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Evaluating the climate resilience in terms of profitability and risk for a long-term corn-soybean-wheat rotation under different treatment systems

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ABSTRACT

Increasing climate variability and extreme weather events impose significant challenges to the crop production systems throughout the world. Alternative agricultural treatment systems have been proposed to manage these challenges. However, these treatments have not been sufficiently studied for their ability to improve climate resilience, especially in terms of profitability and risk management, which are important metrics of resilience that determine farm-level adaptation. Hence, we evaluated the climate resilience of three alternative agricultural treatments for a long-term (27-years) rotation of corn-soybean-wheat, cast in the temperate humid climate of Southwest Michigan, United States. The three alternative treatments include no-till, reduced input, and US Department of Agriculture (USDA) certified organic. These are compared to the conventional treatment along with the same crop rotation. Means and volatility of expected gross margins and risk preferences were used as the evaluation metrics. Results demonstrate that the net revenues from the USDA certified organic are largely expected to exceed the net revenues of conventional treatment. Also, for all commodities, organic treatment may exert greater annual stability in revenues. The no-till treatment dominates conventional and reduced input practices in expected annual net revenues with a relatively lower risk to those revenues in light of climate extremes. Furthermore, the organic and no-till treatments showed appropriateness to cater to a range of farmers with different risk preferences. Therefore, the organic and the no-till treatments were deemed climate-resilient. The conventional and reduced input treatments did not show resilience thus will be vulnerable to the changing climate. Despite the economic support for adopting resilient practices, growers have been slow to adopt new approaches. We suggest future research needs for understanding grower motivations for adopting climate-resilient practices and consider policy implications.

1. Introduction

Growing anthropogenic activities that generate greenhouse gas emissions have caused global warming and lead to significant climate change. These changes include increasing ambient temperature, precipitation variability, and the frequency of extreme events

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such as droughts, floods, and heatwaves (IPCC, 2018). In many regions of the world, climate change and extremes have reduced productivity of major food and feed crops (Adhikari et al., 2015; Challinor et al., 2014; Lesk et al., 2016; Rojas-Downing et al., 2017), leading many commentators to proclaim that climate change, along with the need to feed a human population of about 9.8 billion by the end of 2050, poses a significant threat to regional and global food security (Branca et al., 2013; Pradhan et al., 2015; Rojas-Downing et al., 2017).

US agriculture is not immune to climate change. Despite improved plant genetics and management practices that have brought about long-term improvements in yields, extreme weather events tied to climate change may offset these yield gains (Hatfield et al., 2020; Ortiz-Bobea et al., 2018; Schlenker et al., 2006). Furthermore, climate variability is a major cause for annual variations in crop yields in the Midwestern United States (Hatfield, 2012; Wang et al., 2016) and accounts for more than 60% of the yield variability of major food crops (Ray et al., 2015).

The Midwestern US is one of the most productive and economically important agricultural regions in the world but is increasingly experiencing extreme weather events tied to climate change, including droughts and floods (Hatfield et al., 2020; Andresen et al., 2012). Projecting into the future, an ensemble of eight climate models showed that the frequency of drought in the US Midwest is to increase from the present rate of once every five years to once every other year by 2050 (Jin et al., 2018). Such projected drought events are expected to drive yield losses of corn, soybean, and wheat – outpacing the rate of productivity gains through improved CO_2 fertilization, cultivars and agronomic practices (Jin et al., 2018; Lobell et al., 2014; Troy et al., 2015; Zipper et al., 2016). Such effects may result in amplified economic swings for consumers and producers. For example, the North American drought of 2012 impacted Southern states the most, where corn prices responded with a 53% increase in 2012–2013 relative to the previous 5-year average price and by 146% compared to the decade of 2000–2009 (Boyer et al., 2013).

The substantial extent of the row crop operations in the Midwest is under rain-fed production. Because precipitation is the primary source of moisture in rain-fed agriculture, the impacts of droughts are much more significant (Kuwayama et al., 2019; Sweet et al., 2017). Besides impacting plant available moisture, Midwest growers must also contend with the timing of extreme moisture events, as extreme rain events tied to climate change are most apt to occur during planting and harvesting times (Tomasek et al., 2017), – times where timely access to fields is paramount to maintaining productivity and profitability of their farms.

Recent studies of Midwest farmers show that growers recognize the changing climate (Arbuckle et al., 2013; Doll et al., 2017; Mase et al., 2017) and have, therefore, implemented different adaptation measures (Denny et al., 2019; Morton et al., 2015). For example, farmers who better understand the impacts of climate change and are able to attribute it to the anthropogenic activities are increasingly using climate information, conservation practices, crop insurance and other alternative techniques for mitigating added risks of climate change (Arbuckle et al., 2013; Haigh et al., 2015; Mase et al., 2017; Morton et al., 2017). However, recognition of the threats due to climate change and the uptake of climate-resilient practices still wanes (Church et al., 2017; Lemos et al., 2014). Therefore, the path to greater food stability and security may require a greater concerted effort to promote climate change-resilient practices.

Climate resilience can be defined as the ability of an agricultural system to keep up with its structures and to ensure provisioning of its functions in the face of climate variability and extremes. This can be done by improving resilience capacities, namely robustness, adaptability, and transformability (Meuwissen et al., 2019; Tendall et al., 2015; Urruty et al., 2016) of agricultural practices. Robustness is the capacity of the agricultural system to withstand climate extremes. Adaptability is the capacity to change the agricultural practices, marketing, and risk management to reduce the impacts of climate extremes without altering the structures and feedback mechanism of the system. Transformability is the capacity to substantially change the structures, feedback mechanisms, and functions in response to climate extremes (Meuwissen et al., 2019). Therefore, the goals of improving climate resilience include not only increasing the productivity of crops in the face of climate extremes but also improving the ecosystem services provided in nature while minimizing the environmental degradation from farm-related activities (Peterson et al., 2018).

