts of reduced tillage on operating inputs and machinery requirements. *American Journal of Agricultural Economics*, *64*(5), pp.1039-1046.

Gál, A., Vyn, T.J., Michéli, E., Kladivko, E.J. and McFee, W.W., 2007. Soil carbon and nitrogen accumulation with long-term no-till versus moldboard plowing overestimated with tilled-zone sampling depths. *Soil and Tillage Research*, *96*(1), pp.42-51.

Grandy, A.S., Robertson, G.P. and Thelen, K.D., 2006. Do productivity and environmental trade-offs justify periodically cultivating no-till cropping systems? *Agronomy Journal*, *98*(6), pp.1377-1383.

Griffith, D.R., Kladivko, E.J., Mannering, J.V., West, T.D. and Parsons, S.D., 1988. Long-term tillage and rotation effects on corn growth and yield on high and low organic matter, poorly drained soils. *Agronomy Journal*, *80*(4), pp.599-605.

Gujarati, Damoder N. 2009. *Basic econometrics*. Tata McGraw-Hill Education.

Helms, G.L., Bailey, D. and Glover, T.F., 1987. Government programs and adoption of conservation tillage practices on nonirrigated wheat farms. *American Journal of Agricultural Economics*, *69*(4), pp.786-795.

Hennessy, D.A., 2006. On monoculture and the structure of crop rotations. *American Journal of Agricultural Economics*, *88*(4), pp.900-914.

Indiana State Department of Agriculture. 2015. "ISDA: Cover Crop and Tillage Transect Data, Indiana State Department of Agriculture." Indiana State Department of Agriculture, In.gov. Available at http://www.in.gov/isda/2383.htm. (accessed March 2016).

Intergovernmental Panel on Climate Change (IPCC). 2013a. "Climate Change: The Physical Science Basis." Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. Available online at http://www.ipcc.ch/report/ar5/wg1/.

Intergovernmental Panel on Climate Change (IPCC). 2013b. "Summary for Policymakers. In: Climate Change 2013: The Physical Science Basis." Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. Available online at http://www.ipcc.ch/report/ar5/wg1/.

Karlen, D.L., Wollenhaupt, N.C., Erbach, D.C., Berry, E.C., Swan, J.B., Eash, N.S. and Jordahl, J.L., 1994a. Long-term tillage effects on soil quality. *Soil and Tillage Research*, *32*(4), pp.313-327.

Karlen, D.L., Wollenhaupt, N.C., Erbach, D.C., Berry, E.C., Swan, J.B., Eash, N.S. and Jordahl, J.L., 1994b. Crop residue effects on soil quality following 10-years of no-till corn. *Soil and Tillage Research*, *31*(2), pp.149-167.

Karlen, D.L., Mausbach, M.J., Doran, J.W., Cline, R.G., Harris, R.F. and Schuman, G.E., 1997. Soil quality: a concept, definition, and framework for evaluation (a guest editorial). *Soil Science Society of America Journal*, *61*(1), pp.4-10.

Klemme, R.M., 1985. A stochastic dominance comparison of reduced tillage systems in corn and soybean production under risk. *American Journal of Agricultural Economics*, *67*(3), pp.550-556.

Kling, C.L., 2011. Economic incentives to improve water quality in agricultural landscapes: some new variations on old ideas. *American Journal of Agricultural Economics*, *93*(2), pp.297-309.

Kovar, J.L., Barber, S.A., Kladivko, E.J. and Griffith, D.R., 1992. Characterization of soil temperature, water content, and maize root distribution in two tillage systems. *Soil and Tillage Research*, *24*(1), pp.11-27.

Krause, M.A. and Black, J.R., 1995. Optimal adoption strategies for no-till technology in Michigan. *Review of Agricultural Economics*, *17*(3), pp.299-310.

Kurkalova, L., Kling, C. and Zhao, J., 2006. Green subsidies in agriculture: Estimating the adoption costs of conservation tillage from observed behavior. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie*, *54*(2), pp.247-267.

