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The Predicted Effect of Projected Climate Change on the Economics of Conservation Tillage

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ABSTRACT

We evaluate the economics of conservation tillage (chisel till and no till) and examine the impact of projected climate change on the economic attractiveness of reduced tillage practices. We use data from a long-term (39-yr) field experiment in Indiana to estimate yield response functions describing the relationship between tillage practices and corn (*Zea mays* L.) and soybean (*Glycine max* L.) yields in poorly drained (but systematically tile-drained) soils, and the mediating role of weather and crop rotation on that relationship. We subsequently couple estimated yield functions with stochastic simulations of weather variables under current and projected climatic regimes to construct distributions describing the probability that conservation tillage will result in higher profits than more intensive tillage under alternative crop rotations. We calculate the subsidy, if needed, that would make a risk-neutral farmer indifferent between conservation and intensive tillage practices under alternative climatic regimes. A key finding of this study is that projected climate change enhances the economics of conservation tillage, thereby substantially reducing the economic hurdle required to induce its adoption in the study area. The framework developed and demonstrated can be applied to areas with different soils and growing conditions to examine the economics of conservation tillage under current and future climate.

Core Ideas

- We examine effect of climate change on economics of reduced tillage.
- We use data from a long-term field experiment in Indiana
- We calculate probability that reduced till will result in higher profit
- Projected climate change enhances the economics of conservation tillage
- Climate change may substantially reduce subsidies required for adoption

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Farmers have traditionally used intensive tillage due to its many benefits, which include weed control and seedbed preparation. However, intensive tillage disrupts and exposes the soil, 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. From the perspective of environmental policy, intensive tillage leads to sediment and nutrient runoff resulting in pollution of surface water, as well as increased emission of greenhouse gases.

An alternative management practice that can mitigate some of the adverse effects of intensive tillage is conservation tillage. While scholars have extensively documented the environmental benefits associated with adoption of conservation tillage practices, profitability is a key factor that influencing adoption (Cary and Wilkinson, 1997; Yiridoe et al., 2000). The relative profitability of conservation tillage critically depends on yield and operating cost differentials under alternative tillage practices. Risk management is also an important factor that contributes to farmer choice to adopt a particular practice (Ding et al., 2009; Klemme, 1985). Despite the importance of profitability and risk, farmers' choice to adopt is not exclusively influenced by monetary considerations. Researchers have long been aware of the physical challenges and personal barriers to conservation tillage adoption (Ervin and Ervin, 1982).

This study focuses on evaluation of cost differences and yield responses in a stochastic environment. Conservation tillage can lead to savings in labor, machinery, and energy due to a reduction in the number of field equipment passes (Weersink et al., 1992b), but it can also result in higher cost of chemical inputs as residue cover may increase the prevalence of pests and diseases. Furthermore, conservation tillage affects yields by altering soil structure (e.g., Gál et al., 2007), improving biological and chemical characteristics indicative of soil quality (Karlen et al., 1994), and increasing soil moisture (Díaz-Zorita et al., 2004). Conservation tillage can also affect yields by delaying warming and drying of soil, and slowing plant emergence (Doster et al., 1983). Overall, evidence suggests that yields under different tillage

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Abbreviations: CMIP, Coupled Model Intercomparison Project; CDF, cumulative distribution function; EQIP, Environmental Quality Incentives Program; GHG, greenhouse gases; GDD, growing degree days; iid, independently and identically distributed.

scenarios vary by cropping system, soil properties, land slope, and climatic conditions (e.g., Toliver et al., 2012). Several studies found that adoption of no till results in decreased crop yields (e.g., Vyn and Raimbult, 1993). Corn yield reductions with no till are more likely in continuous corn production than in the more common corn–soybean rotation (West et al., 1996). However, under favorable conditions (warm and dry weather early in the growing season), no till can achieve profits comparable to conventional tillage methods (Kovar et al., 1992; Ogle et al., 2012).

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 under a specific climate regime. Previous literature has used the concept of stochastic dominance (Sriboonchita et al., 2009) to compare the economic performance of conservation tillage relative to more intensive practices (Klemme, 1985; Williams et al., 1990; Weersink et al., 1992a). These studies (and others that do not use stochastic dominance such as Krause and Black, 1995) 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.

The primary objective of this study is to quantify the effect of projected changes in weather patterns on the economic performance of conservation tillage relative to more intensive alternatives. To do so, we develop a framework quantifying cost and yield differentials under stochastic conditions and examine the relative economic attractiveness of three tillage practices (in decreasing order of intensity: moldboard plow tillage, chisel plow tillage, and no till) under current weather patterns, and how relative profitability is likely to be affected by climate change. A relevant issue related to the link between climate change and conservation tillage is whether expected changes in weather patterns will make it easier or harder for governments to induce adoption. The US government has targeted the agricultural sector for improvements to water quality by incentivizing voluntary management practices that reduce soil erosion and runoff (Cooper, 1997; Cooper and Keim, 1996; Kurkalova et al., 2006; Lohr and Park, 1995). The Environmental Quality Incentives Program (EQIP), initiated in 1996, is perhaps the most influential program that subsidizes conservation tillage to reduce nonpoint-source pollution (Doering et al., 1999; Kling, 2011). We contribute to the policy debate by using our framework to quantify subsidies that may induce adoption under alternative rotations and examine the effect of climate change on those subsidy payments.

MATERIALS AND METHODS

To quantify the relative economic performance of competing tillage practices we first estimate yield functions and probability distributions of current and projected weather patterns (i.e., we estimate the data generating process underlying random weather occurrences). We combine these to generate randomly simulated yields under competing tillage practices for each crop and cropping system, as well as for current and projected climatic conditions. We subsequently combine randomly simulated yields with prices and cost estimates to calculate profits from conservation tillage relative to more intensive alternatives. We conduct multiple iterations of this procedure to compute a probability distribution of the relative profitability of alternative tillage practices. Finally, we use these probability distributions to examine the economics of alternative tillage practices under current and projected weather patterns. The following subsections describe each step of this algorithm in more detail.