Alternative agricultural systems have been endorsed to promote climate resilience compared to the conventional agriculture (Branca et al., 2013; Michler et al., 2019; Scialabba and Müller-Lindenlauf, 2010; Tuomisto et al., 2012). These alternative systems may include no-till/reduced tillage practices, the use of sustainable crop rotations and cover crops, reduced applications of inorganic inputs, and certified organic crop production. According to some researchers, such production systems have the potential to mitigate environmental pollution and greenhouse gas emissions, while substantially improving the soil and water quality in the agricultural ecosystems (Behnke et al., 2018; Martens et al., 2015; Syswerda and Robertson, 2014). However, these treatments have not gained sufficient popularity among farmers due to higher risks and profitability concerns (Mausch et al., 2017; Roesch-McNally et al., 2018) and general resistance to changes in farm practices (Fleming and Vanclay, 2010; Takahashi et al., 2016). Some even assert that old practices are strongly reinforced by the markets, legislation, and agribusiness companies that greatly benefit from the currently practiced intensive systems (Roesch-McNally et al., 2018). Hence, conventional agriculture is still widely used regardless of being vulnerable to climate extremes, being a net source of environmental pollution and a source of carbon emissions (Bennett et al., 2014; Foley et al., 2011).

Farm profits are an important source of family and regional incomes. For some, farm income may be the sole source of family earnings. Farm earnings are measured in farm profits or the differences between farm income and farm expenses. Maintaining a consistent and predictable flow of annual earnings is desirable (Martens et al., 2015). Therefore, climate-induced variations in agricultural production should be a motivating factor in growers' willingness to explore and implement climate-resilient practices. However, there are costs and risks to adopting new practices, and growers should target long-term, economic resilience when considering what practices to adopt (Kumar et al., 2016; Mausch et al., 2017; Sain et al., 2017).

Economic resilience can be quantified using both the mean and volatility (Abson et al., 2013; Browne et al., 2013) of the expected net returns, where a system with higher mean and lower volatility can be taken as a relatively resilient system. In general, there are tradeoffs between profitability and farm risk management, as different farmers reflect different behaviors towards risk (Brink and McCarl, 1978; Lu et al., 2003). For example, a system may be profitable on average but risky due to the interannual variations on net returns and/or market demands. Such a venture with high expected returns but a high degree of variation in expected outcomes may not be pursued, depending on risk tolerances (preferences) of the farmer. Profitability also affects the costs and benefits of crop insurance policies, which is considered to be an important tool for climate risk management (Annan and Schlenker, 2015; Tack and Ubilava, 2015). Therefore, both profitability and risks should be evaluated to identify climate-resilient systems that can be successfully transformed into farm-level adaptation.

Data from long-running agricultural experiments are befitting an evaluation of the economic resilience and risks associated with alternative agricultural systems, as they can capture historical climate variations and its impacts on farm net returns. The Main Cropping System Experiment (MCSE) of the Kellogg Biological Station's (KBS) Long-Term Ecological Research program provides an effective backdrop to look at the long-term effect of climate on resilience under alternative agricultural treatment systems. Three alternative treatment systems (i.e., no-till, reduced input, and organic) for a crop rotation of corn-soybean-wheat were compared to the conventional treatment. In a similar experiment, Swinton et al. (2015) compared the profitability of these treatments for the period of 1993–2007. That study compared the economic values of ecosystem services in the context of climate change. The current study augments Swinton et al. (2015) by broadening the time-scale of analysis and focusing on growers' economic incentives for adopting alternative agricultural practices as it relates to economic returns and risks to those returns.

The stability of farm profits is directly related to resilience (Cabell and Oelofse, 2012). Accordingly, this study was designed to evaluate the climate resilience of three alternative treatment systems in terms of long-term profitability and risks compared to the conventional system. To accomplish this task, the following objectives and hypotheses were formulated and tested. The first objective was to evaluate the effects of climate variability on farm net returns under different production and treatment systems. Under this objective, we hypothesize that climate variability has a significant impact on expected net returns. The second objective was to evaluate the risk level for the adaptation of different alternative treatments. We hypothesize that no one treatment system dominates the others in terms of both risk and net return and each treatment system offers different adaptation alternatives for farmers depending on their risk preferences.

2. Materials and methods

2.1. Overview of methodology

Profitability and associated risks are the outcomes of climate resiliency and determine farm-level adaptation in agricultural systems (Mausch et al., 2017). In this study, we evaluate the climate resilience of three alternative treatment systems implemented in a long-term corn-soybean-wheat rotation in comparison to a conventional, or common approach, treatment. Expected gross margin and annual variation in expected gross margin—as a measure of economic risk, are used as evaluation metrics. Annual crop management and production data during the period of 1993–2019 (27 years) were collected, and the gross margins for each crop in the rotation and treatment systems were estimated via static enterprise budgeting. First, we quantify the effects of climate variability on the means of gross margins using a statistical mixed model and volatility of gross margins using relative standard deviation (Objective 1). We judge resiliency based on the combined expected net revenues and expected annual variation in net revenues by defining the resilient system

