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Essays on climate change and resource economics

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DEDICATION

To my family

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ABSTRACT

This dissertation analyzes farmers' behaviors in response to climate change and technology adoption. The first essay analyzes the adaptive responses of Midwestern farmers to regional climate conditions through land use change and crop insurance purchases. The results of this study can be summarized as follows. First, we find that climate conditions have a significant effect on farmers' decisions regarding crops to grow, insurance purchases, and land allocation. Second, federal crop insurance mitigates farmers' incentive to adapt to climate conditions such as intensive rainfall events. Third, federal crop insurance programs have induced Midwest farmers to allocate more acreage to corn and soybeans.

The second essay studies economic and environmental implications of genetically modified (GM) corn and information technology adoption by analyzing Midwestern farmers' corn yield and nutrient management. The findings can be summarized as follows. First, GM corn and its combination with pest scouting increase corn yield and nitrogen use. Second, the effects of GM corn and/or pest scouting adoption on corn yield and nitrogen use are greater for fields having low soil productivity. Third, yield monitor and its combination with pest scouting have positive effects on corn yield and nitrogen use.

The third essay examines the effects of uncertainty regarding climate measures on forecasting future land use: variations in projected weather data sets and methods of forming farmers' expectations regarding weather variables. We analyze decadal land use change over the Midwest based on five general circulation models (GCMs) and six assumptions regarding how to form expected weather conditions. From out-of-sample forecasting tests, we find that the predictive accuracy of models depends on the choice of GCM and methods of forming farmers'

expectations regarding weather variables. However, we find that forecasting results based on models consisting of yearly agronomic variables are more stable and have better predictive accuracy than models consisting of monthly variables. In addition, we estimate forecast land use in 2030 based on the best model and verify that two uncertainties have a significant effect on the forecasting results. Last, the predicted land use over the Midwest in 2030 shows that corn and soybean acreage will expand to the northwest.

CHAPTER 1

GENERAL INTRODUCTION

To assess and alleviate harmful climate change impacts, policy makers must understand farmers' adaptive behaviors to local climate conditions. A farmer's farm management decisions greatly depend on regional climate conditions. In particular, land use change has been a major adaptation strategy of farmers to optimize their profit based on given environmental and market conditions. Farmers also have incorporated federal crop insurance programs to deal with farm operating risk. However, in terms of strategies for adapting to climate conditions, land use change and crop insurance are less well known. In addition, recent agricultural literature has focused on unintended policy effects of federal crop insurance programs on farmers' adaptive behaviors to climate conditions. Given limited conceptual and empirical evidence, one major purpose of this dissertation is to identify the causal relationship between climate conditions and land allocation and analyze the intertwined relationship between subsidized crop insurance and land allocations in terms of farmers' adaptive behaviors to climate conditions (Chapter 2).

In designing future plans for sustainable agriculture and resource management, policy developers and farm operators require credible estimates of climate change impacts on agricultural production. However, lack of knowledge about climate systems and farmers' response to climate conditions creates uncertainty regarding the causal relationship between climate conditions and regional agricultural production as well as the economic impacts of climate change. In particular, no consensus exists regarding how to construct farmers' expected weather conditions in previous land use literature. Also, projected weather data sets based on general circulation models (GCMs) generally differ from realized station-level weather outcomes and have large variations among them. To examine the effects of these two uncertainties regarding climate measures on forecast land use in 2030 and farmers' response, Chapter 4 analyzes decadal land use over the Midwest based on various scenarios and model specifications.

Genetic improvements and advanced crop management practices have been major contributing factors to corn yield growth in the U.S. after the 1930s. During the last decade, adoption of GM corn, pest scouting, and yield monitor has increased significantly. However, insufficient empirical evidence regarding the effects of GM corn and information technologies on corn yield and nutrient management may be an obstacle to understanding the costs and benefits of adopting the technologies. Chapter 3 provides empirical evidence regarding the effects of GM corn and information technologies on corn yield and nitrogen use management.

Chapters 2, 3, and 4 analyze farmers' behaviors in response to given exogenous conditions, including climate conditions, government policies, and technology adoption. The results of our research show that changes in agricultural productivity or profitability resulting from changes in climate conditions, policies, and available technology are key factors in determining agricultural production. This research contributes to our understanding of the implications of recent climate changes, expansion of crop insurance programs, and high adoption of GM corn and information technologies for United States (US) agriculture.

This dissertation is organized as follows: The next three chapters consist of the three essays introduced above. The dissertation closes with a general conclusion, including an overall summary and discussion of the findings.

CHAPTER 2.

ADAPTIVE BEHAVIORS OF MIDWEST FARMERS TO CLIMATE AND RISK

Jae-hoon Sung and John A. Miranowski

Abstract

To assess the effects of climate change on agricultural production, one must understand how farmers change their land use to accommodate climate conditions. Also pertinent is any unintended policy effect of subsidized crop insurance programs on farmers' land use. We analyze Midwestern farmers' decisions regarding cropping patterns and crop insurance purchases in response to regional climate conditions. We consider a simultaneous equation model accounting for farmers' decisions regarding crops to grow, insurance purchases, and land allocation. The estimates are based on the Agricultural Resource Management Survey. The results show that climate conditions have significant effects on farmers' decisions regarding crops to grow, insurance purchases, and land allocation among crops. Also, federal crop insurance programs mitigate farmers' incentive to adapt to increases in intensive rainfall events or decreases in total precipitation by adjusting their land use. Last, the results show that federal crop insurance programs increase the acreage devoted to growing corn and soybeans.

2.1 Introduction

Recent climate models predict that climate change in the Midwest over the next few decades will increase the frequency of extreme weather events such as intensive rainfall (see Figure 2.1). These changes may reduce crop yields and decrease agriculture net returns. The Midwest region is an important component of agriculture in the United States. Farmland accounts for more than half of the land in the Midwest and constitutes roughly 33% of US cropland. The region also produced roughly 62% of US corn and soybeans in 2015. Projected climate change in the Midwest raises concerns about regional agricultural production and may have important national and international effects in commodity markets.

Analyses that do not consider adaptive behaviors tend to overestimate the damage of climate change (Mendelsohn, Nordhaus, & Shaw 1994). Given that agricultural production depends on local climate conditions, farmers generally respond to harmful weather conditions and climate change in the long run. The government also provides indirect and short-term adaptation options for farmers through agricultural policies, such as income support programs, as well as long-term options through public research and development (Malcolm et al. 2012).

This study analyzes the adaptive behaviors of Midwestern farmers to regional climate conditions based on their decisions regarding land allocation and crop insurance purchases. A change in cropping pattern is an important farm-level adaptation option. The regional distribution of agricultural production depends on farm-level cropland allocation. For example, Figure 2.2 shows the changes in the proportion of soybean acreage to cropland. Soybean acreage has expanded to the north and northwest, and these changes in soybean acreage may be caused by changes in climate conditions (Reilly et al. 2003). Changes in cropland allocation also may affect environmental conditions. For example, intensification of row cropping may alter precipitation patterns (Pielke et al. 2007; Anderson et al. 2013). Also, nitrogen-intensive crops may contribute to leaching and runoff, which degrade water quality and contribute to adverse environmental outcomes (Jones et al. 2016).

How federal crop insurance programs are coupled with agricultural production has been an important issue. For example, Goodwin and Smith (2013) point out the production distortion caused by subsidized crop insurance, including changes in production pattern. This production distortion caused by crop insurance is an ongoing issue. After the Federal Crop Insurance Reform Act of 1994, subsidized crop insurance programs expanded tremendously. Approximately 90% of corn and soybean acreage was insured in 2014 (see Figure 2.3). More recently, after the 2014 Farm Bill was passed, federal crop insurance programs expanded coverage and became a primary tool for farmers in dealing with farm operation risk.

Although crop insurance is a farm-level adaptation option, subsidized crop insurance programs may make farmers more vulnerable to extreme weather events and long-term climate changes (GAO 2014; Annan & Schlenker 2015). In particular, subsidized federal crop insurance programs may mitigate farmers' incentive to adjust their land use to accommodate climate conditions for four reasons. First, if land allocation is one way to self-insure, demand for crop insurance and land allocation can substitute for each other (Ehrlich & Becker 1972).[1] Second, crop insurance may encourage farmers to grow riskier high-value crops by guaranteeing a certain amount of revenue (Wu & Adams 2001; Goodwin & Smith 2012). Also, if the amount of subsidy is coupled with production risk, the premium subsidy structure may distort farmers' land use change in response to production risk (Feng, Hennessy, & Miao 2013; Miao, Hennessy, & Feng

[1] Ehrlich and Becker (1972) suggest "self-insurance" and "self-protection." Self-insurance means decisions decreasing the amount of loss when the loss occurs. Self-protection means decisions decreasing the likelihood that the loss will occur.

2016). Last, the Government Accountability Office (GAO 2014) indicates that the Risk Management Agency (RMA) recommends RMA's good farming practices, which focus on maintaining historical crop yields in the short term. However, certain practices, such as conventional tillage, may unintentionally make famers more vulnerable to climate change in the long run.

We seek to answer four specific research questions. First, how do weather and climate conditions influence land allocation of farmers at planting time? Second, how does government-subsidized crop insurance alter farmers' cropland allocation? Third, does federal crop insurance change farmers' incentive to adapt to extreme weather events and climate conditions? Finally, do farmers consider weather and climate conditions when they decide which crops to plant and whether to purchase crop insurance? To answer these four questions, we develop a simultaneous equation model consisting of decisions regarding crops to grow, land allocation, and insurance purchases. We use farm-level data based on the Agricultural Resource Management Survey (ARMS) for estimation. Our findings show that climate conditions have significant effects on farmers' decisions to grow specific crops, purchase federal crop insurance, and allocate their land. Also, federal crop insurance programs change farmers' adaptive behaviors to extreme weather events, such as heavy rainfalls.

The remainder of the paper is organized as follows. The next section reviews relevant literature. Section 3 explains the effects of production risk and federal crop insurance by using a simple conceptual model. Section 4 outlines our empirical model, explains basic assumptions used for estimation, and describes how to estimate the model. Section 5 explains how we specify equations regarding farmers' decisions to grow specific crops, purchase federal crop insurance, and allocate land. This section also shows how we construct farm-level data, county-level climate and soil data, and state-level price data. Section 6 describes the results and economic implications, and Section 7 discusses conclusions and limitations of our study. Section 8 includes references, tables, and figures. Last, the Appendix shows the proof of analytic results in Section 3, how to derive final equations for estimation in Section 4, and climate variables in Section 5.