Yield Function Estimation

Data from a 39-yr long-term tillage study based in West Lafayette, IN allows us to quantify the influence of weather and rotation on relative yield outcomes of comparative tillage practices. We estimate expected corn and soybean yields, conditional on tillage and weather (among other key factors like cropping systems). We do so by exploiting data from a long-term field experiment conducted in west-central Indiana to estimate yield response functions that include interaction terms between weather and tillage variables. A thorough description of the experimental site and citations to different studies reporting on the long-term tillage experiment, along with details of the yield estimation strategy and results, are available in the Supplementary Materials.

Descriptive statistics of key variables used in estimations are presented in Table 1. Values in Table 1 reveal a substantial variability of yields over time and across management practices. No till generally results in lower yields compared to moldboard plow and chisel. Yields under chisel and moldboard plow are similar across cropping scenarios. Table 1 also shows substantial weather variability in the study period, which we exploit to estimate regression equations. While we do control for weather later in the season, we focus on early season weather patterns, which are particularly relevant for our purposes. As discussed later in the economic analysis section, as well as in the supplementary materials section, much of the relative performance of alternative tillage practices depends on weather patterns early in the season, so these variables are interacted with indicators of tillage practices in estimation. Mean values and standard deviations relative to mean values reveal that growing degree days (GDD) are much larger in May than in April, but also much more volatile. Similarly, values in Table 1 indicate that rainfall, on average, is higher May than in April, and that they have a similar (and quite significant) levels of volatility.

Estimation of Current and Projected Weather Distribution

Yield responses to weather occurrences vary by tillage practice, as quantified by coefficients of interaction terms included in the yield functions (Tables A.1 and A.2 of the Supplementary Materials). Our strategy is to take random draws from beginning-of-season (i.e., April and May) probability distributions of weather variables and use estimated yield functions to map those occurrences to yields, in order to obtain a probability distribution of yields by tillage practice. We use recorded weather occurrences over the study period (1975–2014) to estimate probability distributions governing random draws of *current* weather variables, which are displayed in Fig. 1. Random draws sometimes produce outliers, but because of the nature of the data generating process, those outliers do not add up to any meaningful amount

Table 1. Descriptive statistics of variables used in regression.†

	Mean	Median	Standard deviation	Minimum	Maximum
Yield, corn in rotation under moldboard plow	11.7 (187)	11.6 (185)	2.1 (33)	8.2 (131)	16.9 (269)
Yield, corn in rotation under chisel	11.8 (188)	12.1 (193)	2.1 (33)	8.7 (138)	16.4 (262)
Yield, corn in rotation under no till	11.5 (183)	11.6 (185)	2.0 (31)	8.0 (128)	16.0 (255)
Yield, continuous corn under moldboard plow	11.3 (180)	11.3 (180)	2.1 (34)	7.5 (120)	16.3 (260)
Yield, continuous corn under chisel	11.0 (175)	11.8 (178)	2.0 (31)	8.0 (122)	15.1 (241)
Yield, continuous corn under no till	9.9 (157)	10.1 (161)	2.1 (34)	5.3 (84)	14.8 (235)
Yield, soybean in rotation under moldboard plow	3.7 (54)	3.7 (55)	0.5 (7)	2.5 (37)	4.6 (68)
Yield, soybean in rotation under chisel	3.5 (52)	3.5 (52)	0.4 (6)	2.6 (39)	4.3 (64)
Yield, soybean in rotation under no till	3.5 (52)	3.5 (52)	0.6 (9)	2.2 (32)	4.8 (71)
Weather					
Precipitation Apr., cm	9.1	8.8	4.7	2.7	23.0
Growing degree days April	209	206	61	106	337
Precipitation May, cm	11.3	11.2	5.2	2.4	25.0
Growing degree days May	419	417	90	286	606

† Yields are measured in mt ha^{-1} (bu A^{-1})

of probability mass in weather distributions. Thus random draws are smoothed away by parametric approximations of these data. Multiple parametric approximations were fitted to the data, and the best one was identified based on Akaike and Bayesian Information Criteria. The triangular distribution of GDD for both April and May in Fig. 1b and 1d reflect the lower bound for GDD seen in years 1975 to 2014.

Unfortunately, climate change precludes extrapolation of these probability distributions into the future. As anthropogenic greenhouse gases build up in the atmosphere, they currently affect and will continue to affect probability distributions of weather variables. To quantify *future* probability distributions of the same weather variables, we take random draws of temperature and precipitation from climate models and fit parametric approximations to those observations. We source projected weather from an archived, multi-model ensemble dataset that allows us to generate model projections for the exact latitude and longitude of the experimental site location. The dataset is generated by the World Climate Change Research Program, which houses the Working Group on Coupled Modeling. This group established the Coupled Model Intercomparison Project (CMIP), a standard experimental protocol for studying the output of coupled atmosphere–ocean general circulation models. The protocol allows for climate model validation and intercomparison (Taylor et al., 2012). These experiments are currently in their fifth phase (CMIP5), and this model output is the basis for the Intergovernmental Panel on Climate Change's Fifth Assessment Report (IPCC, 2013a).