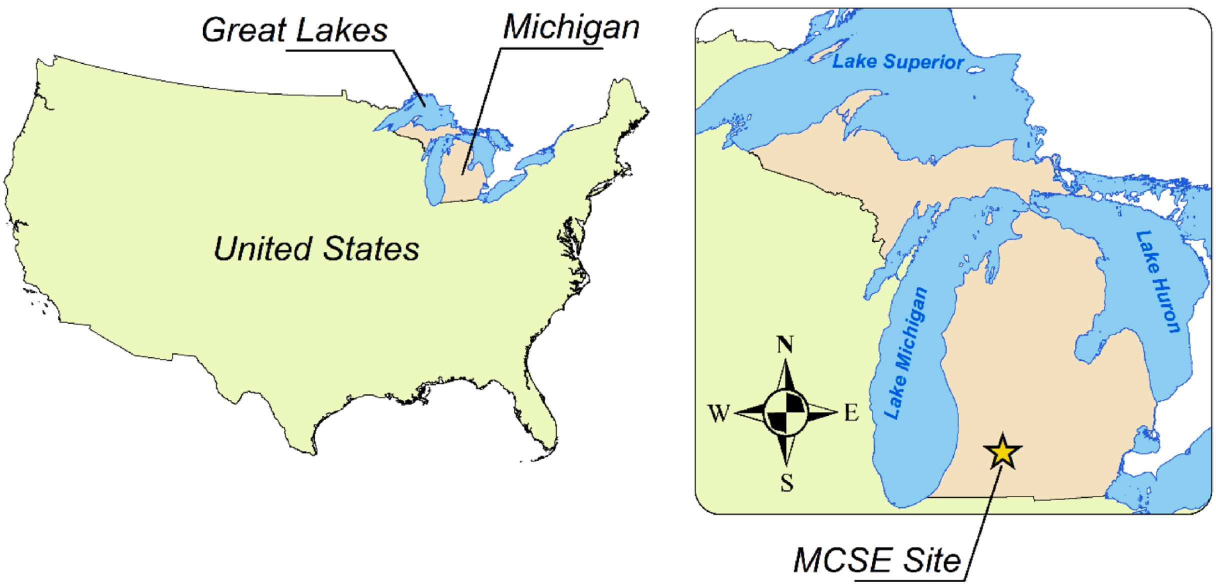

Fig. 1. The location of the Main Cropping System Experiment (MCSE) in Southwest Michigan, United States.

as the one which has the highest expected gross margin and lowest volatility. Finally, we assess the risk level of alternative treatment systems as affected by climate variability using the payoff matrix tool (Objective 2). This will enable us to identify if a climate-resilient system can be a viable option among the farmers with a wide range of risk preferences for adaptation.

2.2. Study location and details of the experiment

This study was conducted using long-term data generated at KBS located in Southwest Michigan, United States. This region represents a humid continental climate and the Köppen climate classification subtype of "Dfa" (Peel et al., 2007). Soils at KBS mainly consist of Kalamazoo (fine loamy) and Oshtemo (coarse loamy), both mixed, mesic Typic Hapludalfs that mainly differ in the thickness of the Bt horizon (Syswerda and Robertson, 2014). A series of long-term ecological research experiments have been established at KBS. One such experiment is the Main Cropping System Experiment (MCSE), which is in the geographic coordinates of 42.41° N, 85.37° W, and the altitude of 288 m AMSL (Fig. 1).

The experimental rotation is corn (Zea mays)-soybean (Glycine max)-winter wheat (Triticum aestivum). We apply four treatments: (i) conventional (CON), (ii) no-till (NT), (iii) reduced input (RI), and (iv) US Department of Agriculture (USDA) certified organic (OR). This study tracks the crop rotations and outcomes beginning in 1993 though 2019, and these fields have been maintained in a common rotation since 1989 (Robertson and Hamilton 2015) of corn followed by soybean and wheat. All experimental blocks follow the same rotation and are uniformly on the same stage of the rotation with other blocks. Therefore, we had a total of nine full rotations by the end of 2019 under each treatment.

All treatment systems are rainfed, and each was assigned to six replicates (blocks) of one-ha, in a randomized complete block design. During the cropping rotations of corn and soybean, CON, NT, RI treatments were planted with Roundup-ready seeds while the OR treatment was planted with conventional and untreated seeds. There was no difference between the treatments on seed types during the winter wheat cycle. The timing of management operations of this corn-soybean-wheat rotation under each treatment is presented in supplementary materialsl (Table S1–S4). The detail agronomic management of the different treatment systems is as follows:

Conventional treatment: Crops were planted following the primary tillage and soil finishing. Primary tillage was applied using moldboard plough until 1998 and after that using chisel plough. Secondary tillage was applied by disking before planting during the years when wheat crop is planted. Inter-row cultivation was performed for corn and soybean. Fertilizer application rates were based on the soil-test recommendations for each crop. Weeds were controlled by a broadcast application of appropriate herbicides, depending on the weed intensity in each crop. No type of manure or compost or insecticides was applied.

No-till treatment: Crops were planted under zero tillage operations using a no-till drill. Fertilizer application rates were based on the soil-test recommendations for each crop. Weeds were controlled by the broadcast application of appropriate herbicides, depending on the weed intensity in each crop. No type of manure or compost or insecticide was applied. According to one anonymous reviewer, one of the potential benefits of no-till treatment, in light of climate change, is that no till improves the chances of planting on time.

Reduced input treatment: Crops were planted following the primary tillage and soil finishing. Primary tillage was applied using moldboard plough until 1998 and after that using chisel plough. Secondary tillage was applied by disking before planting during the years when wheat crop is planted. Inter-row cultivation was performed for corn and soybean. Nitrogen fertilizer and herbicide rates were applied as one-third of nitrogen and herbicides applied to the conventional treatment. Herbicides were not broadcasted but banded within rows. Phosphorus and potassium fertilizer application rates were based on the soil-test recommendations for each crop. A winter cover crop was planted following the corn and wheat crops of the rotation to capture nitrogen in the field for future crop uptake. Commonly, cereal rye (*Secale cereal*) was planted following corn, while red clover (*Trifolium pratense*) was planted following wheat. No type of manure or compost or insecticide was not applied.

Organic treatment: Crops were planted following the primary tillage and soil finishing. Primary tillage was applied using moldboard plough until 1998 and after that using chisel plough. Secondary tillage was applied by disking before planting during the years when wheat crop is planted. Inter-row cultivation was performed for corn and soybean. A winter cover crop was planted following the corn and wheat crops of the rotation to capture nitrogen in the field for future crop uptake. Commonly, cereal rye (*Secale cereal*) was planted following corn, while red clover (*Trifolium pratense*) was planted following wheat. No manure-based fertilizers were applied. This is a USDA certified organic treatment; therefore, no chemical fertilizers/herbicides/insecticides were applied.