2.2 Literature review

Our paper is based on literature regarding land use change, crop insurance, and climate change. First, research on land use change has analyzed the effects of federal crop insurance on farmers' land use and its unintended policy effects on regional environmental conditions (Wu 1999; Wu and Adams 2001; Young, Vandeveer, & Schnepf 2001; Goodwin, Vandeveer, & Deal 2004; Lubowski et al. 2006; Classen et al. 2011; Feng, Henessy, & Miao 2013; Walter et al. 2013; Miao, Hennessy, & Feng 2016).[2] Wu (1999) analyzes the effects of corn crop insurance on land allocation and groundwater quality in the Central Nebraska Basin. He finds that corn crop insurance encourages farmers to shift their land from hay and pasture to corn, but the influence of crop insurance programs diminishes as farm size increases. Goodwin, Vandeveer, and Deal (2004) perform a comprehensive analysis, including cropping pattern and insurance participation. They find modest effects of crop insurance on cropland allocation in the Corn Belt and Upper Great Plains. Miao, Hennessy, and Feng (2016) analyze how crop insurance subsidies and the Sodsaver program affect farmers' decisions regarding land conversion from grasslands to cropland.[3] Their simulation results show that 3% of cropland in the US Prairie Pothole Region covered by crop insurance would have not been converted absent a crop insurance subsidy. Also, they predict that the Sodsaver program can reduce land conversion in that region by about 5%. However, previous

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[2] We focus on studies on US agricultural policies.
[3] The Sodsaver program makes land converted from grasslands to cropland ineligible for crop insurance during the first five years.

literature on land use and agricultural policies has been limited to small study areas and imperfect information about individual farms. Specifically, except for Wu (1999) and Walter et al. (2013), most studies are based on at least county-level data. Walter et al. (2013) analyze only the land allocation among insured crops.

Recently, the literature on climate change has interpreted land use change as a strategy for adapting to regional environmental conditions (Malcolm et al. 2012; Hornbeck & Keskin 2014; Yang & Shumway 2015). For example, Hornbeck and Keskin (2014) show that farmers without groundwater have increased their planting of drought-tolerant crops in arid regions. However, farmers over the Ogallala Aquifer have increased their use of water-intensive and drought-sensitive crops. Although studies examining climate effects on land use have increased, empirical studies are insufficient to gain a full understanding of how government policies and the adaptive behaviors of farmers are correlated.

Methodologically, our empirical model merges the corner solution model and the switching regression model to control for indecisive censoring and simultaneously measures the treatment effects of crop insurance. Cropland allocation by farmers is censored at zero, and this censoring is the result of optimization by individual farmers. Moreover, land allocation for insured crops is only observable when farmers buy crop insurance. Land use studies have controlled for corner solution responses by specifying crop selection equations (Sckokai & Moro 2006; Fezzi & Bateman 2011; Lacroix & Thomas 2011), but less effort has been exerted to measure treatment effects of farmers' insurance purchases. Wu (1999) considers two features of data simultaneously, but his model is based on the self-selection model instead of the corner solution model and he assumes that decisions to grow crops and to purchase insurance are independent. [4]

[4] The difference between the corner solution model and the self-selection model is similar to the difference between censored data and truncated data (Wooldridge 2010, pp. 667). That is, the corner solution model does not have any

Our model is designed to measure the intertwined relationship between two adaptive options of farmers: changing cropping pattern and purchasing subsidized crop insurance. First, our analysis is expected to contribute to the empirical evidence for unintended effects of crop insurance programs on farmers' adaptive behaviors to long-term climate change. Second, our results are based on farm-level data in eight Midwestern states. Since we control for detailed information on management of farmers' decisions, our results are more consistent than studies based on aggregate data. Furthermore, by allowing the correlation between decisions to grow crops and to purchase insurance, our model is more general than previous models assuming independence between the two decisions.

2.3 Conceptual approach

2.3.1 The role of risk in cropping pattern changes

The effects of risk and crop insurance on cropping pattern change can be analyzed by extending the analytic model of Miao, Hennessy, and Feng (2016).[5] Consider farmer *i* who has several land units and grows two crops: crop 1 and crop 2. All areas in a unit are identical, but land units are heterogeneous in production risk across units. We assume that decisions of farmer *i* on his land allocation are based on the unit. The yield function of crop *j* is assumed to be a simple linear form.

$$y_j = \mu_j + \delta\epsilon_j \tag{1}$$

missing data problem. For example, we can observe zero acreage for hay when farmers decide not to grow hay. However, the self-selection model is used for selection bias caused by missing data. Moreover, applying a two-step procedure for the self-selection model (Heckman 1976) to the corner solution model would lead to inconsistent estimates (Shonkwiler & Yen 1999).

[5] They focus on land conversion based on yield risk. Land conversion from marginal land to cropland may not be a relevant issue in the Midwest because total cropland in the Midwest has decreased (NASS quick stat). However, cropland harvested in the Midwest was constant over time, which means that productive land has been used for crop production continuously. As a result, in the Midwest, the allocation of cropland would be more important issues for farmers.

where μ_j is the mean yield of crop *j*, $\delta \in [0,1]$ is a risk parameter varying over land units and follows $H(\delta)$, and $\epsilon_j \in [-\mu_j, \mu_j]$ is a random variable representing yield loss (or gain) from unexpected weather events. We assume that ϵ_j has a zero mean and follows $G(\epsilon_j)$. With the yield function in Equation (1), we can specify the profit from growing crop *j* as follows.

$$\pi_j = (\mu_j + \delta\epsilon_j)(P_j + \theta_j) - c_j \qquad (2)$$

where P_j is the expected output price of crop *j*, $\theta_j \in [-P_j, P_j]$ is a random price shock with a zero mean, and c_j is the field operating cost. We assume independence between θ_j and ϵ_j. Farmer *i* is assumed to have a utility function, $U(\pi)$, defined on profit with $U_\pi > 0$ and $U_{\pi\pi} < 0$. Then, farmer *i*'s decisions regarding how to use land unit *k* having risk level δ can be summarized as

$$V(\delta) = \max\{U(r), EU(\pi_1 \mid \delta), EU(\pi_2 \mid \delta)]\}$$

where r is the deterministic return from non-cropping and

$$EU(\pi_j \mid \delta) = \int_{-P_j}^{P_j} \int_{-\mu_j}^{\mu_j} U[(\mu_j + \delta\epsilon_j)(P_j + \theta_j) - c_j] dG(\epsilon_j) dF(\theta_j)$$

Last, without the loss of generality, we assume that $EU(\pi_j|\delta = 0) > U(r) > EU(\pi_j|\delta = 1)$ and $EU(\pi_1|\delta = 0) > EU(\pi_2|\delta = 0)$. That is, the expected utility from growing crop *j* in the riskiest land unit is less than the expected utility from non-cropping, and the second equality means that crop 1 is more profitable than crop 2 without production risk. Since $\partial EU(\pi_j|\delta)/\partial\delta < 0$ and $\partial^2 EU(\pi_j|\delta)/\partial\delta^2 < 0$, we know that there is δ_j where $EU(\pi_j|\delta = \delta_j) = U(r)$ for *j*=1, 2 (see Appendix A). This result implies that farmers allocate their land until $\delta_u = \max\{\delta_1, \delta_2\}$, and farmers give up growing crops when the risk of land units is greater than δ_u.

Farmer *i* chooses a crop with the highest expected utility from land unit *k*. Cropping patterns in his fields depend on changes in the expected utility due to changes in the risk level.

Changes in expected utility can be represented by the size of the first and second derivative of expected utility with respect to δ: $\partial EU(\pi_j|\delta)/\partial\delta$ and $\partial^2 EU(\pi_j|\delta)/\partial\delta^2$. We cannot determine the relative sizes of $\partial EU(\pi_j|\delta)/\partial\delta$ and $\partial^2 EU(\pi_j|\delta)/\partial\delta^2$ between crop 1 and crop 2 without further qualification. However, by using a Taylor series expansion, we can show that $\partial EU(\pi_j|\delta)/\partial\delta$ depends on the distributions of ϵ_j and θ_j, such as mean and variance, and the farmer's attitude toward the risk, represented by the Arrow-Pratt measure of risk aversion (see Appendix A).

Figures 2.4, 2.5, and 2.6 depict three examples of land allocation between two crops. Figure 2.4 assumes $\partial EU(\pi_1|\delta)/\partial\delta > \partial EU(\pi_2|\delta)/\partial\delta$ for all δ, and we can verify that farmer *i* will grow only crop 1 because the expected utility from growing crop 1 is larger than the expected utility from growing crop 2 for all δ less than δ_1. However, when $\partial EU(\pi_1|\delta)/\partial\delta < \partial EU(\pi_2|\delta)/\partial\delta$ for all δ, then there is a δ^* where $EU(\pi_1|\delta = \delta^*) = EU(\pi_2|\delta = \delta^*)$. Crop 1 is planted in land units having δ less than δ^*, and crop 2 is planted in land units having δ in $[\delta^*, \delta_2]$ (see Figure 2.5). Last, when $\partial EU(\pi_1|\delta)/\partial\delta < \partial EU(\pi_2|\delta)/\partial\delta$ and $\partial^2 EU(\pi_1|\delta)/\partial\delta^2 > \partial^2 EU(\pi_2|\delta)/\partial\delta^2$, there are two values of δ^*, and crops growing in land units with low risk also can be planted in land units having high risk, as in Figure 2.6. The results can be summarized by the following remark.

Remark 1: Farmers allocate their land units to a crop achieving the highest expected utility given the risk level δ, and how to allocate land units to crops over all land units depends on the differences in the expected utility from growing crops at zero risk and the relative size of $\partial EU(\pi_j|\delta)/\partial\delta$ and its curvature among crops.