We use runs available from CMIP5 for the specific latitude and longitude of our experimental plots, which are provided by the Bureau of Reclamation (2013). In particular, we retrieve random draws of daily precipitation, minimum daily temperature and maximum daily temperature output for the years 2030 to 2069 based on 36 different climate model and scenario combinations (listed in Table 2). The 2030 to 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 yr of observed data used to calculate "current" weather patterns. Table 2 lists the CMIP5 climate models and runs that we use in this study. We use multiple models 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 simulations. Random draws are then pulled together to generate a multi-model dataset for analysis (Taylor et al., 2012). The multi-model framework is intended to account for poorly understood feedbacks associated with the carbon cycle and clouds, among other things. Taylor et al. (2012) provides further description on the CMIP5 experiment. Emission scenarios available from CMIP5 include Representative Concentration Pathways (RCP), RCP2.6, RCP4.5, RCP6.0 and RCP8.5, representing a range of 21st century climates (IPCC, 2013b). We consider RCP2.6 and RCP8.5 greenhouse gas scenarios to illustrate the range of possible effects, instead of focusing on an elusive point estimate (Tigchelaar et al., 2018). The RCP2.6 represents a greenhouse gas (GHG) emissions scenario where atmospheric CO_2 concentrations reach 421 mg kg^{-1} by 2100. Under RCP8.5, CO_2 concentrations reach 936 mg kg^{-1} by 2100 and temperature increase is likely to exceed 2°C.

We aggregate daily outputs projected by the climate models into monthly figures (since the yield function is expressed in terms of monthly weather occurrences). We then pool together monthly weather variables from the climate models to create the probability distributions. This means that the distributions

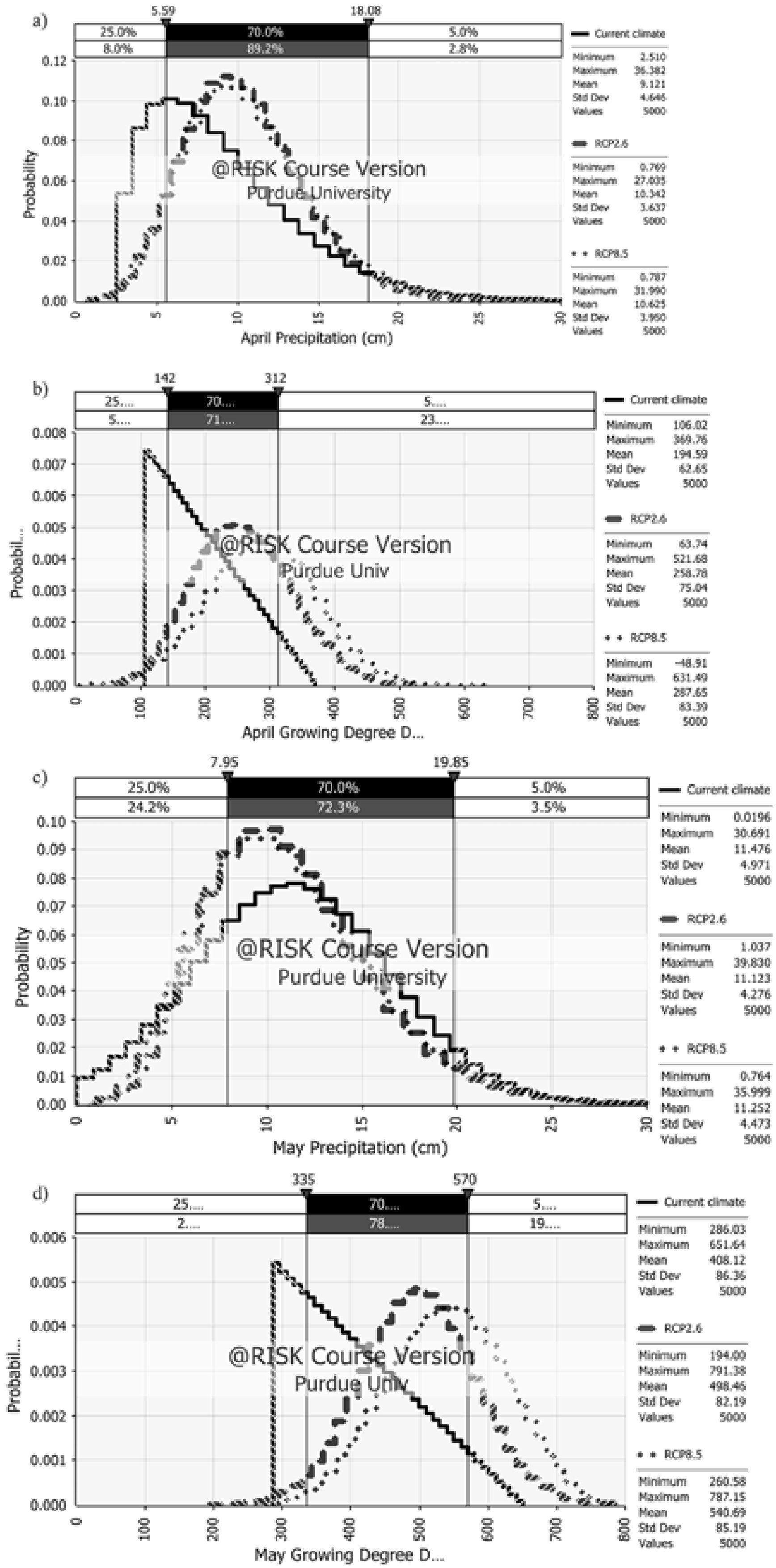

Fig. 1. Probability density functions of weather under current and projected climate. Probability density function of April precipitation- current and projected climate (a), Probability density function of April growing degree days- current and projected climate (b), Probability density function of May precipitation- current and projected climate (c), Probability density function of May growing degree days current and projected climate (d).

Table 2. Main features of 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 Modeling and Analysis	CANESM2	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

capture heterogeneity across models, in addition to intra-model climate variability. We think this is the most appropriate approach, as differences in random draws across models are 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 the projected climate regime and emissions scenarios are displayed alongside the historical distributions in Fig. 1. Plotted distributions seem to indicate that climate change will generally result in wetter and warmer early season weather. A more disaggregated look at these variables reveals some differences across weather variables. Our April precipitation projections indicate an increase in mean of about 10% and a reduction of the standard deviation ranging from 10 to 25% (high and low emissions scenarios respectively) relative to current weather patterns. Rainfall patterns in May change only slightly. Changes in April and May GDD distributions induced by climate change are more dramatic. Mean GDD increases under climate change in all emissions scenarios and across months (ranging from 22% to 47%). Increases in mean GDD are about 10% higher under the high emissions scenario.