2.3. Enterprise budget analyses to estimate gross margin under different treatments

2.3.1. Calculation of cost component

Data on crop management, quantities of inputs, and the rates of application for all four treatments for the period of 1993–2019 were obtained from the agronomic log of the KBS. Clemson University enterprise budgets of 2018 were obtained and modified for each crop in the rotation and each treatment (Clemson 2020). Annual operating costs were estimated using 2018 static prices for relevant inputs. Although other well-established crop enterprise budgets exist for modeling economic outcomes, we selected Clemson's budgets because they consistently represented the inputs and practices across all crops in this analysis and provided sufficient detail required to model the cost components of different treatments. Budgets with this level of detail price information were not available for Michigan-specific farm operations. Farm machinery operations, and crop scouting were valued using the 2018 custom machine and work rate estimates of Michigan State University Extension (Battel, 2018). Costs captured for some of the farming activities in the previous year for the following crop were included in the budget of the main cropping year in which the harvest occurs. For example, costs of land preparation and planting needed for wheat and for establishing cover crops to benefit corn and soybean during the previous year were considered in the calculation of the main cropping year budget of the respective crops. Michigan crop insurance premia were imputed for each commodity to account for Michigan annual crop insurance amounts. Fixed costs, which generally involves land rent, farm equipment insurance, and other overhead costs were excluded in the budget analysis. Therefore, the cost component consists only of the variable costs such that return estimates are best described as farm gross margins. Since type of herbicides, machinery operations, cover crop seed rates and fertilizer applications (depending on soil testing) vary each year, the total cost varied annually. The annual cost of operations to produce crops under different treatments is presented in supplementary material Table S5.

2.3.2. Calculation of returns

Crop yield data was collected from the MCSE for the individual replicates of each production system. Crops from the conventional, no-till and reduced input treatments were priced using traditional commodity prices, while organic crops were priced using the organic commodity prices. Annual marketing year commodity prices (traditional) received in Michigan were obtained from the National Agricultural Statistics Service of the United States Department of Agriculture (NASS, 2020). The reliable organic commodity prices were only available from the Agricultural Resource Management Survey (ARMS) (USDA, 2020) for corn, soybean, and wheat for the years of 2010, 2006, and 2009, respectively. Therefore, we used this organic commodity prices and the respective traditional prices to compute the ratio between organic and traditional commodity prices for each crop. These ratios were then used to estimate annual organic commodity prices for Michigan, as the base year factor multiplied by the annual marketing year prices obtained from NASS. Annually variable marketing year prices received in Michigan for traditional and organic commodities is presented in supplementary material Table S6.

Annual variations in profits were estimated as the calculated gross margins over the 27 years of the study. Expected gross revenues were estimated from projected gross revenues, comprised of yield and crop prices (Table S6). Annual variable cost estimates are provided in Table S5 of the supplemental material. The expected gross margin was then estimated as the average difference between projected gross revenues and variable costs.

2.4. Evaluating the effects of different treatments and climate variability on resilience as measured by the gross margin

In this section, we explain the methodology of statistically testing the effects of different treatments on our economic-based measures of climate resilience.

2.4.1. Categorization of climate variability

The study period (1993–2019) was classified into dry, normal, and wet categories of climate variability using probability analysis based on aggregated seasonal precipitation that covers primary growing season (April-October). As assessing the impact of climate variability requires analyses over relatively long durations (WMO, 2017), thirty years (1989–2018) of total seasonal precipitation data was collected from the KBS weather station located within the experimental site. To categorize climate variability using seasonal precipitation, probability analysis of historical precipitation is a recommended method (Alizadeh, 2013; Eeswaran et al., 2021). Accordingly cropping years were categorized as follows:

i. dry years were designated for years that had observed aggregate precipitation below the 33.3% of cumulative probability of historical precipitation;
ii. normal years were designated for years that had observed aggregate precipitation between 33.3% and 66.6% of cumulative probability of historical precipitation; and
iii. wet years were designated for years that had observed aggregate precipitation greater than 66.6% of cumulative probability of historical precipitation.

Based on the above analysis, dry years received seasonal precipitation $\leq$ 580 mm, wet years had seasonal precipitation $\geq$ 700 mm and normal years received seasonal precipitation in between. For the total of 27-year study period there were 9 dry years, 8 normal years and 10 wet years which ended up with the tercile probabilities of being dry, normal, and wet years as 0.3, 0.3 and 0.4, respectively.

2.4.2. Evaluating the effects of treatments and climate variability on the expected gross margin

A statistical mixed model, which incorporates both fixed and random effects of relevant independent variables (Milliken and Johnson, 2009), was used to test the statistical significance of the effects of the treatments and climate variability on the gross margin. The statistical model was specified as:

$$Y_{ijk} = \mu + c_k + t_i + b_j + (tc)_{ik} + \varepsilon_{ijk} \tag{1}$$

where, Y_{ijk} is the response variable (i.e., gross margin) for the i^{th} treatment, within j^{th} block (replicate) on the k^{th} climate; μ is the mean; c_k is the fixed effect of the climate variability k (dry, normal and wet); t_i is the fixed effect of the treatment i; b_j represents the random effects of the j^{th} block, with $b \sim N(0, \sigma_b^2)$; $(tc)_{ik}$ denotes the fixed interaction between the i^{th} treatment and k^{th} climate; and ε_{ijk} is the error associated with each observation, with $\varepsilon \sim N(0, \sigma_\varepsilon^2)$. We included seasonal mean temperature into this statistical model as a fixed effect; nevertheless, the effect of temperature and its interaction terms were not significant at $p \leq 0.05$ on the gross margin. Therefore, we removed seasonal mean temperature in the final statistical model. The insignificant effect of seasonal mean temperature was most likely a result of small variation (CV = 4.8%) observed for this continuous variable during the period of study. The estimated gross margin data passed the normality test for the residuals and temporal homogeneity of variances (Milliken and Johnson, 2001). Statistical analysis was performed by each individual crop, using PROC GLIMMIX procedure (Milliken and Johnson, 2009) in the SAS software (Version 9.4 SAS Institute Inc. Cary, North Carolina, US). Tukey Test for mean separation was performed when significant differences were detected for the fixed effects by defining $\alpha = 0.05$ (Tukey, 1977). Since we had four treatments with six replications for each treatment and 27 years of evaluation, the total sample size (n) was 648. Based on the Akaike information criterion (AIC), a model with smaller AIC was selected as the best fit to evaluate the effects treatment and climate variability and the overall model was significant at $\alpha = 0.05$.