2.3.2 The effects of subsidized crop insurance

For simplicity, we only consider yield protection crop insurance and assume that the expected output prices are the same as the projected price established by the Risk Management Agency. [6] When farmer *i* decides to use federal crop insurance for crop *j*, then the profit function becomes

$$\begin{aligned}\pi_j^{ins} &= (\mu_j + \delta\epsilon_j)(P_j + \theta_j) + \\ &\max\{\lambda_j\mu_j P_j - (\mu_j + \delta\epsilon_j)P_j, 0\} - c_j - (1-s)v_j(\delta)\end{aligned} \tag{3}$$

where λ_j means the coverage level chosen for crop j and *s* is the subsidy rate. $v_j(\delta)$ is the unsubsidized actuarially fair premium without administration cost, calculated by

$$v_j(\delta) = \int_{-\mu_j}^{\mu_j} \max\{\lambda_j\mu_j P_j - (\mu_j + \delta\epsilon_j)P_j, 0\} dG(\epsilon_j) = \int_{-\mu_j}^{\varphi_j} [\lambda_j\mu_j P_j - (\mu_j + \delta\epsilon_j)P_j] dG(\epsilon_j) \tag{4}$$

where $\varphi_j = \frac{\lambda_j\mu_j - \mu_j}{\delta}$. The indemnity is paid when $\epsilon_j < \varphi_j$. Also, we know that $EU(\pi_j^{ins}|\delta) = EU(\pi_j|\delta)$ at $\delta = 1 - \lambda_j$, and crop insurance is purchased for land units whose risk levels are larger than $1 - \lambda_j$ because φ_j is smaller than $-\mu_j$ when δ is less than $1 - \lambda_j$. Since crop insurance increases the expected utility of growing insured crops, farmers replace land for uninsured crops with land for insured crops after purchasing federal crop insurance, as in Figure 2.7. [7]

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[6] The indemnity price for yield protection crop insurance is the average futures market price during the month before the sales closing. For example, the February price is used for corn and soybeans. Farmers can choose a price from 60 to 100 percent of the indemnity price. However, most producers choose their coverage based on 100 percent of the projected price (Edward 2011). In addition, the difference between yield protection crop insurance and revenue protection crop insurance is when indemnity is paid. In the case of yield protection crop insurance, indemnity is paid when the average yield per acre is less than the yield guarantee. However, in the case of revenue protection crop insurance, indemnity is paid when farmers' actual revenue is less than their revenue guarantee.

[7] Even though the expected profit after buying crop insurance equals the expected profit without crop insurance, the concavity assumption regarding farmers' utility function makes the expected utility after buying crop insurance larger than the expected utility without crop insurance.

The sign of $\partial EU(\pi_j^{ins}|\delta)/\partial\delta$ depends on the subsidy rates and coverage levels. That is, it can be positive for given risk levels when the subsidy rate and the coverage level are high (see Appendix A).[8] Also, we can easily show that $\partial EU(\pi_j^{ins}|\delta)/\partial s > 0$, which means that increases in the subsidy rates may increase acreage of the insured crop by enhancing the expected utility from growing the insured crop at the given risk level (see Figure 2.7). From these results, we can imagine that the subsidy structure decreasing the incremental cost of coverage can distort farmers' cropping pattern more than the subsidy structure decoupled from farmers' choice of coverage. We can summarize the effects of crop insurance on farmers' cropping pattern change as follows:

Remark 2: Adopting yield protection crop insurance changes cropping patterns by increasing the expected utility from growing insured crops and changing the size of $\partial EU(\pi_j^{ins}|\delta)/\partial\delta$. Since high subsidy rates and coverage rates change the sign of $\partial EU(\pi_j^{ins}|\delta)/\partial\delta$, subsidy structures coupled with coverage levels bring about more distortions in farmers' land allocation decisions.

From the conceptual approach, we can answer our research questions with a simple theoretical model. The model shows that, without crop insurance, the production risk decreases farmers' expected utility from growing crops. The decreasing rates of expected utility in response to increases in the risk level and their curvatures are heterogeneous among crops. Farmers' cropping pattern thus depends on differences in the marginal expected utility with respect to risk level and its curvature among crops. It also shows that federal crop insurance programs can change farmers' cropping pattern by altering the responsiveness of farmers' expected utility to production risk. In the next section, we try to find empirical evidence regarding our research questions. In particular, we use extreme weather events such as intensive rainfalls and extreme heat degree days

[8] Even though we need further qualification to derive necessary and sufficient conditions, we can show that there exist s^* and λ_j^* such that $\partial EU(\pi_j^{ins}|\delta)/\partial\delta < 0$ for $s > s^*$ and $\lambda > \lambda_j^*$ (see Appendix A).

as proxy variables for production risk and measure the effects of federal crop insurance on farmers' response to these extreme weather events.

2.4 Empirical model and estimation

Consider the problem of farmer *i*, who must decide whether to grow crop *j* or not, whether to buy crop insurance for crop *j* or not, and how much acreage to allocate to crop *j* if he chooses to grow it. The farmer's decisions regarding crops to plant, insurance purchases, and acreage allocation can be correlated. For example, unobserved conditions of farmer *i* and his farm, such as his attitude toward the risk or heterogeneous soil quality in his fields, can affect his crop insurance purchase and land allocation decisions at the same time.

To begin this analysis, we specify the linear acreage allocation equation in the context of the switching regression model to account for the effects of crop insurance on farmers' land allocation (Wu 1999; Wooldridge 2010, pp. 948):

$$\begin{aligned} A_{ij}^{*} &= (1-I_{ij})(X_{ij}\beta_{0j}+\epsilon_{oij})+I_{ij}(X_{ij}\beta_{1j}+\epsilon_{1ij}) \\ &= X_{ij}\beta_{0j}+I_{ij}X_{ij}(\beta_{0j}-\beta_{1j})+\epsilon_{oij}+I_{ij}(\epsilon_{1ij}-\epsilon_{0ij}) \\ &\equiv X_{ij}\beta_{j}+(I_{ij}X_{ij})\alpha_{j}+\epsilon_{ij} \end{aligned} \tag{5}$$

where A_{ij}^{*} is the latent acreage for farmer *i*'s land allocation to crop *j*. I_{ij} is a crop insurance dummy for crop *j*. X_{ij} is the vector of explanatory variables for land allocation. α_j and β_j are the parameters. α_j means changes in farmers' behavior resulting from crop insurance purchases, and the effects of a climate condition on land allocation decisions of farmers having crop insurance can be measured by the sum of α_j and β_j corresponding to the climate measure and the interaction term between the climate measure and an insurance dummy for crop *j*. ϵ_{1ij} and ϵ_{0ij} are error terms corresponding to each decision: buying crop insurance for crop *j* or not. We assume that $\epsilon_{1ij} = \epsilon_{0ij} = \epsilon_{ij}$ for simplicity.

Equation (5) has two limitations in identifying the effects of federal crop insurance programs on farmers' land allocation decisions. First, we incorporate insurance dummies as a measure of insurance demand. Even though insurance dummies capture the effects of crop insurance participation, they do not reflect the intensity of crop insurance demand, such as high coverage or demand for revenue protection crop insurance.[9] Second, crop insurance effects may depend on the combination of crops grown and crops covered by insurance. For example, assume that farmer *i* decides to grow corn and soybeans. The effects of corn insurance on corn acreage when farmer *i* buys only corn insurance will differ from the effects of corn insurance for corn on corn acreage when farmer *i* buys insurance for corn and soybeans at the same time. Likewise, the effects of corn insurance will vary when farmer *i* grows only corn. However, with our model specification, only the aggregate effects of crop insurance can be identified.

Second, we construct a simultaneous equation model for farmer *i*'s decisions to grow crop *j* and purchase crop insurance for crop *j*:

$$
\begin{aligned}
&A_{ij}^{*} = X_{ij}\beta_j + (I_{ij}X_{ij})\alpha_j + \epsilon_{ij};\\
&A_{ij} = \begin{cases} A_{ij}^{*} & \text{if } \tau_{ij}^{*} = Z_{ij}\gamma_j + e_{ij} > 0 \\ 0 & \text{otherwise} \end{cases},\\
&I_{ij} = \begin{cases} 1 & \text{if } \omega_{ij}^{*} = S_{ij}\eta_j + \nu_{ij} > 0 \\ 0 & \text{otherwise} \end{cases}, \; j = 1,\ldots,M
\end{aligned} \tag{6}
$$

where τ_{ij}^{*}, and ω_{ij}^{*} are latent variables for farmer *i*'s decisions to grow crop *j* and purchase insurance for crop *j*, respectively. A_{ij} is the observed amount of land allocated to crop *j*. Z_{ij} and

[9] To account for the intensity of crop insurance demand, O'Donoghue (2014) suggests three measures of crop insurance demand: level of total premium, level of total premium per acre, and level of total liability per acre. Also, Goodwin (1993) and Goodwin and Smith (2012) use liability per planted acre. Last, Goodwin, Vandeveer, and Deal (2004) incorporate liability/maximum possible liability of each crop. Since premiums and liability are determined by coverage levels and insured acres, measures based on liability or premium can simultaneously capture the changes in intensity of use such as coverages and changes in enrollment.