Profit Distribution Calculation

We model profits of a representative farmer under each tillage practice, defining profits simply as revenue (crop price times yield) minus cost. We keep all other production inputs and management (i.e., planting date) constant, which allows us to focus our attention on the tillage decision. This amounts to a "no adaptation" study of climate change effect on yield under alternative tillage practices and crop rotations. Therefore, the usual caveats apply to insights from this study; that is, once adaptation takes place, yields are likely to respond more favorably to changing weather patterns across tillage practices, and such adjustments need not be uniform across them. Consequently, adaptation might alter our insights, both in direction and magnitude. With these caveats in mind, a profit-maximizing farmer is likely to adopt a more intensive tillage practice (e.g., moldboard plow tillage) if it results in higher profits relative to a less intensive practice (e.g., chisel tillage), per unit of land. We conduct three pairwise economic comparisons of tillage practices: no till vs. moldboard plow, no till vs. chisel tillage, and chisel tillage vs. moldboard plow.

In this study, we use a single-period model, instead of a multiple-period model (i.e., net present value of future stream of profits). The use of a single-period profit model is innocuous (i.e., results in the same ranking of competing tillage choices as a multi-period model), provided that the set of random draws of weather in each period is independently and identically distributed (iid). We assume that annual measures of monthly and seasonal weather variables are independent and identically distributed. While not explicitly stated, this is a common assumption in the literature on climate change and its predicted implications under alternative adaptation scenarios (Angel et al., 2018). Furthermore, small deviations from this assumption (i.e., weak serial correlation) are unlikely to modify our insights.

The relative profitability of conservation tillage for a farmer growing crop *c* is calculated by subtracting profits under more intense tillage practices from profits under a less intense practice. We formally characterize this expression by $\pi_i^c - \pi_j^c$, where crop *c* can be corn or soybean, and *i* and *j* are, respectively, no till and moldboard plow, no till and chisel tillage, and chisel tillage and moldboard plow. Profits under tillage practice *i* can be written as $\pi_i^c = p^c y_i^c(\omega) - e_i^c - e^c$, where p^c is the price of crop *c*, $y_i^c(\omega)$ represents yield under weather occurrence ω (yield varies by tillage practice as quantified in our estimated yield functions), and production costs. Costs are separated into two categories that will soon be specified: tillage-specific costs (e_i^c), and costs that are common to all tillage practices (e^c). The profitability of tillage practice *i* relative to *j* can then be written as $\pi_i^c - \pi_j^c = p^c\left[y_i^c(\omega) - y_j^c(\omega)\right] - \left[e_i^c - e_j^c\right]$. Note that all terms that are common to π_i^c and π_j^c drop out of the relative profitability expression, including late season weather (which, as

Table 3. Cost differences ($ ha^{-1}) between tillage practice.†

Equipment used in Purdue tillage experiment	Moldboard plow baseline Chisel corn	Chisel soybean	No-till corn	No-till soybean	Chisel plow baseline 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	(27.53)	(27.53)	–	–	–	–
90-foot boom sprayer or a 30-foot 3-point hitch mounted sprayer	–	–	(9.14)	–	(9.14)	–
Moldboard plow savings	57.77	57.77	57.77	57.77		
Chisel plow savings					27.53	27.53
Field cultivator savings	–	–	29.03	29.03	29.03	29.03
Subtotal field operations expenditures	30.25	30.25	77.66	86.81	47.42	56.56
Increased chemical expenditures						
Roundup 1.8 L ha^{-1} for corn and 1.7 L ha^{-1} for soybean	–	–	(11.21)	(10.34)	(11.21)	(10.34)
2, 4-D ester 1 ml ha^{-1}	–	–	(8.03)	(8.03)	(8.03)	(8.03)
Ammonium sulfate (3.6 kg/935 L water)	–	–	(1.01)	(1.01)	(1.01)	(1.01)
Subtotal increased chemical expenditures	–	–	(20.26)	(19.38)	(20.26)	(19.38)
Total $O_k^m - O_k^n$	$30.24	$30.24	$57.40	$67.43	$27.16	$37.19

† Parentheses represent cost increases relative to the baseline practice. Values not in parentheses represent cost savings relative to the baseline practice. Machinery costs were taken from Michigan State's custom rates for machinery (includes tractor cost, fuel, lubricants, repairs, maintenance, depreciation, labor and overhead). Herbicide costs were obtained from Crop Production Services (C. Padgett, personal communication, 2015).

shown in our estimated yield functions, affect yields symmetrically across tillage practices) and common costs.

We compute probability distributions of relative profitability of tillage practices ($\pi_i^c - \pi_j^c$) as follows: First, we take random draws from probability distributions of the weather variables (April GDD, May GDD, April precipitation, and May precipitation) estimated and reported in Fig. 1. Second, we use these random draws to estimate the difference in yields across tillage practices (by inserting the random draws of weather into the estimated yield functions). Third, we combine predicted yield differentials with prices and the respective operating cost budgets to calculate differences in profits between tillage practices. We conduct 5000 iterations of this procedure (which results in 5000 randomly generated values of $\pi_i^c - \pi_j^c$) and produce a probability distribution of the relative profitability of competing tillage practices.