2.4.3. *Defining climate resilience*

As growers will take into account both the expected returns and the expected risks in their agricultural enterprises, in this section we define climate resilience based on both the means and volatility of the expected gross margins.

2.4.3.1. Defining climate resilience based on the means of expected gross margins. Of the four treatments, the conventional treatment was considered as the baseline, or control case, for which alternative treatments were compared. The conventional treatment was taken as the control because of its widespread practice in present agriculture throughout the world, although it has been found to be vulnerable to climate change and extremes (Foley et al., 2011; Kassam et al., 2019).

We estimate expected economic returns as the means of gross margins for each treatment system. Statistical significance was tested for each climate category-commodity combination (dry, normal and wet – corn, soybean, and wheat), resulting in nine cases for each of the four treatments. A treatment is deemed resilient if that treatment provides six or more cases (above 2/3 of outcomes) of gross margins that are statistically higher than the conventional treatment across all climatic conditions. A treatment was identified as non-resilience if it performs significantly lower than the conventional treatment in six or more cases as a measure of the mean of gross margin. A treatment that falls in between the above two categories was considered as moderate resilience. In this approach, the measure of treatment resilience is relative to the conventional treatment. Moreover, there are almost equal chances of experiencing dry, normal, and wet years in this crop rotation as the tercile probabilities of being dry, normal, and wet years was almost equal. Therefore, a resilient treatment should be able to significantly increase the revenues from all crops in the rotation across the observed range of climate variability.

2.4.3.2. Defining climate resilience based on the volatility of expected gross margins. The volatility of expected gross margins is another indicator of climate resilience, where an agricultural system with volatile expected revenues will be less resilient to climate perturbations (Abson et al., 2013; Gil et al., 2017; Urruty et al., 2016). Relative standard deviation (RSD) is used to quantify the volatility of agricultural outcomes (Rigolot et al., 2017). RSD is the normalized measure of the dispersion of a probability distribution, which is defined as the ratio between the standard deviation and the absolute mean, presented in percentage terms (Abson et al., 2013). The absolute mean is used in calculating RSD instead of the coefficient of variation to avoid negative measures of variation. In this way, RSD estimates are scale-invariant and comparable across all climate category-commodity combinations. In this study, we calculated the RSD for each treatment under each category of climate variability for all three crops in the rotation. Moreover, the distribution of expected gross margins for each treatment, as affected by climate variability, was also presented. Here, we define the resilient treatment as the one that holds a higher expected gross margin with lowest RSD.

2.5. *Evaluating the risk level for the adaptation of different treatment systems by producers*

Risk is defined as the chance of adverse outcomes associated with an action (Nelson, 1997). While making decisions for the adaptation of alternative treatment systems, producers would prefer to avoid risks. To understand the risks associated with each potential adaptation actions, producers require decision-making tools that permit them to incorporate uncertainty and risk into their adaptation planning. To this end, a payoff matrix can be considered as a suitable decision-making tool for analyzing adaptation decisions in terms of alternative actions, possible events, and payoffs (Hoag and Parsons, 2010; Nelson, 1997).

We used the payoff matrix to evaluate the risk level for the adaptation of different treatments considering the gross margin for each crop in the rotation. The producer (decision-maker) can choose among alternative actions with differing predicted reward/risk structures that refer to different treatment systems. However, the expected outcomes (i.e., gross margin) from each action may depend on uncertain events, which represent climate variability impacts on gross margins for each of the commodity-treatment combinations. This uncertainty information can be incorporated into the payoff matrix as probabilities (Nelson et al., 1978; Senapati, 2020). Here we incorporated the tercile probabilities of climate variability (i.e., dry, normal, wet) as the uncertainty information to the payoff matrix.

Producers can make decisions, either by incorporating the probability of uncertain events or not incorporating these events. There are two types of risk preferences among the producers who do not incorporate the probabilities of uncertain events into their decision-making process: i) risk-averse decision-makers are those who select the best among the worst gross margins for each adaptation action; and ii) risk-loving decision-makers are those who select the best among the best gross margins for each adaptation action. Producers who do incorporate the probabilities of uncertain events into their decision-making process are called risk-neutral decision-makers. They maximize the expected monetary value (EMV) of gross margins. The above decision-rules were based on Nelson et al. (1978) and used to identify the alternative treatments which can be selected by the producers with different risk preferences.

3. Results and discussion

3.1. Effects of treatment systems and climate variability on the gross margin of different production systems

The statistical mixed model (Equation (1)) was used to analyze the gross margins – taking it as a response variable for the individual crops in the rotation. The probability of the effects of treatment and climate variability on the gross margin for each crop is presented in Table 1. Accordingly, the effect of treatments and climate variability on the gross margin was significant ($p < 0.05$) for all crops; notably the effect of climate variability was strongly significant ($p < 0.0001$). The interaction between treatment and climate variability was not significant in any of the crops. Table 1 shows that the gross margin significantly varies with treatments and climate variability in this study.