S_{ij} are the vectors of explanatory variables for the decision to grow crop j and purchase crop insurance for crop j. γ_j and $\eta_j$are the parameters. Last, e_{ij} and ν_{ij} are error terms. We assume that ϵ_{ij}, e_{ij}, and ν_{ij} follow a multivariate standard normal distribution, and $e_{ij} \perp e_{ik}$, $\nu_{ij} \perp \nu_{ik}$, and $e_{ij} \perp \nu_{ik}$ for $j \neq k$.[10]

Third, Lacroix and Thomas (2011) suggest that the expected allocation for a crop is correlated with the probability of other crops being planted in the same year ($\Pr[\tau_{ik}^* > 0], k = 1, \ldots, M, j \neq k$) and that the source of this correlation is crop rotation. Thus, we allow the correlation between ϵ_{ij} and e_{ik} for $j \neq k$. Based on Equation (6), the unconditional expectation of farmer i's land allocation to crop j becomes:

$$\begin{aligned} &E(A_{ij}^* \mid X_{ij}, S_{ij}, Z_{ij}) = P(\tau_{ij}^* > 0, \omega_{ij}^* > 0 \mid S_{ij}, Z_{ij}) E(A_{ij}^* \mid X_{ij}, \tau_{ik}^* > 0, \omega_{ij}^* > 0, k = 1, \ldots, M) \\ &+ P(\tau_{ij}^* > 0, \omega_{ij}^* \leq 0 \mid S_{ij}, Z_{ij}) E(A_{ij}^* \mid X_{ij}, \tau_{ik}^* > 0, \omega_{ij}^* \leq 0, k = 1, \ldots, M) + P(\tau_{ij}^* \leq 0 \mid S_{ij}) \cdot 0 \\ &= P(\tau_{ij}^* > 0, \omega_{ij}^* > 0 \mid S_{ij}, Z_{ij}) [X_{ij}(\alpha_j + \beta_j) + E(\epsilon_{ij} \mid \tau_{ik}^* > 0, \omega_{ij}^* > 0, k = 1, \ldots, M)] \\ &+ P(\tau_{ij}^* > 0, \omega_{ij}^* \leq 0 \mid S_{ij}, Z_{ij}) [X_{ij}\beta_j + E(\epsilon_{ij} \mid X_{ij}, \tau_{ik}^* > 0, \omega_{ij}^* \leq 0, k = 1, \ldots, M) \end{aligned} \tag{7}$$

From Fishe, Trost, and Lurie (1981), the conditional expectation of error terms in Equation (7) is as follows:

$$\begin{aligned} E(\epsilon_{ij} \mid \tau_{ik}^* > 0, \omega_{ij}^* > 0, k = 1, \ldots, 4) &= \sigma_{jj}^{\tau} \frac{\phi(Z_{ij}\gamma_j)\Phi(S_{ij}^*)}{P_1} + \sigma_{jj}^{\omega} \frac{\phi(S_{ij}\eta_j)\Phi(Z_{ij}^*)}{P_1} + \sum_{j \neq k}^{4} \sigma_{jk}^{\tau} \lambda_{i,kj} \\ E(\epsilon_{ij} \mid \tau_{ik}^* > 0, \omega_{ij}^* \leq 0, k = 1, \ldots, 4) &= \sigma_{jj}^{\tau} \frac{\phi(Z_{ij}\gamma_j)\Phi(-S_{ij}^*)}{P_2} + \sigma_{jj}^{\omega} \frac{-\phi(S_{ij}\eta_j)\Phi(Z_{ij}^*)}{P_2} + \sum_{j \neq k}^{4} \sigma_{jk}^{\tau} \lambda_{i,kj} \end{aligned} \tag{8}$$

where $S_{ij}^* = \frac{S_{ij}\eta_j - \rho_j Z_{ij}\gamma_j}{(1-\rho_j^2)^{1/2}}$, and $Z_{ij}^* = \frac{Z_{ij}\gamma_j - \rho_j S_{ij}\eta_j}{(1-\rho_j^2)^{1/2}}$. $P_1 = P\left(\tau_{ij}^* > 0, \omega_{ij}^* > 0 \middle| Z_{ij}, S_{ij}\right) = \Phi_2\left(Z_{ij}\gamma_j, S_{ij}\eta_j; \rho_j\right)$, $P_2 = P\left(\tau_{ij}^* > 0, \omega_{ij}^* \leq 0 \middle| Z_{ij}, S_{ij}\right) = \Phi_2\left(Z_{ij}\gamma_j, -S_{ij}\eta_j; -\rho_j\right) = \Phi\left(Z_{ij}\gamma_j\right) -$

[10] If we allow general correlation among crop selection equations and crop insurance equations, it would be difficult to derive $E\left(A_{ij}^* \middle| X_{ij}, S_{ij}, Z_{ij}\right)$ analytically. Lacroix and Thomas (2011) use panel data structure and information regarding farmers' previous land use to control for correlations among crop selection equations. However, since the ARMS data do not include information regarding farmers' historical land use, we cannot control for dynamic agronomic constraints, such as crop rotation and pest management. This is a limitation of our approach.

$\Phi_2(Z_{ij}\gamma_j, S_{ij}\eta_j; \rho_j)$. ϕ and Φ represent a probability density function and a cumulative density function of standard normal distribution. Φ_2 is a cumulative density function of the standard bivariate normal distribution. ρ_j is the correlation coefficient between e_{ij} and v_{ij}. σ_{jk}^{τ} is the covariance between ε_{ij} and e_{ik}. σ_{jj}^{ω} is the covariance between ε_{ij} and v_{ij}. $\lambda_{i,kj} = \phi(Z_{ik}\gamma_j)/\Phi(Z_{ik}\gamma_j), k = 1, \ldots, M$, and it is the correction term from an equation regarding farmer *i*'s decision to grow crop *k*. As a result, the final acreage equation for crop *j* is as follows:

$$\begin{aligned} A_{ij} &= E(A_{ij}^* \mid X_{ij}, S_{ij}, Z_{ij}) + \xi_{ij} \\ &= \Phi(Z_{ij}\gamma_j)[X_{ij}\beta_j + \sum_{k=1}^{4} \sigma_{jk}^{\tau} \lambda_{i,kj}] + \Phi_2(Z_{ij}\gamma_j, S_{ij}\eta_j; \rho_j) X_{ij}\alpha_j + \xi_{ij} \end{aligned} \tag{9}$$

where $\xi_{ij} = \epsilon_{ij} - E(A_{ij}^*|X_{ij}, S_{ij}, Z_{ij})$.[11] The estimation proceeds in two steps (Shonkwiler & Yen 1999). In the first step, we estimate equations regarding decisions to grow crops and purchase crop insurance. In our data, we can observe a decision of farmer *i* on crop insurance for crop *j* only when farmer *i* decides to harvest crop *j*.[12] To control for missing observations, we use a probit model with sample selection, as in Van de ven and Van Praag (1981), instead of the bivariate probit model. In the second stage, linear regression is applied to Equation (9) based on the predicted probabilities of growing crop *j* and purchasing crop insurance for crop *j*.

We have to account for the sampling design of our farm-level data for inference (Dubman 2000). To account for the survey design of the ARMS data, we generate 2,000 random bootstrap

[11] How to derive Equation (8) and (9) is in the Appendix-B

[12] We assume that the decisions of farmers regarding crop insurance purchases and crops to grow are simultaneous, not sequential (Wu 1999). The criterion regarding this assumption is the likelihood that farmers do not plant insured crops. That is, if $P(\tau_{ij}^* < 0, \omega_{ij}^* > 0 | Z_{ij}, S_{ij}) \neq 0$, we consider the two choices as simultaneous. In reality, to use federal crop insurance, farmers have to apply their coverage and products prior to the "sales closing data" before planting. However, after the insurance application is accepted, they may fail to plant the insured crop due to unexpected events or unfavorable environmental conditions, such as residual salt in the soil, irrigation water supply, and hurricane and flood. "Prevented planting provisions" may apply in such cases, as long as the event occurred during the prevented planting period. As a result, even though we can only observe harvested acreage for insured crops from our data, this does not imply that farmers bought crop insurance only for crops harvested or planted.

samples using probability weights, estimate Equation (9) 2,000 times, and then use the mean and variance of the replicated estimates as estimates of parameters and their variances (Goodwin, Mishra, & Ortalo-Magné 2003; Goodwin & Mishra 2005). There are several practical reasons to use the bootstrapping method based on probability weights.[13] First, even though the ARMS data provide replicate weights for delete-a-group jackknife estimators, the number of replicate weights was changed from 15 to 30 after 2008. Thus, incorporating only 15 replicate weights means using more samples in 2009 and 2010 AMRS data than for previous years during estimation. Second, Goodwin, Mishra, and Ortalo-Magné (2003) argue that the jackknife procedure may not be valid when using only a subset of the data. Third, the two-step estimation procedure does not account for variations in the first-stage estimates. Also, the error term in Equation (9) is heteroscedastic because it is a function of individual exogenous variables. Thus, if we use ordinary least squares (OLS), the estimated variance in Equation (9) is inconsistent.

The marginal effect of a continuous variable (q_{ij}) including the three equations in Equation (6) is calculated as follows (Chritofides, Stengos, & Swidinsky 1997):

$$\begin{aligned}\frac{\partial E(A_{ij}^{*} \mid X_{ij})}{\partial q_{ij}} &= \Phi(Z_{ij}\gamma_j)\{\beta_{j,q} - \sum_{k=1}^{4} \sigma_{jk}^{\tau}\gamma_{k,q}[\lambda_{ik} Z_{ik}\gamma_k + \lambda_{ik}^{2}]\} + \\ &\phi(Z_{ij}\gamma_j)\gamma_{j,q}[X_{ij}\beta_j + \sum_{k=1}^{4}\sigma_{jk}^{\tau}\lambda_{ik}] + \alpha_{j,q}\Phi(Z_{ij}\gamma_j, S_{ij}\eta_j; \rho_j) + \\ &[\phi(Z_{ij}\gamma_j)\Phi(S_{ij}^{*})\gamma_{j,q} + \phi(S_{ij}\eta_j)\Phi(Z_{ij}^{*})\eta_{j,q}]X_{ij}\alpha_j\end{aligned} \tag{10}$$

Last, based on estimates in Equation (9), we calculate the marginal effects of crop insurance on acreage for crop *j* based on Wu (1999):

$$\begin{aligned}&\Delta E(A_{ij}^{*}) = E(A_{ij}^{*} \mid I_{ij} = 1) - E(A_{ij}^{*} \mid I_{ij} = 0) \\ &= \Phi(Z_{ik}\gamma_i)[X_{ij}(\alpha_j + \beta_j) + \sum_{k=1}^{4}\sigma_{jk}^{\tau}\lambda_{ik}] - \Phi(Z_{ik}\gamma_i)[X_{ij}\beta_j + \sum_{k=1}^{4}\sigma_{jk}^{\tau}\lambda_{ik}] = \Phi(Z_{ik}\gamma_i)X_{ij}\alpha_j\end{aligned} \tag{11}$$

[13] This approach assumes that the sampling scheme and population of the ARMS data are constant from 2003 to 2010.

Equation (11) represents the impact of crop insurance on acreage for crop *j* when we do not know famers' decisions regarding crops to grow. The first term of Equation (11) means the expected acreage of crop *j* with crop insurance, and the latter term indicates the expected acreage of crop *j* without crop insurance. To calculate the expected change in acreage for crop *j* due to crop insurance purchases, we use the weighted average of $\Delta E(A_{ij}^{*})$ for all farms, with sampling weights in our data.