Prices and operating costs, including their sources, are reported in Table 3. We employ crop prices from the 2014 Purdue Crop Cost and Return Guide (Purdue University Extension, 2015). We assume a price of corn of $138 mt^{-1} ($3.50 bu^{-1}) and a price for soybean of $334 mt^{-1} ($9.10 bu^{-1}). Management practices (actual herbicides) for the tillage experiment have been described in the 2014 Long Term Tillage Survey. We use this detailed description of the practices implemented in the field experiment to identify and compute cost differences between each tillage practice pairing ($e_i^c - e_j^c$). We do not report production costs that are constant across tillage practices (e.g., cost of land, crop insurance, seeds, etc.) because they are immaterial for *relative* profitability. 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. Machinery cost estimates accounted for all relevant costs including annual cost of ownership, maintenance, and operation of machinery and fuel cost to run the equipment on a per hectare basis (at $0.95 L^{-1}). Many farmers using conservation tillage may be inclined to maintain ownership of their equipment, thus eliminating savings in ownership costs. Therefore, our machinery cost savings are perhaps better interpreted as an upper bound.

As reported in Table 3, no till corn and soybean require more herbicides for weed control. In contrast, weed control under chisel and moldboard plow is done primarily through field cultivation. There are a wide variety of implements farmers can use to prepare a looser seed bed, temporarily avoid compaction, or to remove weeds, but the moldboard plow represents the most extreme case of field disturbance. Greater field disturbance requires more fuel to cover multiple field passes as well as more power so that the equipment can dig deeper into the earth and overturn the soil. The cost savings of no till over the moldboard plow in corn and soybean is between $77 and $87 ha^{-1} in field equipment, with only a slight increase in the required herbicide costs of $20 ha^{-1}. Compared with the chisel plow, no till saves $47 to $57 ha^{-1} in machinery costs and adds $20 ha^{-1} in herbicide costs. Nutrient applications did not vary by tillage practice in this study.

RESULTS AND DISCUSSION

We use probability distributions of profits to conduct three pairwise comparisons of tillage practices: no till vs. moldboard plow, no till vs. chisel, and chisel vs. moldboard plow. Combinations of three pairwise comparisons and four crop scenarios (continuous corn, corn in rotation, soybean in rotation, and continuous soybean) result in 12 relative profitability distributions. We present results for these combinations, except continuous soybean, due to low prevalence of this system in the US Corn Belt in general, and Indiana in particular. Cumulative distribution functions for each pairwise comparison are plotted in Fig. A.1–3 of the Supplementary Materials. We conduct each pairwise comparison for each crop scenario 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 cumulative distribution function (CDF) curves comparing the effect of climate change on the profitability of conservation tillage.

We interpret the height of CDF at zero as the probability that conservation tillage will result in higher profits than a more intense alternative. To simplify the discussion, we extract and report these probabilities in Fig. 2. Under current weather

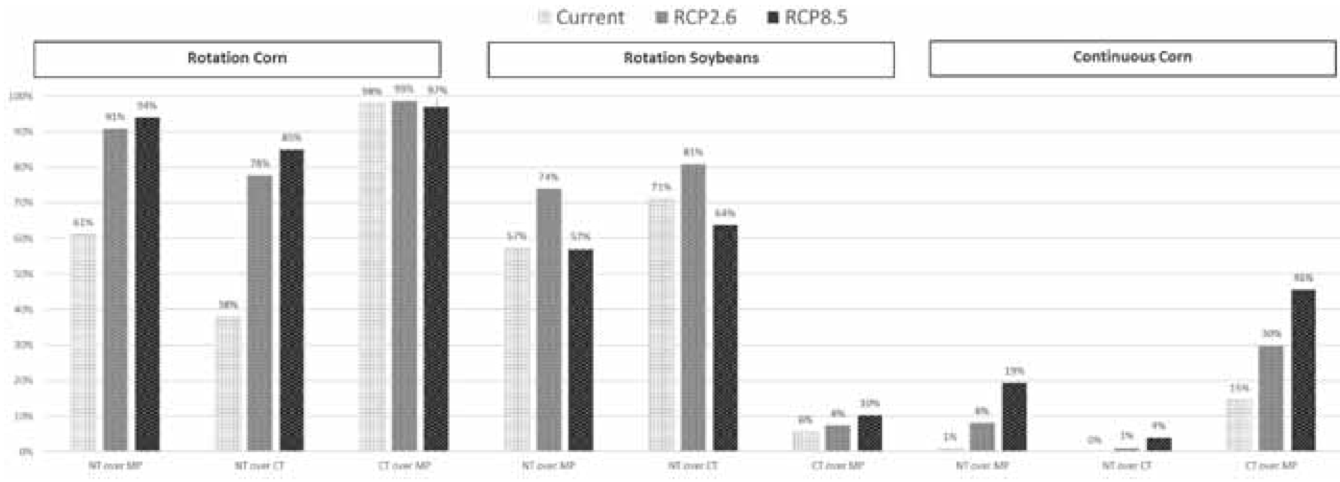

Fig. 2. Probability that less intensive tillage practices are more profitable than more intensive practices. Bars indicate the percent likelihood that a less intensive practice will be more profitable than ("over") a more intensive practice. Detailed cumulative distribution functions of the simulated difference in profitability are plotted in figures A1-A3 in the Supplementary Materials. NT denotes no tillage, CT denotes chisel plow tillage, and MP denotes moldboard plow tillage.

patterns a risk-neutral farmer growing corn in rotation would find chisel plowing more economically attractive than no till (no till is only 38% likely to result in higher profit) and moldboard plow (chisel is 98% likely to result in higher profit), as indicated by Fig. 2. Results in Fig. 2 also reveal that projected changes in climate favor conservation tillage. 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 future climate scenario with low emissions, and to 85% in a high emissions scenario. 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 (Fig. 1). In turn, our results indicate that higher early season GDD would favor corn yields under conservation tillage. Therefore, the improvement in the economics of conservation tillage is mostly driven by higher temperatures associated with climate change (Fig. 1b). While climate change is also expected to result in more rainfall in April as revealed by Fig. 1a (and mostly unchanged rainfall patterns in May as revealed by Fig. 1c), which would harm performance under conservation tillage, the projected change is not quantitatively large enough to offset the warming effect. Note, however, that 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 in experimental fields. However, this is hardly an unusual circumstance since tile drainage is present in more than half of cropland in the Corn Belt (Meyer and Keiser, 2016).