3.2. Resilience of treatments as measured by the net return

The means of gross margins for different treatments for each crop in the rotation as affected by climate variability, are presented in Table 2. For a total of nine cases for each treatment, the no-till treatment had higher number of cases (seven cases) where it had significantly higher gross margins than the conventional system. Meanwhile, the organic treatment had six cases where the gross margins were significantly higher than that of the conventional treatment. In contrast, the reduced input treatment had six cases where gross margins were significantly lower or insignificant in comparison to the conventional treatment. Therefore, based on our criteria, the findings assert that the no-till and the organic treatments are resilient systems, while the reduced input treatment is non-resilient or vulnerable.

Although the crop yields of no-till treatment outperform the other treatments in the majority of the crop and climate variability combinations (Table S7), the organic treatment supersedes the economic performance. This is largely the result of the relative revenue-cost differential of organic over other treatments, where organic produce command higher per-unit selling prices and marginally lower variable production costs. Gross margins were substantially lower for all crops during the dry years, which highlights the impacts of climate on farm profitability, and the differential performances of treatments signify the potential of alternative treatments (no-till/organic) to mitigate these impacts. Meanwhile, the differences among treatments were not significant during the wet years in this rotation except in soybean (Table 2).

The average annual gross margin for the full crop rotation (i.e., corn-soybean-wheat) during the period of study is presented in Fig. 2. The gross margins for all nine rotations were highest for the organic treatment, followed by the no-till treatment. The gross margins of the reduced input treatment showed a similar trend to the conventional treatment. Negative gross margins during the early years in the crop rotations were due to cyclically lower market prices of commodities and yields. Additionally, because the base year of input costs was relatively recent (i.e., 2018), input prices for earlier years were somewhat inflated relative to farm-commodity prices - possibly resulting in negative bias estimates of absolute measures of gross margins in early years. Nevertheless, our objective here is to evaluate the comparative performances of treatments, and we are not intended to present a representative absolute gross margin to real farms which is impossible using the management data from a research farm which was designed with the focus on agronomic and biological experiments. The peak gross margin observed in Fig. 2 during the rotation period of 2011–2013 was primarily due to the increased marketing year commodity prices followed by the 2012 North America drought.

Despite lower yields in the organic treatment (Table S7), organic offered higher gross margins mainly because of premium prices and lower production costs compared to other treatments—as highlighted by Nemes (2009). Our findings also support those of Toliver (2010), who demonstrates that no-till cropping is more profitable than the conventional cropping systems. This is mainly due to the higher yields in the no-till treatment in comparison to the conventional treatment (Table S7). No-till also has lower production cost from zero tillage operations, which for chisel/moldboard plowing, can be cost intensive.

Volatility to climate change, as measured by the RSD, was presented against the gross margin in the scatter plot in Fig. 3. Overall, the organic and the no-till treatments had greater gross margin with lower volatility across different crops and climate variability, which demonstrates the resiliency of these treatments over the conventional and the reduced input treatments. This was highlighted by one anonymous reviewer on an earlier draft of this article.

The average changes in gross margin as affected by the drastic transition in climate under each treatment is presented in Table 3.

Table 1
Probabilities for the effects evaluated in the statistical mixed model for the gross margin.

Crop in the rotation	Evaluated effects	Probability (p-value)[a]
Corn	Treatment (t)	**0.0348**
	Climate variability (c)	**<0.0001**
	Interaction between treatment and climate variability (tc)	0.1664
Soybean	Treatment (t)	**<0.0001**
	Climate variability (c)	**<0.0001**
	Interaction between treatment and climate variability (tc)	0.2241
Wheat	Treatment (t)	**0.0011**
	Climate variability (c)	**<0.0001**
	Interaction between treatment and climate variability (tc)	0.0855

[a] Bold values denote statistical significance of evaluated effects at the $p < 0.05$ level.

Table 2
Means of gross margin under different treatments as affected by climate variability.

Crop in the rotation	Treatment	Expected Gross Margins (USD/ha)*		
		Dry years	Normal years	Wet years
Corn	CON	(485.70)[c]	116.10[b]	803.00[a]
	NT	**(398.60)**[b]	**357.10**[a]	1083.00[a]
	RI	**(423.90)**[b]	19.40[c]	851.50[a]
	OR	**(27.50)**[a]	81.00[b]	1066.80[a]
Soybean	CON	(271.50)[c]	(119.80)[c]	82.80[c]
	NT	**28.00**[b]	**150.20**[b]	**266.60**[b]
	RI	(357.70)[c]	(202.90)[c]	63.10[c]
	OR	**659.60**[a]	**682.30**[a]	**1232.40**[a]
Wheat	CON	(98.50)[c]	(26.80)[c]	227.00[a]
	NT	**88.60**[a]	**131.50**[b]	200.50[a]
	RI	**(31.80)**[b]	**85.10**[b]	191.60[a]
	OR	**92.30**[a]	**236.40**[a]	211.80[a]

* Means with the same letter in a single column for each crop are not significantly different at $p < 0.05$. Means of gross margin with negative values are presented in parenthesis. CON: Conventional treatment; NT: No-till treatment; RI: Reduced input treatment; and OR: Organic treatment. Means of gross margin, which are significantly higher in comparison to the conventional treatment, are presented in bold letters.