Li, Changsheng, Narayanan, V. and Harriss, R.C., 1996. Model estimates of nitrous oxide emissions from agricultural lands in the United States. *Global Biogeochemical Cycles*, *10*(2), pp.297-306.

Lohr, L. and Park, T.A., 1995. Utility-consistent discrete-continuous choices in soil conservation. *Land Economics*, pp.474-490.

Lund, M.G., Carter, P.R. and Oplinger, E.S., 1993. Tillage and crop rotation affect corn, soybean, and winter wheat yields. *Journal of production agriculture*, *6*(2), pp.207-213.

Midwestern Regional Climate Center. "MRCC Application Tools Environment" Midwestern Regional Climate Center. Available at http://mrcc.isws.illinois.edu/CLIMATE/. (accessed August 2015). Data gathered from this website is on file with the authors.

Natural Resources Conservation Service. 2011. "Residue and Tillage Management" Available at http://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/nrcs142p2_006307.pdf. NRCS, U.S. Department of Agriculture, Washington, D.C. (accessed February 2016).

Natural Resources Conservation Service. 2016a. "NRCS EDirectives - Part 512 - Conservation Program Contracting." Available at http://directives.sc.egov.usda.gov/OpenNonWebContent.aspx?content=37718.wba. NRCS, U.S. Department of Agriculture, Washington, D.C. (accessed March 2016).

Natural Resources Conservation Service. 2016b. "National Conservation Practice Standards" Available at http://directives.sc.egov.usda.gov/OpenNonWebContent.aspx?content=36890.wba. NRCS, U.S. Department of Agriculture, Washington, D.C. (accessed March 2016).

Natural Resources Conservation Service. 2016c. “FY16 Corn Belt Payment Scenarios” Available at https://efotg.sc.egov.usda.gov/references/public/IN/2016_Corn_Belt_Payment_Scenarios.pdf. NRCS, U.S. Department of Agriculture, Washington, D.C. (accessed May 2016).

Ogle, S.M., Swan, A. and Paustian, K., 2012. No-till management impacts on crop productivity, carbon input and soil carbon sequestration. *Agriculture, Ecosystems & Environment*, *149*, pp.37-49.

Omonode, R.A., Vyn, T.J., Smith, D.R., Hegymegi, P. and Gál, A., 2007. Soil carbon dioxide and methane fluxes from long-term tillage systems in continuous corn and corn–soybean rotations. *Soil and Tillage Research*, *95*(1), pp.182-195.

Omonode, R.A., Smith, D.R., Gál, A. and Vyn, T.J., 2011. Soil nitrous oxide emissions in corn following three decades of tillage and rotation treatments. *Soil Science Society of America Journal*, *75*(1), pp.152-163.

Padgett, Charles. 2015. Crop Production Services, Indiana. Personal communication.

Pagliai, M., Vignozzi, N. and Pellegrini, S., 2004. Soil structure and the effect of management practices. *Soil and Tillage Research*, *79*(2), pp.131-143.

Phillips, R.E., Blevins, R.L. and Thomas, G.W., 1980. No-Tillage Agriculture.*Science, 208*, pp. 1108-1113.

Purdue University Extension. 2015. “2015 Purdue Crop Cost & Return Guide” Available at https://www.agecon.purdue.edu/extension/pubs/id166-w_2015_sept_2014.pdf. Purdue University. West Lafayette, IN (accessed September 2015).

Rabotyagov, S., Campbell, T., Jha, M., Gassman, P.W., Arnold, J., Kurkalova, L., Secchi, S., Feng, H. and Kling, C.L., 2010. Least-cost control of agricultural nutrient contributions to the Gulf of Mexico hypoxic zone. *Ecological Applications*, *20*(6), pp.1542-1555.

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

Rosenzweig, C., Jones, J.W., Hatfield, J.L., Ruane, A.C., Boote, K.J., Thorburn, P., Antle, J.M., Nelson, G.C., Porter, C., Janssen, S. and Asseng, S., 2013. The agricultural model intercomparison and improvement project (AgMIP): protocols and pilot studies. *Agricultural and Forest Meteorology,170*, pp.166-182.