2.5 Model specification and data

2.5.1 Model specification

We impose the following assumptions for our model specification: (1) Farmers are risk-averse and their utility depends on the risk of profit and expected profit, (2) farmers seek to maximize their expected utility by allocating their land to crops and buying crop insurance, (3) farmers are price takers; that is, we assume that output prices and production (crop yield) are independent at the farm level (Hendricks, Smith, & Sumner 2014), (4) farmers have expectations regarding weather conditions during the growing season and these expectations are based on previous weather conditions, and (5) farmers' expectations about profit after harvesting crops and variance of profit depend on output prices, variance of output prices, expected weather conditions including extreme weather events, and agricultural policies. In simple linear model specifications for farmer i's acreage allocation to crop *j* (A_{ij}^{*}), the corresponding crop selection equation (τ_{ij}^{*}) and an equation for his crop insurance purchase (ω_{ij}^{*}) are as follows:

$$\begin{aligned} A_{ij}^{*} &= \beta_{0j} + X_{i,p}^{'}\beta_{1j} + X_{i,c}^{'}\beta_{2j} + I_{ij}(\alpha_{0j} + X_{i,p}^{'}\alpha_{1j} + X_{i,c}^{'}\alpha_{2j}) + \epsilon_{ij} \\ \tau_{ij}^{*} &= \gamma_{0j} + Z_{ij,\tau}^{'}\gamma_{1j} + X_{i,c}^{'}\gamma_{2j} + e_{ij} \\ \omega_{ij}^{*} &= \eta_{0j} + S_{ij,\omega}^{'}\eta_{1j} + X_{i,c}^{'}\eta_{2j} + v_{ij} \end{aligned} \quad (12)$$

where $X_{i,p} = (\boldsymbol{p},\ \Omega_p)'$. $\boldsymbol{p}$ is a vector of output and input prices, and Ω_p is a vector containing variances of output prices. $X_{i,c}$ includes variables related to soil quality, expected weather conditions, state dummies, and year dummies.

2.5.2 Identification

For identification, we impose at least one exclusion restriction on $Z_{ij,\tau}$ and $S_{ij,\omega}$ (Wooldridge 2010, pp. 698-699). One disadvantage of the two-step procedure for self-selection or the corner solution model is identification of parameters in the second step. That is, when $Z_{ij,\tau}$ and $S_{ij,\omega}$ only include $X_{i,p}$ and $X_{i,c}$, the parameters' corresponding explanatory variables in acreage equations are poorly identified.

$Z_{ij,\tau}$ includes off-farm income and age as well as $X_{i,p}$ and $X_{i,c}$. Off-farm income can be used as a proxy for off-farm activity. Since farmers allocate their time between on-farm and off-farm activity, the extent of off-farm work can affect production decisions. For example, high off-farm income requires a high commitment to the off-farm job and, therefore, off-farm income is negatively correlated to labor-intensive crop choices and farm management. Also, farmers prefer to grow the most profitable crops based on available technologies. Off-farm activity may give disincentive to farmers to adopt management-intensive technologies but motivate them to adopt management-saving technologies (Fernandez-Cornejo 2007). Thus, off-farm income can influence farmers' decisions on crops to grow through available technologies.

Age is positively correlated with landownership, and landownership can affect farmers' decisions regarding crops to grow. In particular, Bigelow, Borchers, and Hubbs (2016) show that younger farmers rent a large portion of the land they operate, but older farmers are more likely to be full owners. Also, Varble, Secchi, and Druschke (2016) show that, in Iowa, renters are more likely to use crop rotation than full owners. Last, age is positively correlated with farming experience (Khanna, Epouhe, & Hornbaker 1999), and greater experience can lead to better knowledge of the fields and more efficient land use.

$S_{ij,\omega}$ consists of variables regarding prices and climate conditions and variables representing farmer *i*'s financial status, such as debt ratio and equity. Equity means the difference between farms' assets and debt and has been used as a proxy of farms' wealth. Debt ratio means the debt-to-assets ratio and measures farms' risk exposure and ability to overcome adverse financial events. Goodwin (1993) argues that farms' debt is positively correlated to their demand for crop insurance because farms having a higher level of debt are more likely to be subject to borrower-imposed insurance purchases. However, the effect of debt on crop insurance choice is an empirical question. Specifically, large farms are more likely to have higher debt ratios than small farms (Ifft, Novini, & Patrick 2014; Ifft, Kuethe, & Morehart 2015), and small farms are more likely to buy crop insurance because they may not be able to survive a crop failure (Wu 1999). Last, Farrin, Miranda, and O'Donoghue (2016) show that, when examining crop insurance demand over multiple years, demand for crop insurance is affected by farmers' financial wealth more than their attitude toward risk. They also find that, except for low-income farmers, demand for crop insurance is negatively correlated with farms' level of wealth.

2.5.3 Data

Farm-level data

This study constructs a farm-level data set based on the Agricultural Resource Management Survey Phase III version 1. Aggregate land use change can mask farmers' cropland allocation decisions, even though aggregate land use data are easily accessible and convenient for estimation.[14] Farmers respond to local market and environmental conditions in different ways

[14] Fezzi and Bateman (2011) summarize the advantages of using aggregated land use data. For example, since most land use in aggregated data are larger than zero, researchers do not take into account corner solution problems.

because of heterogeneous features of their farm. Capturing heterogeneity between farms is necessary in measuring weather and climate effects on farmers' land allocation.

Farm-level data include land allocation, crop insurance status, financial status, and socioeconomic characteristics. To include the relatively homogeneous group of farms, we select 10,056 farms satisfying five conditions (Goodwin & Mishra 2005): (1) The farm's largest sources of gross income are grains, oilseeds, dry beans, and dry peas,[15] (2) the farm was operating in one of eight Midwestern states during 2003 – 2011,[16] (3) the farm has more than 50 acres of total cropland, (4) the principal operator is not retired from farming or ranching, and (5) the insured crops of the farm are identifiable.[17] Since the ARMS data only cover harvested land, we use harvested land as a proxy for planted land. The crops considered are corn, soybeans, winter wheat, and other. We consider acreage allocated to other crops as residual land use and assume that choices regarding other crops are independent of choices regarding corn, soybeans, and wheat conditional on explanatory variables in acreage equations. In the case of Minnesota, we include spring wheat instead of winter wheat. Table 2.1 summarizes the farm-level data and market variables.

However, some disadvantages are associated with the ARMS Phase III data. First, since the ARMS data is repeated cross-sectional data, it may be difficult to control for unobserved characteristics of each farm. Also, the ARMS Phase III data do not include historical land use,

[15] These farms correspond to Type I farms in the ARMS data.
[16] The eight states are Iowa, Illinois, Indiana, Michigan, Minnesota, Missouri, Ohio, and Wisconsin. We choose these states as our study area to control for irrigation status. Figure 2.8 shows the regional distribution of observations.
[17] Specifically, we include farms whose entire cropland is covered by crop insurance programs, as well as farms whose cropland is partially covered by crop insurance. For example, when a farmer plants four crops, and the sum of acreage allocated to three crops is less than the acreage covered by crop insurance, we assume that the remaining crop is also insured. Finally, when the sum of the acreage of any combination of crops is the same as the acreage covered by crop insurance, then we assume that farmers bought crop insurances for those crops. For example, if the sum of corn and wheat acreage is the same as the acreage covered by insurance, we assume that corn and wheat are covered by crop insurance, even though there may be other crops planted.

which means that we cannot explicitly control for the effects of crop rotation. Second, the ARMS Phase III data do not provide locational information, which means that farm-specific environmental conditions are uncontrolled. Last, to merge the multiple-year survey for estimation, we assume that the survey design and population density of the samples are constant during the study periods.[18]

Market Variables

For expected output prices, state-level futures prices are constructed by adjusting regional differences in farm-gate prices (Barr et al. 2011). For example, the expected price of corn (p_c^e) is calculated as follows:

$$p_c^e = \bar{F}_c^f - B_c,\ B_c = \bar{F}_c^d - \bar{p}_c^r$$

where $\bar{F}_c^f$ is the average of daily February closing prices of December corn futures contracts. B_c is called the "basis" and is used to account for systematic differences between farm-gate prices and futures prices. $\bar{F}_c^d$ is the average of daily December closing prices of December corn futures contracts, and $\bar{p}_c^r$ is the state-level farm received price. For futures prices of soybean and winter wheat, we use daily February closing prices of November soybean futures contracts and daily February closing prices of July winter wheat futures contracts, respectively. Chicago Board of Trade (CBOT) futures prices are used for corn and soybeans, and Kansas City Board of Trade futures prices are used for wheat. To control for price support programs, we use the higher price between futures prices and national loan rates (Wu et al. 2004).

The expected variance of output prices is calculated as $Var(p_{j,t}) = \sum_{k=1}^{3} \omega_k [p_{j,t-k} - E_{t-k-1}(p_{j,t-k})]^2$ where ω_k are 0.5, 0.33, and 0.17, respectively (Chavas & Holt 1990; Sckokai &

[18] Missing information and spurious information make a nontrivial proportion of observations useless. For example, to clear our final data, we exclude observations whose harvested land or acreage covered by crop insurance is larger than the total cropland. We also drop observations having negative land values or negative values of total production.

Moro 2006; Wu et al. 2004). $p_{j,t-k}$ is the state-level farm-received price of crop *j* in year *t-k* and E_{t-k-1} is farmers' expectation of harvest output price at planting time in year *t-k*. All economic variables are normalized by the planting year price index for the other inputs.[19]

Climate and Soil Variables

Table 2.1 also summarizes the statistics of environmental conditions. Daily Parameter-elevation Regression on Independent Slope Model (PRISM) data are used to construct weather variables: growing degree days (GDD), extreme heat degree days (HDD), precipitation, and intensive rainfall. Based on daily maximum and minimum temperatures in the PRISM data, we use Snyder's (1985) simple method to compute GDD and HDD during the growing season (see Appendix C). GDD and HDD measure the amount of exposure to beneficial heat and harmful heat, respectively. Precipitation is calculated as the sum of total precipitation during the growing season. Intensive rainfall means the number of daily rain events above 25.4 mm during the growing seasons (Groisman, Knight, & Karl 2012). We assume that farmers' expected weather conditions are the averages of weather conditions over the previous 20 years. State-level growing seasons for corn, soybeans, and wheat are applied (NASS quick stat, USDA 2010). Last, since high soil moisture caused by rainfall during the early spring has negative effects on corn root development, spring rainfall can prompt farmers to plant soybeans instead of corn. Thus, we include April-May precipitation in equations regarding corn and soybeans.