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 (no till is 1% likely to result in higher profit) and chisel till (chisel is 15% likely to result in higher profit). The farmer would also find chisel till more economically attractive than no till (there is a zero chance that no till will result in higher profit), as indicated in Fig. 2. 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 the absence of policy interventions. In other words, the likelihood that conservation tillage (in all its forms) will result in higher profits than moldboard plow remains lower than 50% in continuous corn systems. It is worth noting, however, that profitability of chisel tillage relative to moldboard plow greatly increases; in fact, chisel tillage is predicted to be more profitable than moldboard plow 46% of the time.

Results in Fig. 2 also indicate that a farmer growing soybean in rotation would prefer less intensive tillage practices. In fact, no till is likely to result in higher profits than moldboard plow (57%) and very likely to result in higher profits than chisel till (71%). Projected climate change is unlikely to change this; that is, no till performs better than other practices under current and projected climate despite a slight improvement in the economics of more intensive tillage practices under the high emissions scenario.

An important dimension of the comparison between alternative tillage practices is relative performance at the tails. While Fig. 2 reports how likely a conservation practice is to result in a higher profit than a more intensive alternative, it remains silent regarding downside risk and upside potential. In other words, it does not provide information on how large losses can be, when the conservation practice turns out to be less profitable. Nor does it provide information regarding how large gains can be under favorable conditions. Adoption would be hampered if the former is large relative to the latter. These dimensions are captured by the lower and upper tails of the probability distributions plotted in Fig. A.1 through A.3, of which Fig. 2 only reports the height at zero profits.

Figures A.1.1–3 and A.2.1–3 reveal that climate change reduces downside risk associated with no-till corn and increases upside potential of chisel tillage relative to moldboard plow. The effect of climate change on the economics of conservation tillage for soybean is slightly more complicated. Climate change increases downside risk associated with no till, but also upside potential (Fig. A.3.1–3). The increase in downside risk relative to upside potential is small under the RCP2.6 scenario, but very large under the RCP8.5. Therefore, in the high emissions scenario, increased downside risk may deter adoption of no till by farmers that are sufficiently risk-averse even though no till is predicted to dominate competing tillage practices 60% of the time.

Our results for corn *under current climate* are only partially consistent with those of previous studies. Klemme (1985), using data from Indiana, found that it was more profitable to produce corn under intensive tillage practices. He found this for both continuous and rotation corn, while our results indicate this is true for the former but not the latter. Yiridoe et al. (2000) found that conventional tillage dominates no till and chisel plow tillage in Ontario, as did Williams et al. (1990) for wheat and sorghum systems. In contrast, Weersink et al. (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 soybean grown in rotation. Second, our analysis reveals that projected changes in climate are expected to favor the less intensive practices.

These results should be interpreted with caution, as we are implicitly keeping important factors constant for a long period of time. First, we did not incorporate biased technical progress (although we do control for unbiased technical change through time trends); that is, changes in technology that would favor one form of tillage over others, such as unforeseen improvements to no-till planting technologies , which could enhance the performance of crops under conservation tillage. Moreover, increases in yield due to genetic and management improvements will likely result in larger amounts of crop residue, which can have a negative impact on crop development for conservation tillage (Karlen et al., 1994). However, this may be partially offset if decomposition of crop residue accelerates under higher temperatures, which are expected in the future.

Furthermore, we assume a risk-neutral producer throughout this analysis. Instead of preserving risk neutrality, we could re-run our analysis with a certain set of risk preferences over the probability distribution of profits. But we prefer to refrain from this for two reasons. First, we have no reliable empirical guidance on what preference structure (e.g., constant absolute or relative risk aversion) or parameter values should be used. Second, and perhaps more importantly, risk aversion would interact in complicated ways with insurance policies and other institutional arrangements. Therefore, modeling how risk aversion alters the ranking of tillage choices would imply adding several additional layers of complexity to the economic model.

Finally, we conduct our analysis under the assumption that the quantity and cost of all inputs remain constant, where fluctuations in fuel, fertilizer, and chemical costs are likely to affect our results. Climate will influence 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, along 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. Moreover, 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 which adjust subsidies and/or 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. We note that climate projections considered here do not consider acute and extreme events, which may increase in frequency and harm crop development (Smith, 2011).

Subsidies Supporting Conservation Tillage

Results from our simulation analysis show that a risk-neutral farmer growing soybean will prefer no till and therefore will not require a subsidy to adopt conservation tillage. Under our profitability distributions, 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 where less intensive tillage practices are likely to be preferred from a social point of view (e.g., if water quality or climate regulation benefits are large enough). The analysis also shows that climate change would favor less intensive practices, possibly reducing the subsidy required to induce socially desired behavioral changes.

We solve for the government payment that would make a risk-neutral farmer indifferent between adopting a less intensive tillage practice and a more intensive alternative. Specifically, when corn is grown in rotation with soybean, 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.

Subsidies that would make the farmer indifferent between alternative tillage practices are reported in Table 4. We can contextualize the magnitude of subsidy payments by comparing them with total expected revenue per hectare (acre), as well as current EQIP payments, which are geared toward 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 \$1,532 ha^{-1} (\$620 A^{-1}) for corn and \$1,149 ha^{-1} (\$465 A^{-1}) for soybean. EQIP payments for Indiana are \$37 ha^{-1} (\$15 A^{-1}) for no till and \$10 ha^{-1} (\$4 A^{-1}) for chisel till (Natural Resources Conservation Services, 2016).