Rosenzweig, C., Iglesias, A., Yang, X.B., Epstein, P.R. and Chivian, E., 2001. Climate change and extreme weather events; implications for food production, plant diseases, and pests. *Global change & human health*, *2*(2), pp.90-104.

Schlenker, W. and Roberts, M.J., 2009. Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proceedings of the National Academy of sciences*, *106*(37), pp.15594-15598.

Schlenker, W. and Roberts, M.J., 2006. Nonlinear effects of weather on corn yields. *Applied Economic Perspectives and Policy*, *28*(3), pp.391-398.

Sengupta, A. and Dick, W.A., 2015. Bacterial community diversity in soil under two tillage practices as determined by pyrosequencing. *Microbial ecology*, *70*(3), pp.853-859.

Shortle, J.S. and Dunn, J.W., 1986. The relative efficiency of agricultural source water pollution control policies. *American Journal of Agricultural Economics*, *68*(3), pp.668-677.

Smith, M.D., 2011. An ecological perspective on extreme climatic events: a synthetic definition and framework to guide future research. *Journal of Ecology*, *99*(3), pp.656-663.

Snedecor, G.W., Cochran, W.G., 1989. Statistical Methods, 8th Edition, Iowa State University Press

Stonehouse, D.P., 1991. The economics of tillage for large-scale mechanized farms. *Soil and Tillage Research*, *20*(2), pp.333-351.

Taylor, S.E., 2012. Water Stress in Corn: Estimating from Stress Degree Days (SDD).

Toliver, D.K., Larson, J.A., Roberts, R.K., English, B.C., De La Torre Ugarte, D.G. and West, T.O., 2012. Effects of no-till on yields as influenced by crop and environmental factors. *Agronomy journal*, *104*(2), pp.530-541.

Vetsch, J.A. and Randall, G.W., 2004. Corn production as affected by nitrogen application timing and tillage. *Agronomy Journal*, *96*(2), pp.502-509.

Vyn, T.J. and Raimbult, B.A., 1993. Long-term effect of five tillage systems on corn response and soil structure. *Agronomy Journal*, *85*(5), pp.1074-1079.

Weersink, A., Walker, M., Swanton, C. and Shaw, J., 1992a. Economic comparison of alternative tillage systems under risk. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie*, *40*(2), pp.199-217.

Weersink, A., Walker, M., Swanton, C. and Shaw, J.E., 1992b. Costs of conventional and conservation tillage systems. *Journal of Soil and Water Conservation*, *47*(4), pp.328-334.

West, Terry. 2015. Research Agronomist, Purdue University, West Lafayette, IN. Personal communication.

West, T.D., Grifith, D.R., Steinhardt, G.C., Kladivko, E.J. and Parsons, S.D., 1996. Effect of tillage and rotation on agronomic performance of corn and soybean: Twenty-year study on dark silty clay loam soil. *Journal of Production Agriculture*, *9*(2), pp.241-248.

West, T.O. and Post, W.M., 2002. Soil organic carbon sequestration rates by tillage and crop rotation. *Soil Science Society of America Journal*, *66*(6), pp.1930-1946.

Williams, J.R., 1988. A stochastic dominance analysis of tillage and crop insurance practices in a semiarid region. *American Journal of Agricultural Economics*, *70*(1), pp.112-120.

Williams, J.R., Llewelyn, R.V. and Barnaby, G.A., 1990. Risk analysis of tillage alternatives with government programs. American Journal of Agricultural Economics, 72(1), pp.172-181.

Wooldridge, Jeffrey. *Introductory econometrics: A modern approach*. Nelson Education, 2015.

Yamoah, C.F., Francis, C.A., Varvel, G.E. and Waltman, W.J., 1998. Weather and management impact on crop yield variability in rotations. *Journal of production agriculture*, *11*(2), pp.219-225.

Yiridoe, E.K., Weersink, A., Hooker, D.C., Vyn, T.J. and Swanton, C., 2000. Income risk analysis of alternative tillage systems for corn and soybean production on clay soils. *Canadian Journal of Agricultural Economics*, 48(2), pp.161-174.