In addition to spatial variations of expected weather variables, temporal variation in expected weather variables is useful in assessing the effects of climate on farmers' land use decisions. Figures 2.9 and 2.10 show the changes in expected weather conditions between 2003

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[19] We construct the price index for the other inputs as $I = \sum_j \omega^j I_{PPI}^j$, where ω^j is the relative weight of the *j*th input and I_{PPI}^j is the United States Department of Agriculture (USDA) published price paid index of the *j*th input. The other inputs include several production items, financial fees, and family living expenses (USDA 2011).

and 2010. From the figures, we can verify that the amount of intensive rainfall and precipitation increased more in western Iowa, eastern Illinois, and Missouri than in other parts of the Midwest. Also, HDD and GDD during the corn growing season decreased slightly in the Midwest.

Soil data are based on the Soil Survey Geographic database (SSURGO). We include slope, saturated hydraulic conductivity (Ksat), available water capacity (AWC), K-factor, depth to water table, and percentage of organic matter as variables representing soil quality and land characteristics. Slope is the difference in elevation, expressed as a percentage. Ksat measures the permeability of soil, while AWC represents how much water the soil can store. K-factor indicates the susceptibility of soil to water erosion. Depth to water table is the minimum depth above a wet soil layer. Organic matter is the amount of decomposed plant and animal residue in the soil. Since the ARMS Phase III data contain only county-level location information, all climate and soil variables are aggregated to the county.

2.6 Results

2.6.1 Estimation results

Table 2.2 shows that Midwest farmers' decisions to grow crops are closely related to climate conditions. The estimates in Table 2.2 represent coefficients of a probit model with a sample selection model. First, spring precipitation has negative effects on the decision to grow corn but positive effects on the decision to grow soybeans. This result is because the high soil moisture during the early spring makes farmers delay planting corn and, in the end, may shift their cropping pattern from corn to soybeans. Second, GDD, the beneficial heat, has positive effects on the decision to grow corn, soybeans, and wheat. However, the coefficients on HDD, the harmful heat, in all equations regarding crops choices are negative. Last, an increase in total precipitation during the growing season increases the likelihood of growing corn. However, the results show that an increase in total precipitation decreases the likelihood of growing wheat or soybeans, even though the effect of total precipitation on the probability of growing soybeans is insignificant. Since corn is a water-intensive crop, farmers are more likely to grow corn when precipitation is sufficient and corn is profitable.

The results related to purchasing crop insurance are also shown in Table 2.2. First, the coefficients on intensive rainfall in equations regarding insurance purchases for corn and soybeans are positive, suggesting that farmers expecting frequent intensive rainfall during the growing season are more likely to purchase crop insurance for corn and soybeans. Since intensive rainfall reflects a potential risk of loss, farmers protect their revenue from such risk by purchasing federal crop insurance. Second, an increase in GDD decreases the likelihood of purchasing insurance for soybeans, but HDD positively affects the decision to purchase insurance for soybeans. However, the results show that the effects of GDD and HDD on purchasing federal crop insurance for corn are insignificant. Third, insurance purchases are more likely in areas having less precipitation. As a result, we interpret results regarding heat and precipitation as good weather conditions, including enough precipitation, adequate GDD, and fewer HDD, may give farmers incentive to grow the three crops. However, good weather conditions may also give farmers disincentive to purchase crop insurance because there is less risk of loss caused by harmful weather conditions.

Table 2.3 shows the effects of climate conditions on acreage adjustment of farmers among three crops, given their decisions regarding crops to grow and crop insurance purchases.[20] The results show that farmers' response to intensive rainfall and total precipitation during the growing

[20] In our data set, most insurance users purchased insurance for all crops that they planted at the same time. To be specific, among farmers growing corn and soybeans, about 73% purchased insurance for corn and soybeans at the same time, but 25% did not purchase any crop insurance. In the case of farmers growing corn, soybeans, and wheat, about 61% purchased insurance for corn, soybeans, and wheat at the same time. However, about 34% of farmers did not use any federal crop insurance program. As a result, the estimates regarding the insurance dummy for each crop can be interpreted as the effects of crop insurance generally instead of the effects of insurance for each crop.

seasons depends on their insurance status. Without crop insurance, corn (soybean) growers are more likely to decrease corn (soybean) acreage when the frequency of intensive rainfall events increases or total precipitation decreases during the growing season. However, the coefficients corresponding to intensive rainfall events (total precipitation) and the interaction term between intensive rainfall (total precipitation) and the crop insurance dummy have opposite directions. The coefficients of interaction terms between crop insurance dummies and climate measures can be interpreted as changes in farmers' behaviors due to crop insurance purchases. The results, thus, indicate that crop insurance makes farmers less sensitive to increases in intensive rainfall events or decreases in total precipitation. Last, as we hypothesized, the results show that total precipitation during the early spring has positive effects on soybean acreage.

However, the estimates in Table 2.3 do not consider the effects of climate measures on farmers' decisions regarding crops to grow and crop insurance purchases. Also, the large size of the estimates and units of climate measure are less intuitive to understand the effects of climate conditions on farmers' land allocation decisions. [21] To understand the total effects of climate conditions on farmers' land allocation decisions more clearly, we calculate the average acreage response elasticities to climate conditions based on Equation (10) (see Table 2.4). These elasticities are weighted averages of each acreage response elasticity across our samples based on sampling weights of the ARMS (Arnade & Kelch 2007). [22] First, the results show that GDD has positive

[21] The large sizes of coefficients corresponding to weather measures and variances of output prices in Table 2.3 result from two factors. First, explanatory variables in Equation (9) are multiplied by the probability of growing a specific crop or the probability of purchasing crop insurance for the crop. Second, changes in some explanatory variables by one unit implies the huge change in market or environmental conditions. For example, an increase in HDD or variances of output prices by one unit may be unrealistic changes: the average and the standard deviation of HDD are about one (see Table 2.1). Thus, to interpret the results more clearly, we need to account for two factors. In addition to these two factors, the correlation among output prices and state dummies would make the size of coefficient large.

[22] To reduce the effects of observations having extreme values on the average marginal effects and acreage response elasticities, we also calculate the trimmed weighted average. To be specific, after calculating marginal effects and acreage response elasticity of climate variables on land allocation of each observation, we exclude values larger than 95% quantile and less than 5% quantile. Especially, in the case of the expected land allocation to wheat, some

effects on acreage for the three crops. To be specific, when GDD increases by 1%, corn, soybean, and wheat acreage increases by 1.7%, 3.6%, and 2.6%, respectively. This is intuitive because GDD can be interpreted as beneficial heat for crop development. Farmers who expect sufficient GDD have an incentive to increase acreage for crop production. Second, soybean acreage is negatively affected by HDD, but the effects of the extreme heat are modest: An increase in HDD of 1% decreases soybean acreage by 0.6%. Third, the results show that an increase in precipitation of 1% decreases soybean acreage by 2.9%. However, the results indicate that increases in HDD and precipitation have insignificant effects on corn and wheat acreage. Last, the effects of intensive rainfall events on acreage allocation are insignificant.

From Figures 2.9 and 2.10, we can verify the spatial variations in GDD and HDD. Also, Table 2.6 shows differences in the two variables among states. To be specific, the table shows that Illinois has the highest GDD, and the difference in GDD between Illinois and Iowa is approximately 10% of the GDD of Iowa. Indiana has the lowest HDD, and the difference in HDD among three states is larger than 10% of the HDD of Indiana. Also, our data set shows that, in Iowa, variation in GDD among counties is about 5% of the average GDD over Iowa.

Previous literature finds a nonlinear relationship between temperature and corn yield (Schlenker & Roberts 2006; Schlenker & Roberts 2009). In particular, Schlenker and Roberts (2009) show that corn yield growth increases gradually only within a certain range of temperature, but, beyond this range, corn yield decreases sharply. Also, the agronomic literature typically represents the effects of temperature on plant growth in terms of cumulative exposure to heat and postulates that plant growth is linear in temperature only within a certain range. GDD and HDD capture this agronomic relationship, and previous literature shows that GDD (HDD) has positive

observations have too large the marginal effects of crop insurance purchases to wheat acreage and make the mean and variance of the average acreage response elasticity too large (see Table 2.4).

(negative) effects on corn yield (Schlenker, Roberts, & Eyer 2013; Miao, Khanna, & Huang 2015). As a result, spatial variations in GDD and HDD may imply differences in productivity of land; our results in Table 2.4 reflect farmers' responses to changes in productivity of land across the Midwest.

However, the empirical evidence regarding the effects of GDD and HDD on land allocations is not sufficient and varies among studies. For example, Kaminski, Kan, and Fleischer (2013) show that increases in the annual sum of degree days increase the acreage for field crops by 0.5%. Also, Feng, Hennessy, and Miao (2013) show that increases in GDD (precipitation) of one unit of normalized GDD (precipitation) increase the share of corn acreage across the Dakotas by approximately 3%. However, these results do not consider the effects of climate variables on farmers' decisions regarding crops to grow and insurance purchases.

To identify the effects of crop insurance on farmers' responses to climate conditions, we separate the acreage response elasticity in Table 2.4 into two parts (see Table 2.5). The first part is the acreage response elasticity to climate conditions without crop insurance (the upper part of Table 2.5). To calculate the estimates in the upper part of Table 2.5, we use the sum of the first two terms in Equation (10) as the marginal effects of climate conditions. The second part is changes in the acreage response elasticity to climate conditions due to crop insurance purchases (the lower part of Table 2.5). We use the sum of the last two terms in Equation (10) as the marginal effects of climate measures when calculating estimates in the lower part of Table 2.5. Last, the estimates in Table 2.5 are weighted averages for all observations based on sampling weights in our data.

The results show that, without crop insurance, increases in intensive rainfall events of 1% decrease corn and soybean acreage by 3.6% and 6.4%, respectively. In addition, the results indicate that increases in total precipitation increase crop acreage, even though only the effects of total precipitation on soybean acreage are statistically significant. However, the results regarding the second part show that corn and soybean acreage response elasticity to intensive rainfall events increases by 4.0% and 6.3% due to crop insurance purchases. Also, corn and soybean acreage response elasticity to total precipitation decreases by 4.7% and 14.12%, respectively, after purchasing crop insurance. In sum, from the results in Table 2.4 and Table 2.5, we can verify that crop insurance distorts farmers' incentive to adapt to climate conditions by adjusting their land allocation for crops. Also, less intuitive results regarding total precipitation and intensive rainfall events shown in Table 2.4 reflect the effects of crop insurance on farmers' land allocation.