Results in Table 4 indicate that a \$18-ha^{-1} 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 2% of total expected revenue. Under continuous corn, the subsidy that would make no till better than chisel till 50% of the time is \$123 ha^{-1}, while the subsidy that would make chisel preferable to moldboard plow 50% of the time is \$18 ha^{-1}. Therefore, current EQIP payments would be insufficient to trigger adoption of these specific conservation tillage practices in continuous corn under conditions prevalent in our experiments. Our results underscore the importance of considering the cropping system when developing and evaluating policies to

Table 4. Subsidy ($ ha^{-1}) projections for less intensive tillage practice that would make a risk-neutral farmer indifferent with respect to the more intensive practice 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	$18→ $0→ $0	$0→ $0→ $0	$0→ $0→ $0
Rotation soybean	$0→ $0→ $0	$0→ $0→ $0	$19→ $15→ $16
Continuous corn	$123→ $69→ $55	$143→ $80→ $56	$18→ $12→ $3

incentivize conservation tillage. Losses in yield with conservation tillage are significant in a continuous corn system, substantially increasing the subsidy required to make it breakeven with more intensive practices.

However, our analysis reveals that projected changes in climate will drastically reduce subsidies that make conservation tillage competitive with moldboard plow. In rotation corn, climate change improves the performance of no till over chisel plow such that a subsidy is no longer required in the moderate or higher emissions scenarios. When corn is planted continuously, the subsidy to induce adoption of no till over chisel is reduced from $123 ha^{-1} under current climate to $69 ha^{-1} under moderate emissions, and to $55 ha^{-1} under high emissions. The subsidy that would make chisel plow preferable to moldboard plow 50% of the time decreases from $18 ha^{-1} to $12 ha^{-1} in the moderate emissions and to $3 ha^{-1} in the high emissions scenarios for continuous corn.

Therefore, while current payments offered by EQIP may be insufficient to trigger adoption of conservation tillage in continuous corn systems, they may suffice to 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.

CONCLUSIONS

This study uses data from long-term experimental plots to examine the relative (stochastic) profitability of alternative tillage practices under current and, more importantly, projected weather patterns. 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. On the other hand, no till is likely to be preferred to both chisel plow tillage and moldboard plow under soybean. Finally, moldboard plow would be preferred by a risk-neutral profit maximizing farmer growing continuous corn.

Conservation tillage is likely to be more attractive for corn in rotation and soybean in part because 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. Our results may not generalize to areas with dissimilar soil types and agro-climatic conditions. However, our framework can be applied easily in different settings to examine if our insights can be replicated across space and over time. That being said, it is worth noting that the long-term experiment based on which we estimate yield functions is conducted on Mollisol soils, the dominant soil type in the Corn Belt.

Most importantly, our results show that changes in weather patterns projected by 2030 to 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, with all else constant, as consequences of one market failure intensify (i.e., as climate change unfolds), water and air pollution may be alleviated by an increase in adoption of conservation tillage.

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REFERENCES

Al-Kaisi, M.M., and X. Yin. 2005. Tillage and crop residue effects on soil carbon and carbon dioxide emission in corn–soybean rotations. J. Environ. Qual. 34:437–445. doi:10.2134/jeq2005.0437

Angel, J., C. Swanston, B.M. Boustead, K.C. Conlon, K.R. Hall, J.L. Jorns, K.E. Kunkel, et al. 2018. Midwest. In: Reidmiller, D.R., C.W. Avery, D.R. Easterling, K.E. Kunkel, K.L.M. Lewis, T.K. Maycock, and B.C. Stewart, editors, Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment, Volume II. US Global Change Research Program, Washington DC, USA, p. 872–940. doi:10.7930/NCA4.2018.CH21

Archer, D.W., and D.C. Reicosky. 2009. Economic performance of alternative tillage systems in the northern Corn Belt. Agron. J. 101:296–304. doi:10.2134/agronj2008.0090x

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 R.L. Wilkinson. 1997. Perceived profitability and farmers' conservation behaviour. J. Agric. Econ. 48:13–21. doi:10.1111/j.1477-9552.1997.tb01127.x

Cooper, J.C. 1997. Combining actual and contingent behavior data to model farmer adoption of water quality protection practices. J. Agr. Resour. Econ. 30-43.

Cooper, J.C., and R.W. Keim. 1996. Incentive payments to encourage farmer adoption of water quality protection practices. Am. J. Agric. Econ. 78:54–64. doi:10.2307/1243778

Díaz-Zorita, M., J.H. Grove, L. Murdock, J. Herbeck, and E. Perfect. 2004. Soil structural disturbance effects on crop yields and soil properties in a no-till production system. Agron. J. 96:1651–1659. doi:10.2134/agronj2004.1651

Ding, Y., K. Schoengold, and T. Tadesse. 2009. The Impact of Weather Extremes on Agricultural Production Methods: Does drought increase adoption of conservation tillage practices? J. Agr. Resour. Econ. 395-411.

Doering, O.C.F., C. Diaz-Hermelo, R. Howard, F. Heimlich, R. Hitzhusen, J. Kazmierczak, L. Lee, W. Libby, T. Milon, M. Prato, and M. Ribaudo. 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., D.R. Griffith, J.V. Mannering, and S.D. Parsons. 1983. Economic returns from alternative corn and soybean tillage systems in Indiana. J. Soil Water Conserv. 38:504–508.

Ervin, C.A., and D.E. Ervin. 1982. Factors Affecting the Uses of Soil Conservation Practices: Hypotheses, Evidence, Policy Implications. Land Econ. 58:277–292. doi:10.2307/3145937

Gál, A., T.J. Vyn, E. Michéli, E.J. Kladivko, and W.W. McFee. 2007. Soil carbon and nitrogen accumulation with long-term no-till versus moldboard plowing overestimated with tilled-zone sampling depths. Soil Tillage Res. 96:42–51. doi:10.1016/j.still.2007.02.007

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 Univ. 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 Univ. Press, Cambridge, United Kingdom and New York, NY, USA. Available online at http://www.ipcc.ch/report/ar5/wg1/.