APPENDICES

Appendix A. Budgets of Tillage Operations

Full quantification of the relative profitability of competing tillage practices ($X = P_k\left(Y_{k,j}^m - Y_{k,j}^n|w\right) + (O_k^n - O_k^m) + q_{k,j}^m$) requires (in addition to yield functions, probability distributions of weather variables, and the subsidy$q_{k,j}^m$) a quantification of crop prices P_k, and differences in operating costs $(O_k^n - O_k^m)$. This appendix describes the calculation of these parameters.

Crop prices were taken from the 2015 Purdue Crop Cost and Return Guide (Purdue University Extension, 2015). Price of corn is estimated at \$3.50 per bushel and the price for soybeans is \$9.10 bushels per acre. The 2014 Long Term Tillage Survey report discusses the management practices and provides details of the equipment, herbicides, and fertilizers used on each experimental plot in each year. We used Michigan State's per acre custom rates for machinery and associated machinery operational costs.[8] These costs are considered to be an estimate of the ownership and operation of machinery. These are broken down on a per acre basis and include tractor, fuel cost (at \$3.60 per gallon), lubricants, repairs, maintenance, labor and overhead costs including depreciation. Herbicide costs were obtained from Crop Production Services (Padgett, personal communication, September 8, 2015). The only other costs that varied by tillage practice were the costs of herbicides. A detailed breakdown of relative expenses as well

[8] These rates include tractor cost, fuel cost, lubricants, repairs, maintenance, labor and overhead costs including depreciation. This could be considered as an estimate of the ownership cost and operation of this machine on a per acre basis. These rates were found using actual farm survey data and are approximations of what would be used on the average corn and soybean operation in Indiana. Rates can vary with different assumptions about exact equipment make and model and other financial calculations like use of equipment, depreciation and interest.

as descriptions of the machinery used in the Purdue University experimental plots are outlined in Table A.1.

The expense breakdown in Table A.1 shows cost savings attained with conservation tillage practices. Both reduced tillage practices result in savings on field work; No till results in higher herbicide expenditures. Table A.1 shows that chisel till results in savings relative to moldboard plow for both corn and soybeans ($O_c^{MP} - O_c^{CT}$= \$12.24 and $O_s^{MP} - O_s^{CT}$= \$12.24). In addition, no till results in savings relative to moldboard plow in both corn and soybeans ($O_c^{MP} - O_c^{NT}$= \$23.23 and $O_s^{MP} - O_s^{NT}$= \$27.29). Finally, no till results in savings relative to chisel till in both corn and soybeans ($O_c^{CT} - O_c^{NT}$= \$10.99 and $O_s^{CT} - O_s^{NT}$= \$15.05). Management practices that differ by tillage alternative remained consistent over time, avoiding the risk of attributing yield differences to tillage practices instead of other confounding factors.

Table A.1. Breakdown of expenses that vary by tillage practices*

	Moldboard plow baseline				Chisel plow baseline	
Equipment used in Purdue tillage experiment	Chisel corn	Chisel soybean	No till corn	No till soybean	No till corn	No till soybean
Field operations expenditures						
DMI 7-shank coulter-chisel plow equipped with 4-inch twisted chisel points on 15-inch centers and a Danish-tine sweep leveling bar	(11.14)	(11.14)	-	-	-	-
90-foot boom sprayer or a 30-foot 3-point hitch mounted sprayer	-	-	(3.70)	-	(3.70)	-
Moldboard plow savings	23.38	23.38	23.38	23.38		
Chisel plow savings					11.14	11.14
Field cultivator savings	-	-	11.75	11.75	11.75	11.75
Subtotal field operations expenditures	12.24	12.24	31.43	35.13	19.19	22.89
Increased chemical expenditures						
Roundup 25 oz/acre for corn and 23 oz/acre for soybeans	-	-	(4.54)	(4.18)	(4.54)	(4.18)
2, 4-D ester 1 pt/acre	-	-	(3.25)	(3.25)	(3.25)	(3.25)
Ammonium sulfate (8 lbs/100 gallons water)	-	-	(0.41)	(0.41)	(0.41)	(0.41)
Subtotal increased chemical expenditures	-	-	(8.20)	-	(8.20)	-
Total $O_k^m - O_k^n$	\$ 12.24	\$ 12.24	\$ 23.23	\$27.29	\$ 10.99	\$ 15.05

* Values reported in the table represent cost differences between tillage practices.