Last, the total effects of federal crop insurance programs on crop acreage are summarized in the last row of Table 2.4. The estimates in Table 2.4 are the averages of percentage change in crop *j* acreage caused by insurance for crop *j*. However, since the majority of farmers purchased insurance for all crops they planted, we can consider the results as the acreage response elasticity of crop insurance. The estimates show the significant effects of federal crop insurance on farmers' land allocation decisions: The results show that purchasing crop insurance increases corn and soybean acreage by about 5.1% and 10.7%, respectively.

However, the estimates of insurance effects on farmers' land allocation have large variations in the previous literature, and these variations depend on study areas, study periods, estimation methods, and measures of insurance demand. For example, Wu (1999) shows that crop insurance participation changes the share of corn (soybeans) in the Central Nebraska basin from 0.27 to 0.05 (from 0.04 to 0.05), and the size of insurance effects depends on farm size. The simulation results of Wu and Adams (2001) show that a 75% coverage level for revenue protection crop insurance for corn (soybeans) increases corn acreage in the Corn Belt by 9.8% (0.1%). The results of simulation in Goodwin, Vandeveer, and Deal (2004) show that decreases in premium rates of 30% increase corn acreage over the Heartland region only by 0.20%.

Compared to previous literature, our result regarding the insurance effect on corn acreage is located within the range of previous findings, but the insurance effect on soybean acreage is larger than results of previous studies. However, it may be difficult to compare our results directly with previous results. To begin with, most of the literature analyzes land use change before the Agricultural Risk Protection Act of 2000 (ARPA), which means that most previous studies do not account for the effects of changes in subsidy structures after 2000. For example, Goodwin and Smith (2013) find that the effects of insurance are larger for soybean acreage than corn acreage. Also, except for Wu (1999), most studies assume that farmers' decisions regarding crops to grow and crop insurance purchases are independent of farmers' land allocation among crops.

2.6.2 Implications

To deal with the risks caused by unexpected weather conditions, farmers have adopted crop insurance. The federal government introduced federal crop insurance programs to eliminate the need for ad hoc disaster assistance and has motivated farmers to use crop insurance by providing subsidies. In particular, ARPA has ensured that the subsidy rates fall more slowly than premium rates. The purpose of this change is to motivate farmers to increase coverage levels and insured crop acreage. In addition, based on the "shallow loss" programs introduced in the 2014 farm bill, farmers can use higher coverage levels. As a result, the cost of subsidies has increased as the program has expanded and, in 2014, the federal government paid $6.2 billion as premium subsidies.

However, the benefits of subsidized crop insurance are controversial (Paulson, Babcock, & Coppess 2014).[23] Our results provide evidence regarding the distortions caused by subsidized crop insurance. The conceptual approach shows that crop insurance can weaken farmers' responsiveness to production risk and increase land allocation to insured crops, even when farmers recognize the potential risks of growing insured crops. The analytic results also indicate that the expected utility from growing insured crops can increase as the level of risk increases when subsidy rates and coverage levels are high. These results imply that the subsidy structure after ARPA and higher coverage of "shallow loss" programs can increase the distortion of federal crop insurance. Our empirical results also show that federal crop insurance gives disincentive for farmers to adjust their land allocation for potential production risks such as an increase in intensive rainfall events. We thus imagine that subsidized crop insurance programs will make farmers more susceptible to an increase in extreme weather events in the future. An increased potential risk of yield loss from climate change may increase farmers' premium rates and the government's expenditure for crop insurance subsidies.

2.7 Conclusions

To assess and alleviate harmful climate change impacts, policy makers need to understand farmers' adaptive behavior to local environmental conditions. This study identifies responses of Midwest farmers to climate conditions and federal crop insurance programs by analyzing their cropping patterns. The study has four key findings. First, sufficient precipitation, adequate GDD, and less HDD have positive effects on farmers' decision to grow crops but negative effects on their decision to purchase crop insurance. Intensive rainfall has positive effects on insurance purchases for corn and soybeans. Second, we calculate the overall effects of climate variables on land

[23] Paulson, Babcock, and Coppess (2014) summarize the debate regarding the justification of public support for crop insurance program: elimination of ad-hoc disaster payment, decreases in adverse selection, and market failure.

allocation decisions of Midwest farmers. These effects include climate effects on farmers' decision to grow crops, purchase insurance, and allocate their land to crops at the same time. The results show that a 1% increase in GDD increases corn, soybean, and wheat acreage by 1.7%, 3.6%, and 2.6%, respectively. When HDD increase by 1%, soybean acreage decreases by 0.6%. An increase in precipitation of 1% decreases soybean acreage by 2.9%. However, increases in HDD and precipitation have insignificant effects on corn and wheat acreage. Third, without crop insurance, farmers are more likely to increase corn and soybean acreage when intensive rainfall events decrease and total precipitation increases during the growing seasons. However, our results show that federal crop insurance mitigates farmers' incentive to adopt increases in intensive rainfall events or decreases in total precipitation by adjusting their land use. Fourth, federal crop insurance programs induced Midwest farmers to allocate more acreage to corn and soybeans.

The findings in this paper contribute broadly to our understanding of climate change, land allocation, and crop insurance. To be specific, by constructing a simultaneous equation model consisting of decisions to grow crops, purchase crop insurance, and allocate land, our results identify the effects of climate variables on the intensive margin, the extensive margin, and insurance purchases separately. Also, we identify the effects of crop insurance on cropping pattern, and the results can stand as empirical evidence of the unintended policy effects of subsidized crop insurance programs. Last, our results offer one answer to a controversial question: How does crop insurance alter farmers' response to long-term climate risks?

The results in this paper have some limitations. First, county-level climate and soil variables fail to capture farm-level spatial heterogeneity of climate and soil. Second, our model heavily depends on distributional assumptions, including independence among crop selections and normality assumptions on error terms. Third, because of the lack of information on historical land use, we do not control for the effects of crop rotation even though we allow for the correlation between decisions on land allocation and crops to grow. Last, the merging of the multiple-year surveys without consideration of changes in sampling design and population may bias our estimates.

References

Anderson, C. J., Anex, R. P., Arritt, R. W., Gelder, B. K., Khanal, S., Herzmann, D. E., & Gassman, P. W. (2013). Regional climate impacts of a biofuels policy projection. *Geophysical Research Letters, 40*(6), 1217-1222.

Annan, F., & Schlenker, W. (2015). Federal crop insurance and the disincentive to adapt to extreme heat. *The American Economic Review*, *105*(5), 262-266.

Arnade, C., & Kelch, D. (2007). Estimation of area elasticities from a standard profit function. *American Journal of Agricultural Economics*, *89*(3), 727-737.

Barr, K. J., Babcock, B. A., Carriquiry, M. A., Nassar, A. M., & Harfuch, L. (2011). Agricultural Land Elasticities in the United States and Brazil. *Applied Economic Perspectives & Policy*, *33*(3), 449-462.

Chavas, J. P., & Holt, M. T. (1990). Acreage decisions under risk: the case of corn and soybeans. *American Journal of Agricultural Economics*, *72*(3), 529-538.

Christofides, L. N., Stengos, T., & Swidinsky, R. (1997). On the calculation of marginal effects in the bivariate probit model. *Economics Letters*, *54*(3), 203-208.

Claassen, R., Carriazo, F., Cooper, J. C., Hellerstein, D., & Ueda, K. (2011). *Grassland to cropland conversion in the Northern Plains. Economic Research Report*, *120*. U.S. Department of Agriculture, Economic Research Service.

Dubman, R. W. (2000). *Variance estimation with USDA's farm costs and returns surveys and agricultural resource management surveys*, (Economic Research Report AGE 00-01). Washington, DC: U.S. Department of Agriculture, Economic Research Service.

Edward, W. (2011). *Yield Protection Crop Insurance*. Ag Decision Maker A1-53.

Ehrlich, I., & Becker, G. S. (1972). Market insurance, self-insurance, and self-protection. *Journal of political Economy*, *80*(4), 623-648.

Farrin, K., Miranda, M. J., & O'Donoghue, E. (2016). *How Do Time and Money Affect Agricultural Insurance Uptake? A New Approach to Farm Risk Management Analysis*.

(Economic Research Report 212), U.S. Department of Agriculture, Economic Research Service.

Feng, H., Hennessy, D. A., & Miao, R. (2013). The effects of government payments on cropland acreage, conservation reserve program enrollment, and grassland conversion in the Dakotas. *American Journal of Agricultural Economics*, *95*(2), 412-418.

Fezzi, C., & Bateman, I. J. (2011). Structural agricultural land use modeling for spatial agro-environmental policy analysis. *American Journal of Agricultural Economics*, *93*(4), 1168-1188.

GAO, (2014). *Climate Change: Better Management of Exposure to Potential Future Losses Is Needed or Federal Flood and Crop Insurance.* (GAO-15-28), Washington, D.C.

Goodwin, B. K. (1993). An empirical analysis of the demand for multiple peril crop insurance. *American Journal of Agricultural Economics, 75*(2), 425-434.

Goodwin, B. K., & Mishra, A. K. (2005). Another look at decoupling: additional evidence on the production effects of direct payments. *American Journal of Agricultural Economics*, *87*(5), 1200-1210.

Goodwin, B. K., Mishra, A. K., & Ortalo-Magné, F. N. (2003). What's wrong with our models of agricultural land values? agricultural land values, government payments, and production. *American Journal of Agricultural Economics*, *85*(3), 744-752.

Goodwin, B. K., Vandeveer, M. L., & Deal, J. L. (2004). An empirical analysis of acreage effects of participation in the federal crop insurance program. *American Journal of Agricultural Economics*, *86*(4), 1058-1077.

Goodwin, B. K., & Smith, V. H. (2013). What harm is done by subsidizing crop insurance? *American Journal of Agricultural Economics*, *95*(2), 489-497.

Groisman, P. Y., Knight, R. W., & Karl, T. R. (2012). Changes in intense precipitation over the central United States. *Journal of Hydrometeorology*, *13*(1), 47-66.