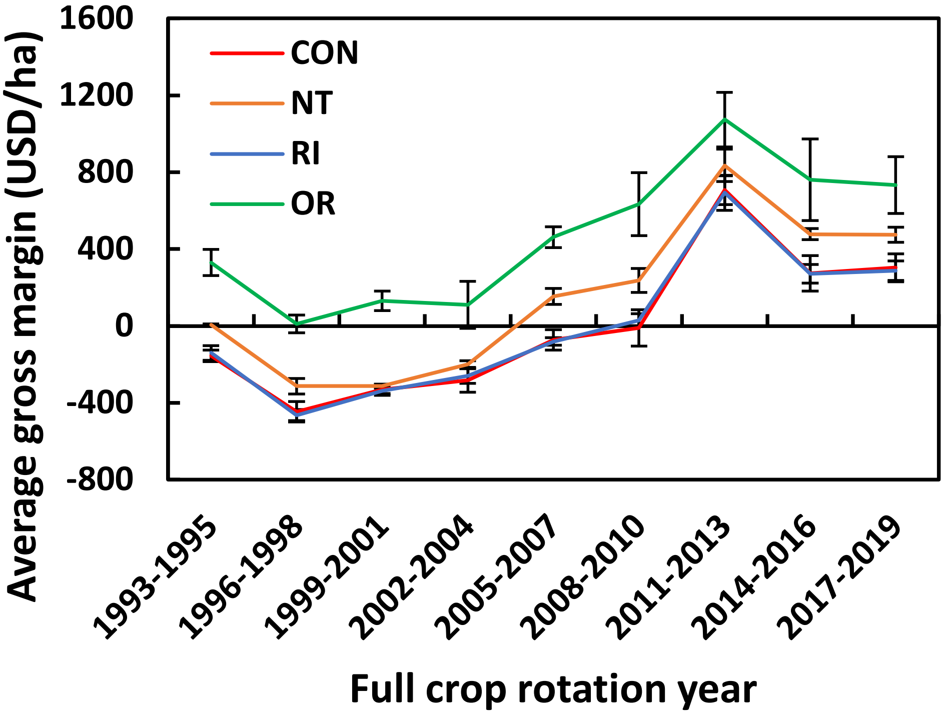

Fig. 2. Average annual gross margin for the full crop rotation during the period of 1993–2019.

During the transition from wet year to dry year, the gross margin decreases while it increases when the transition is in the opposite for all treatments. The reduction in gross margin during wet- to dry-year transition was the lowest for the no-till treatment while it was highest for the organic treatment. The reduction under the reduced input treatment was not substantially different from that under the conventional treatment. During the transition from dry year to wet year, the organic treatment had higher gain than the conventional treatment, while the no-till and the reduced-input treatments had lower gains than the conventional treatment. This shows the resilience of the no-till treatment in buffering the losses of profits during drought events.

3.3. Producer risk levels for the adaptation of alternative treatments

The payoff matrix for corn, soybean, and wheat crops are presented in Tables 4. According to the decision rules explained in section 2.5, a risk-averse farmer who does not consider the uncertainty of climate variability, would prefer to select the organic treatment. In contrast, a risk-loving farmer would prefer to select the no-till treatment for corn production. However, for a corn producer who considers the uncertainty of climate variability, risk-neutral action would be the selection of the organic treatment which maximizes

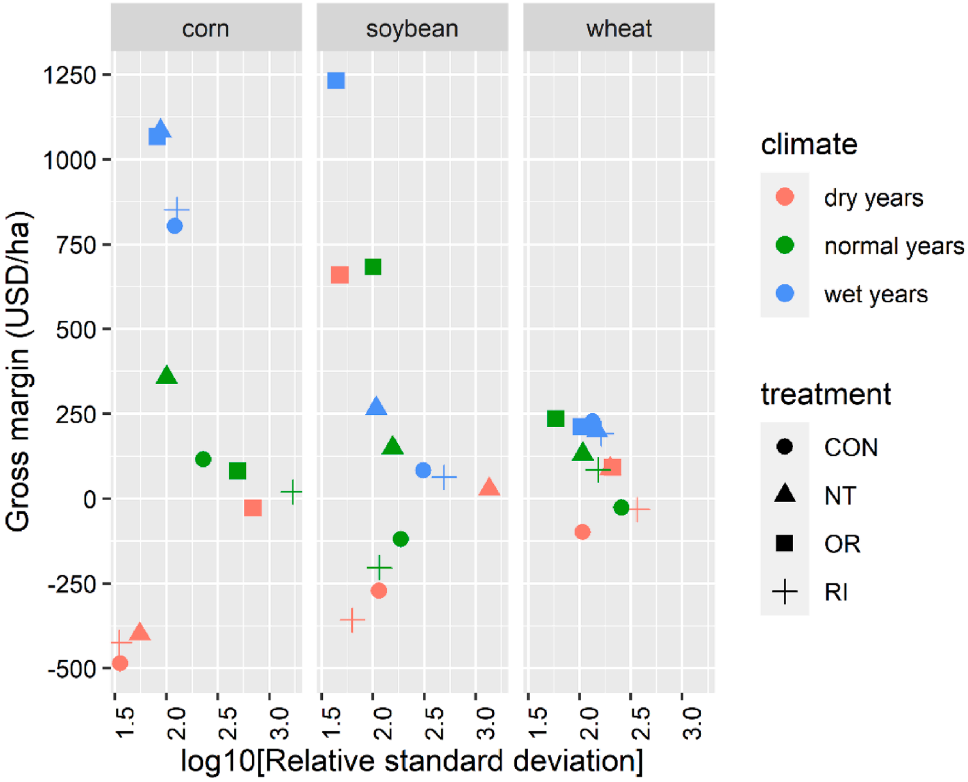

Fig. 3. Scatter plot between the expected gross margin and the relative standard deviation for different treatments as affected by climate variability.

Table 3
Changes in gross margin during the drastic climate scenarios under different treatments.

Transition scenario	Number of observations	Treatment	Average change in gross margin (USD/ha)
Wet-Dry	24	CON	−499.20
		NT	−398.60
		RI	−487.80
		OR	−588.90
Dry-Wet	24	CON	233.90
		NT	146.30
		RI	150.20
		OR	327.00

EMV (Table 4). Regardless of the consideration of the uncertainty in climate variability, the organic treatment is shown to be the selected action for soybean and wheat producers with risk-averse, risk-loving, and risk-neutral preferences (Table 4). No-till and organic treatments generally posit higher returns over most climatic conditions, though organic returns outperform others in adverse climate years, while no-till exhibits the highest returns for normal climate years—especially in corn. However, expected profits is only one consideration when selecting production practices. Risks, which generally relate to the minimum lower bound of outcomes, is also a factor. Those seeking strictly to minimize risk would select the same combination as those solely considering expected profits. That is, no-till provides the best downside, or risk, during normal years, while organic provides the best downside risk during adverse climatic years.