Appendix B. Probability distributions of weather under current and projected climate

Figures B.1 - B.4 below display probability density functions of beginning-of-season rainfall and GDD under current and projected climate regimes. Two scenarios of projected climate are considered: 1) low emissions (RCP2.6), and 2) high emissions (RCP8.5). The solid line probability distribution is drawn from 5,000 iterations of 1975-2014 (excluding 2011) monthly weather data. Similarly, the dashed and dotted lines come from 5,000 draws of the monthly projected climate change data collected for 2030-2069 under the RCP2.6 and RCP8.5 scenarios.

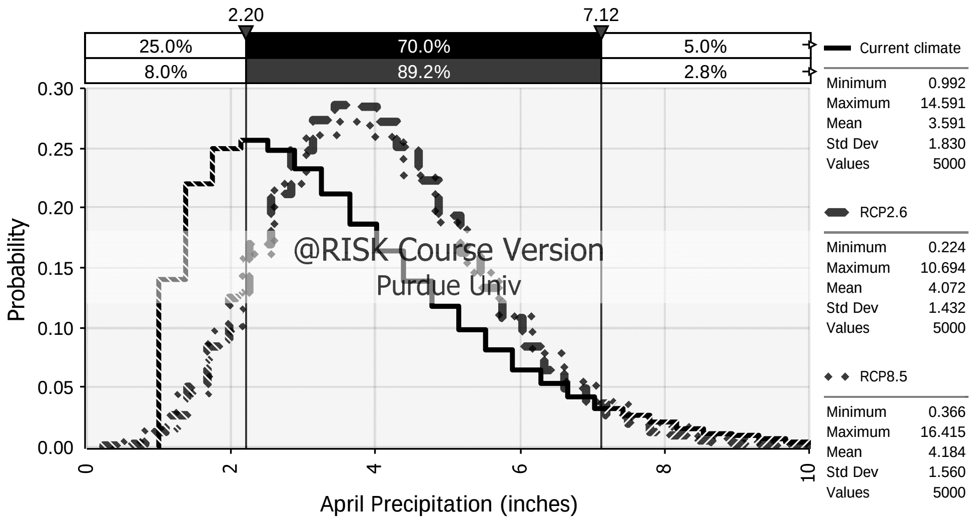

Figure B.1. Probability distribution of April precipitation- current and projected climate

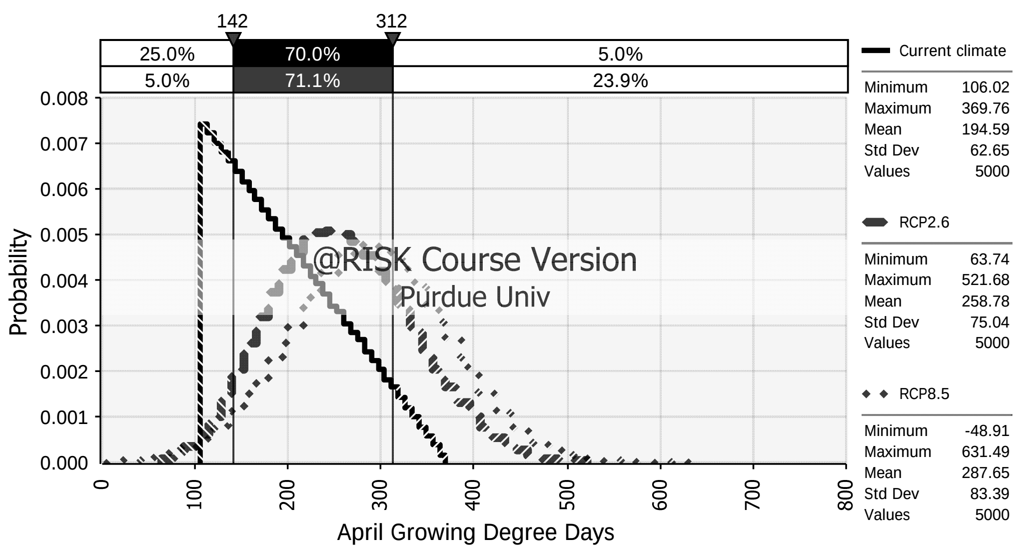

Figure B.2. Probability distribution function of April GDD- current and projected climate