Karlen, D.L., N.C. Wollenhaupt, D.C. Erbach, E.C. Berry, J.B. Swan, N.S. Eash, and J.L. Jordahl. 1994. Crop residue effects on soil quality following 10-years of no-till corn. Soil Tillage Res. 31:149–167. doi:10.1016/0167-1987(94)90077-9

Klemme, R.M. 1985. A stochastic dominance comparison of reduced tillage systems in corn and soybean production under risk. Am. J. Agric. Econ. 67:550–556. doi:10.2307/1241074

Kling, C.L. 2011. Economic incentives to improve water quality in agricultural landscapes: Some new variations on old ideas. Am. J. Agric. Econ. 93:297–309. doi:10.1093/ajae/aaq190

Kovar, J.L., S.A. Barber, E.J. Kladivko, and D.R. Griffith. 1992. Characterization of soil temperature, water content, and maize root distribution in two tillage systems. Soil Tillage Res. 24:11–27. doi:10.1016/0167-1987(92)90069-N

Krause, M.A., and J.R. Black. 1995. Optimal adoption strategies for no-till technology in Michigan. Rev. Agric. Econ. 17:299–310. doi:10.2307/1349575

Kurkalova, L., C. Kling, and J. Zhao. 2006. Green subsidies in agriculture: Estimating the adoption costs of conservation tillage from observed behavior. Can. J. Agric. Econ. 54:247–267. doi:10.1111/j.1744-7976.2006.00048.x

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

Meyer, K. and D.A. Keiser. 2016. Adapting to Climate Change through Tile Drainage: A Structural Ricardian Analysis. 2016 Annual Meeting, Boston, MA. July 3–Aug. 2. Agricultural and Applied Economics Association, Milwaukee, WI.

Natural Resources Conservation Service. 2016. "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, DC. (accessed May 2016).

Ogle, S.M., A. Swan, and K. Paustian. 2012. No-till management impacts on crop productivity, carbon input and soil carbon sequestration. Agric. Ecosyst. Environ. 149:37–49. doi:10.1016/j.agee.2011.12.010

Omonode, R.A., T.J. Vyn, D.R. Smith, P. Hegymegi, and A. Gál. 2007. Soil carbon dioxide and methane fluxes from long-term tillage systems in continuous corn and corn–soybean rotations. Soil Tillage Res. 95:182–195. doi:10.1016/j.still.2006.12.004

Padgett, C. Personal communication. Crop Production Services, Indiana.

Pagliai, M., N. Vignozzi, and S. Pellegrini. 2004. Soil structure and the effect of management practices. Soil Tillage Res. 79:131–143. doi:10.1016/j.still.2004.07.002

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).

Randall, G.W., and D.J. Mulla. 2001. Nitrate nitrogen in surface waters as influenced by climatic conditions and agricultural practices. J. Environ. Qual. 30:337–344. doi:10.2134/jeq2001.302337x

Smith, M.D. 2011. An ecological perspective on extreme climatic events: A synthetic definition and framework to guide future research. J. Ecol. 99:656–663. doi:10.1111/j.1365-2745.2011.01798.x

Sriboonchita, S., W.K. Wong, S. Dhompongsa, and H.T. Nguyen. 2009. Stochastic dominance and applications to finance, risk and economics. CRC Press, New York. doi:10.1201/9781420082678

Taylor, K.E., R.J. Stouffer, and G.A. Meehl. 2012. An Overview of CMIP5 and the Experiment Design. Bull. Am. Meteorol. Soc. 93:485–498. doi:10.1175/BAMS-D-11-00094.1

Tigchelaar, M., D.S. Battisti, R.L. Naylor, and D.K. Ray. 2018. Future warming increases probability of globally synchronized maize production shocks. Proc. Natl. Acad. Sci. USA 115:6644–6649. doi:10.1073/pnas.1718031115

Toliver, D.K., J.A. Larson, R.K. Roberts, B.C. English, D.G. De La Torre Ugarte, and T.O. West. 2012. Effects of no-till on yields as influenced by crop and environmental factors. Agron. J. 104:530–541. doi:10.2134/agronj2011.0291

Vyn, T.J., and B.A. Raimbult. 1993. Long-term effect of five tillage systems on corn response and soil structure. Agron. J. 85:1074–1079. doi:10.2134/agronj1993.00021962008500050022x

Weersink, A., M. Walker, C. Swanton, and J. Shaw. 1992a. Economic comparison of alternative tillage systems under risk. Can. J. Agric. Econ. 40:199–217. doi:10.1111/j.1744-7976.1992.tb03690.x

Weersink, A., M. Walker, C. Swanton, and J.E. Shaw. 1992b. Costs of conventional and conservation tillage systems. J. Soil Water Conserv. 47:328–334.

West, T.D., D.R. Grifith, G.C. Steinhardt, E.J. Kladivko, and S.D. Parsons. 1996. Effect of tillage and rotation on agronomic performance of corn and soybean: Twenty-year study on dark silty clay loam soil. J. Prod. Agric. 9:241–248. doi:10.2134/jpa1996.0241

West, T.O., and W.M. Post. 2002. Soil organic carbon sequestration rates by tillage and crop rotation. Soil Sci. Soc. Am. J. 66:1930–1946. doi:10.2136/sssaj2002.1930

Williams, J.R., R.V. Llewelyn, and G.A. Barnaby. 1990. Risk analysis of tillage alternatives with government programs. Am. J. Agric. Econ. 72:172–181. doi:10.2307/1243157

Yiridoe, E.K., A. Weersink, D.C. Hooker, T.J. Vyn, and C. Swanton. 2000. Income risk analysis of alternative tillage systems for corn and soybean production on clay soils. Can. J. Agric. Econ. 48:161–174. doi:10.1111/j.1744-7976.2000.tb00272.x