The organic treatment commands a higher expected net revenue as a result of the current market value proposition afforded to the organic crops. The organic crop production practices, which consist of the use of non-genetically modified crops and avoidance of any synthetic agrochemicals, have comparably lower costs and consumers are willing to pay higher prices for these attributes. As, more farmers enter into organic agriculture to take advantage of relative profits in this segment, the supply of organic produce increases. Of course, the law of supply dictates that as entrants increase the supply of organic produce, the price will fall until all excess profits that can be gleaned from organics are exhausted. However, there are barriers to entry that may protect profits to the organic sector. Such barriers include a three-year transition period requirement, where farmers face supressed transitional yields and revenues (Bravo-Monroy et al., 2016; Bowman and Zilberman, 2013). Other barriers include surmounting the learning curve for managing a profitable organic operation. Though not a barrier to entry to organic, farmers are often unwilling to change current practices despite the

Table 4
Payoff matrix of different treatments for the crop rotation as affected by climate variability.

Crop in the rotation	Climate variability	Probability	Gross margin (USD ha^{-1})			
			CON*	NT	RI	OR
Corn	Dry year	0.3	**(485.70)**	**(398.60)**	**(423.90)**	**(27.50)**
	Normal year	0.3	116.10	357.10	19.40	81.00
	Wet year	0.4	*803.00*	*1083.00*	*851.50*	*1066.80*
	Expected Monetary Value (EMV)≈(0.3)(-485.7)+(0.3)(116.1)+(0.4)(803)		210.32	420.75	219.25	***442.77***
Soybean	Dry year	0.3	**(271.50)**	**28.00**	**(357.70)**	**659.60**
	Normal year	0.3	(119.80)	150.20	(202.90)	682.30
	Wet year	0.4	*82.80*	*266.60*	*63.10*	*1232.40*
	Expected Monetary Value (EMV)≈(0.3)(-271.5)+(0.3)(-119.8)+(0.4)(82.8)		(84.27)	160.10	(142.94)	***895.53***
Wheat	Dry year	0.3	**(98.50)**	**88.60**	**(31.80)**	**92.30**
	Normal year	0.3	(26.80)	131.50	85.10	*236.40*
	Wet year	0.4	*227.00*	*200.50*	*191.60*	211.80
	Expected Monetary Value (EMV)≈(0.3)(-98.5)+(0.3)(-26.8)+(0.4)(227)		53.21	146.23	92.63	***183.33***

Note: The worst outcome from each crop under different treatments is in bold format. The best outcome from each crop under different treatments is in italic format. The maximum EMV for each crop in the rotation is in bold-italic format. *shows how EMV is calculated under the conventional treatment, and the similar equation was used to calculate EMV in other treatments.

potential for gains (Fleming and Vanclay, 2010; Takahashi et al., 2016). In addition, as organic operations become more common, biotic outbreaks such as pests and diseases will likely increase production costs (Röös et al., 2018), thereby reducing the net earnings advantage afforded by organic systems. Finally, there is the threat that widespread organic production has on aggregate food supply. If widespread organic production reduces aggregate farm productivity, the conventional market will shrink, giving rise to the price of non-organic foods, and thereby eroding the organic food price advantage. That is, in the long run, many factors will be at play, impacting the future direction of the agri-food economy.

This study also showed that the no-till production provides improved gross margins compared to conventional production, especially during dry and normal years. Alternatively, reduced-input treatment exhibits inferior returns to conventional in the majority of years. This is likely associated with the additional costs associated with planting and killing the cover crop, that while improving soil quality, may not provide yield enhancements sufficient to cover the costs of managing the cover crop.

4. Conclusions

Identifying alternative agricultural practices to improve climate resilience in current cropping systems is an urgent response to the challenges of increasing climate extremes. Profitability and associated risks are the key determinants of climate resilience, as they affect the decision of farmers for transition and adaptation. In this study, we evaluated the climate resilience of three alternative treatments; namely, no-till, reduced input, and organic treatments in comparison to a conventional treatment. The assessment tracks 27-years of corn-soybean-wheat rotation in Southwest Michigan, USA. Historical seasonal precipitation data was used to categorize the climate variability during the study period, and an appropriate enterprise budget analysis was conducted to derive expected annual gross margins using the crop management and production data collected from the long-term field experiments. A statistical mixed model was used to evaluate the effects of treatments and climate variability on the expected gross margins. Means and volatilities of the expected gross margins were used to define climate-resilient treatments. A payoff matrix approach was used to identify the suitability of alternative treatments for farmers with different risk preferences.

According to the findings of this study, the organic and the no-till treatments were identified as resilient treatments. The conventional and the reduced input treatments showed lower levels of resilience to climate variability. The findings are significant in showing that no-till practices dominate conventional and reduced input practices in both expected annual net revenues with relatively lower risk to those revenues in light of climate extremes, and this finding could motivate the expansion of conservation practices in agriculture. It also shows that while organic production revenues are largely expected to exceed net revenues of conventional food crops across all climate environments modeled here, for many commodities, organic systems may exert greater annual stability in revenues. However, market conditions assert that such an advantage is likely to wane over time as growers migrate to this more profitable option. Related to this is the question of why migration to organic has not occurred faster than experienced. Part of the reason may be the high transition costs of going to organic, while another component likely arises from market structures that favor conventional practices and psychological barriers to significant disruptions of existing production practices. Overcoming these constraints will require policy and industry buy-in for alternative agricultural practices, including an expansion of crop insurance offerings, favorable Natural Resources Conservation Service (USDA-NRCS) – Environmental Quality Incentives Programs, and industry support for sustainably-produced food crops.

Disclaimer

Any opinions, findings, conclusions, or recommendations expressed in this paper are those of the authors and do not necessarily reflect the views of the National Science Foundation or the United States Department of Agriculture.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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