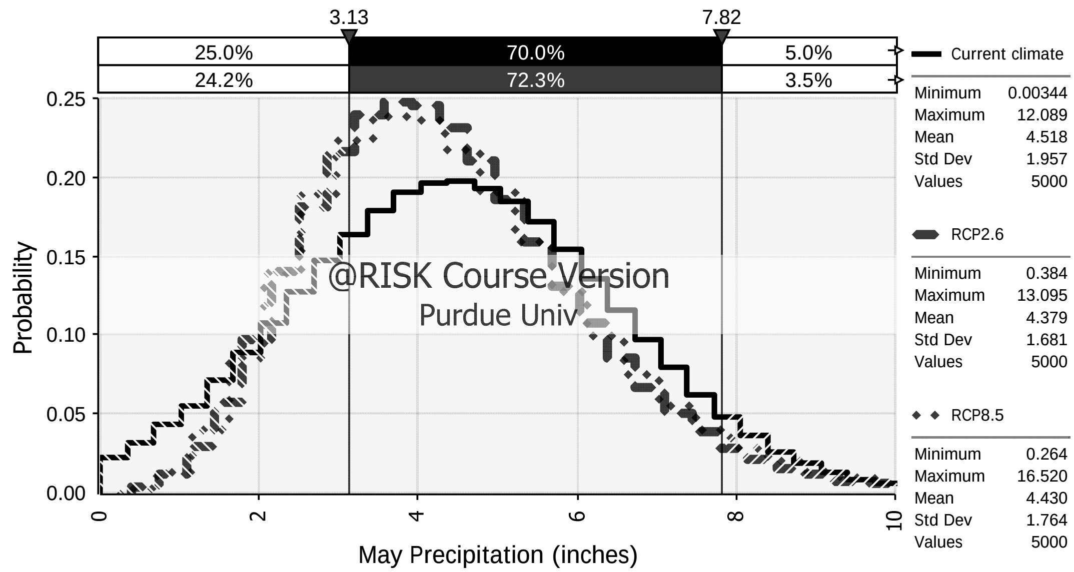

Figure B.3. Probability distribution of May precipitation- current and projected climate

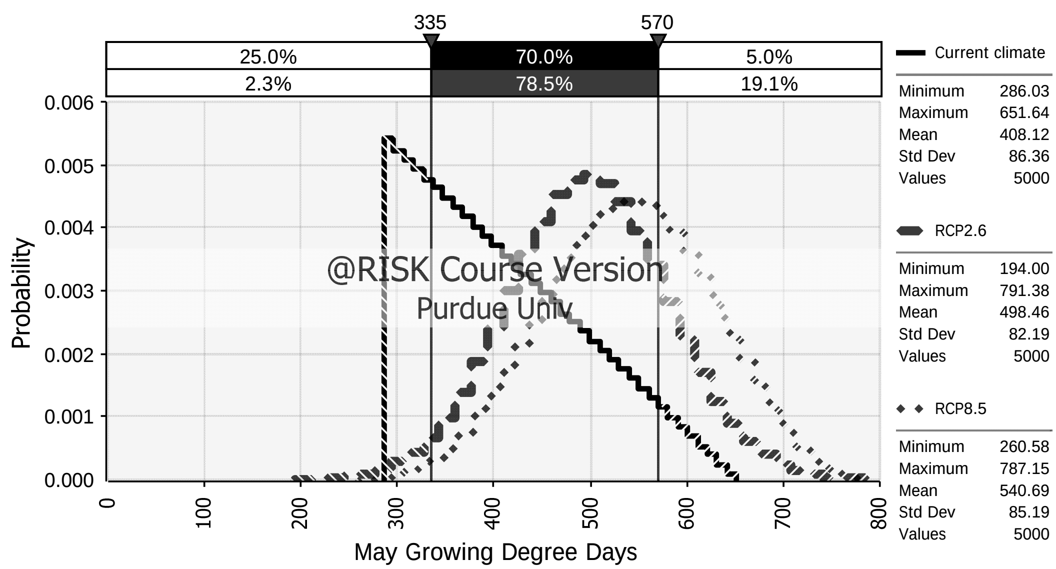

Figure B.4. Probability distribution of May GDD- current and projected climate

Appendix C. Description of Climate Models

Climate models used in this study (described in Table C.1 below) represent a number of best-effort attempts to simulate the climate system. Multiple models are used in order to capture the wide range of available predictions. Under the CMIP5 framework, a “core” set of specifications (e.g. location, greenhouse gas emissions scenario) is provided and each modeling center or group contributing to CMIP5 is required to generate a complete set of “core” simulations. Random draws are then pulled together to generate a multimodel dataset for analysis (Taylor et al., 2012). The multimodel framework is intended to account for poorly understood feedbacks associated with the carbon cycle and with clouds, among other things. Taylor et al. (2012) provides further description on the CMIP5 experiment.

Table C.1. CMIP5 Models

Modeling Center (or Group)	WCRP CMIP5 Climate Model ID	RCP2.6 runs	RCP8.5 runs
Beijing Climate Center, China Meteorological Administration	BCC-CSM1.1	1	1
Canadian Centre for Climate Modelling and Analysis	BCC-CSM1.1(m)	1-5	1-5
National Center for Atmospheric Research	CCSM4	1-2	1-2
Commonwealth Scientific and Industrial Research Organization, Queensland Climate Change Centre of Excellence	CSIRO-Mk3.6.0	1-10	1-10
NOAA Geophysical Fluid Dynamics Laboratory	GFDL-CM3	1	1
NOAA Geophysical Fluid Dynamics Laboratory	GFDL-ESM2G	1	1
NOAA Geophysical Fluid Dynamics Laboratory	GFDL-ESM2M	1	1
Institut Pierre-Simon Laplace	IPSL-CM5A-LR	1-3	1-3
Institut Pierre-Simon Laplace	IPSL-CM5A-MR	1	1
Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	MIROC-ESM	1	1
Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	MIROC-ESM-CHEM	1	1
Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology	MIROC5	1-3	1-3
Max-Planck-Institut für Meteorologie (Max Planck Institute for Meteorology)	MPI-ESM-LR	1-3	1-3
Max-Planck-Institut für Meteorologie (Max Planck Institute for Meteorology)	MPI-ESM-MR	1	1
Meteorological Research Institute	MRI-CGCM3	1	1
Norwegian Climate Centre	NorESM1-M	1	1

Appendix D. Correlation among Predictors

We run a correlation test between linear, quadratic and interaction terms involving conservation tillage dummies. This analysis shows a substantial degree of correlation between predictors. For illustration purposes, we portray the case of no till in Table D.1, although a similar patterns is observed in the case of chisel tillage. Table D.1 reveals that interaction terms are highly correlated with their individual components. Moreover quadratic and linear weather variables are also highly correlated.

Table D.1. Matrix of correlation coefficients

	No till	Precipitation April	Precipitation April*no till	Precipitation April squared	Precipitation April squared*no till
No till	1				
Precipitation April	0	1			
Precipitation April*no till	0.85	0.35	1		
Precipitation April squared	0	0.97	0.30	1	
Precipitation April squared*no till	0.60	0.44	0.92	0.46	1

As a robustness check, we re-estimated the model with a subset of predictors. In particular, the quadratic and singular terms were dropped. Such exercise resulted in substantial changes to estimated coefficients of interaction terms, revealing a high instability of estimates to the choice of model. This is another symptom of multicollinearity. consequently, and given that our objective is to maximize the predictive power of the model, it is preferable to include the full set of predictors even at the risk of increasing multicollinearity (see Chapter 3 in Wooldridge, 2015 for a discussion).

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