Heckman, J. J. (1976). The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models. In *Annals of Economic and Social Measurement, Volume 5, number 4* (pp. 475-492). NBER.

Hendricks, N. P., Smith, A., & Sumner, D. A. (2014). Crop Supply Dynamics and the Illusion of Partial Adjustment. *American Journal of Agricultural Economics*, *96*(5), 1469-1491.

Hornbeck, R., & Keskin, P. (2014). The historically evolving impact of the ogallala aquifer: Agricultural adaptation to groundwater and drought. *American Economic Journal: Applied Economics*, *6*(1), 190-219.

Ifft, J., Novini. A., & Patrick, K. (2014). *Debt Use by US Farm Businesses, 1992-2011*. (Economic Information Bulletin 122), U.S. Department of Agriculture, Economic Research Service.

Ifft, J. E., Kuethe, T., & Morehart, M. (2015). Does federal crop insurance lead to higher farm debt use? Evidence from the Agricultural Resource Management Survey (ARMS). *Agricultural Finance Review*, *75*(3), 349-367.

Jones, C. S., Seeman, A., Kyveryga, P. M., Schilling, K. E., Kiel, A., Chan, K. S., & Wolter, C. F. (2016). Crop rotation and Raccoon River nitrate. *Journal of Soil and Water Conservation*, *71*(3), 206-219.

Khanna, M., Epouhe, O. F., & Hornbaker, R. (1999). Site-specific crop management: adoption patterns and incentives. *Review of Agricultural Economics*, *21*(2), 455-472.

Lacroix, A., & Thomas, A. (2011). Estimating the environmental impact of land and production decisions with multivariate selection rules and panel data. *American journal of agricultural economics*, *93*(3), 780-798.

Lubowski, R. N., Bucholtz, S., Claassen, R., Roberts, M. J., Cooper, J. C., Gueorguieva A., & Johansson, R. (2006). *Environmental Effects of Agricultural Land-Use Change: The Role of Economics and Policy*. (Economic Research Report 125), U.S. Department of Agriculture, Economic Research Service.

Malcolm, S, Marshall, E., Aillery, M., Heisey, P., Livingston, M., and Day-Rubenstein, K. (2012) *Agricultural Adaptation to a Changing Climate: Economic and Environmental Implications Vary by U.S. Region*, Economic Research Report -136, U.S. Department of Agriculture, Economic Research Service.

Mendelsohn, R., Nordhaus, W. D., & Shaw, D. (1994). The impact of global warming on agriculture: a Ricardian analysis. *The American economic review*, 753-771.

Miao, R., Hennessy, D. A., & Feng, H. (2016). The Effects of Crop Insurance Subsidies and Sodsaver on Land-Use Change. *Journal of Agricultural and Resource Economics*, *41*(2), 247-265.

NASS (2010). *Field Crops: Usual Planting and Harvesting Dates*. (Agriculural Handbook 628) USDA National Agricultural Statistics Service.

NASS (2011). *Price Program: Histoty, Concepts, Methodology, Analysis, Estiamates and Dissemination*, USDA National Agricultural Statistics Service.

Natural Resources Conservation Service, United States Department of Agriculture. 2013. Description of SSURGO Database. Website. url: http://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/?cid=nrcs142p2_053627.

O'Donoghue, E. (2014) *The Effects of Premium Subsidies on Demand for Crop Insurance*. (Economic Research Report 169), U.S. Department of Agriculture, Economic Research Service.

Pielke, R. A., J. Adegoke, A. Beltran-Przekurat, C. A. Hiemstra, J. Lin, U. S. Nair, D. Niyogi, and T. E. Nobis. "An overview of regional land-use and land-cover impacts on rainfall." *Tellus B* 59, no. 3 (2007): 587-601.

D. Paulson, N., Babcock, B., & Coppess, J. (2014). The potential for crop insurance reform. *Agricultural Finance Review*, *74*(4), 464-476.

PRISM Climate Group. 2004. PRISM AN81m Data. Website. url: http://prism.oregonstate.edu.

Reilly, J., Tubiello, F., McCarl, B., Abler, D., Darwin, R., Fuglie, K., & Mearns, L. (2003). US agriculture and climate change: new results. *Climatic Change*, *57*(1-2), 43-67.

Sckokai, P., & Moro, D. (2006). Modeling the reforms of the common agricultural policy for arable crops under uncertainty. *American Journal of Agricultural Economics*, *88*(1), 43-56.

Snyder, R. L. (1985). Hand calculating degree days. *Agricultural and forest meteorology*, *35*(1), 353-358.

Van de Ven, W. P., & Van Praag, B. M. (1981). The demand for deductibles in private health insurance: A probit model with sample selection. *Journal of econometrics*, *17*(2), 229-252.

Varble, S., Secchi, S., & Druschke, C. G. (2016). An examination of growing trends in land tenure and conservation practice adoption: Results from a farmer survey in Iowa. *Environmental management*, *57*(2), 318-330.

Walters, C. G., Shumway, C. R., Chouinard, H. H., & Wandschneider, P. R. (2012). Crop insurance, land allocation, and the environment. *Journal of Agricultural and Resource Economics*, 301-320.

Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data (2d ed.)*. Cambridge, MA: MIT Press.

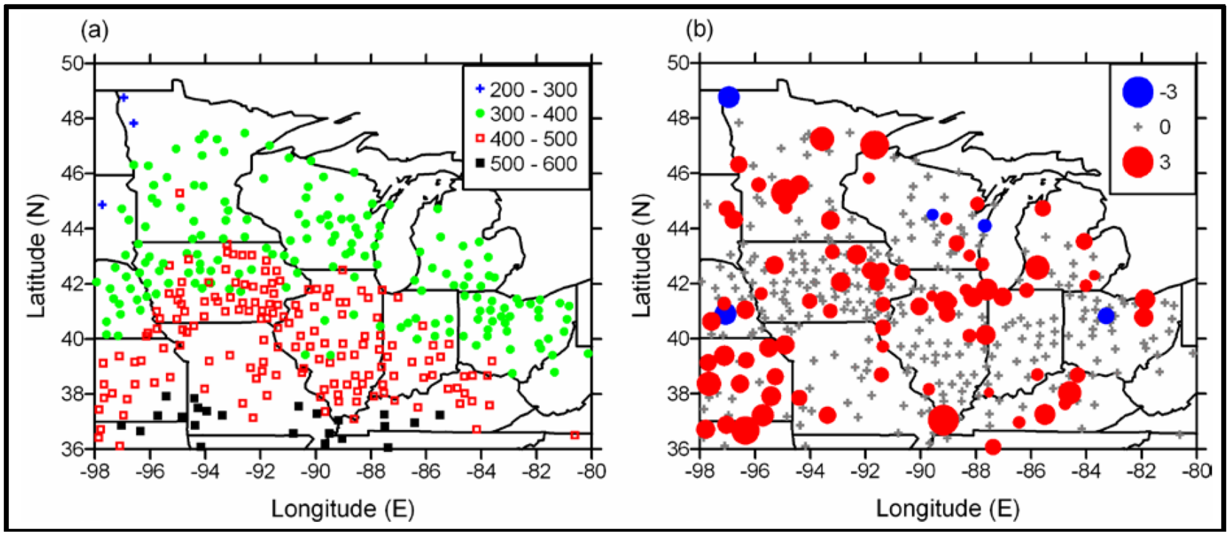
Wu, J., & Adams, R. M. (2001). Production Risk, Acreage Decisions and Implications for Revenue Insurance Programs. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie*, *49*(1), 19-35.

Wu, J. (1999). Crop insurance, acreage decisions, and nonpoint-source pollution. *American Journal of Agricultural Economics*, *81*(2), 305-320.

Wu, J., Adams, R. M., Kling, C. L., & Tanaka, K. (2004). From microlevel decisions to landscape changes: an assessment of agricultural conservation policies. *American Journal of Agricultural Economics*, *86*(1), 26-41.

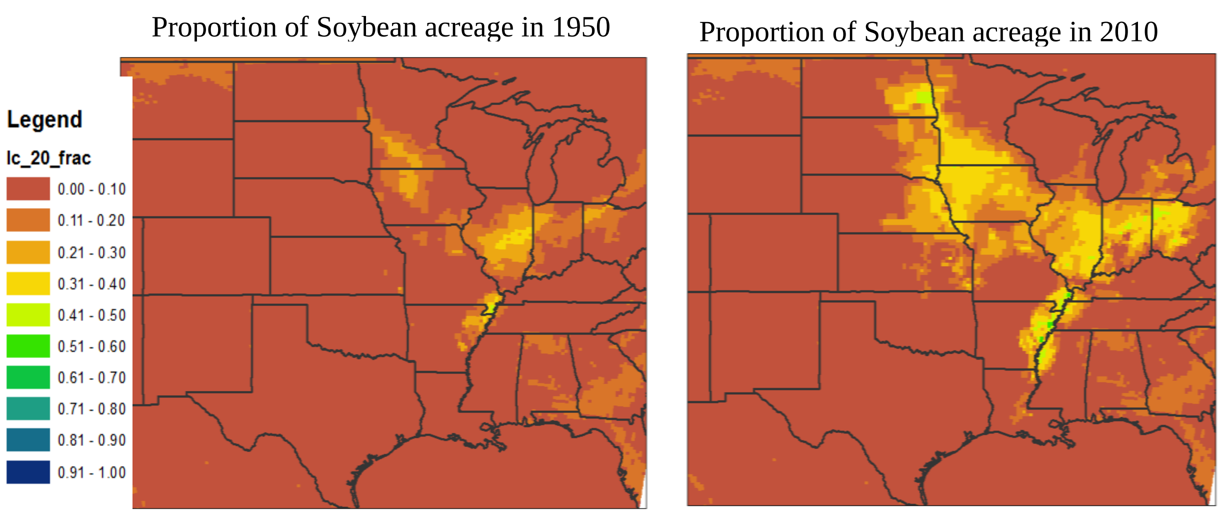
Yang, S., & Shumway, C. R. (2015) *Dynamic Adjustment in US Agriculture under Climate Change*. Working Paper, School of Economic Sciences, Washington State University.

Young, C. E., Vandeveer, M. L., & Schnepf, R. D. (2001). Production and price impacts of US crop insurance programs. *American Journal of Agricultural Economics*, *83*(5), 1196-1203.



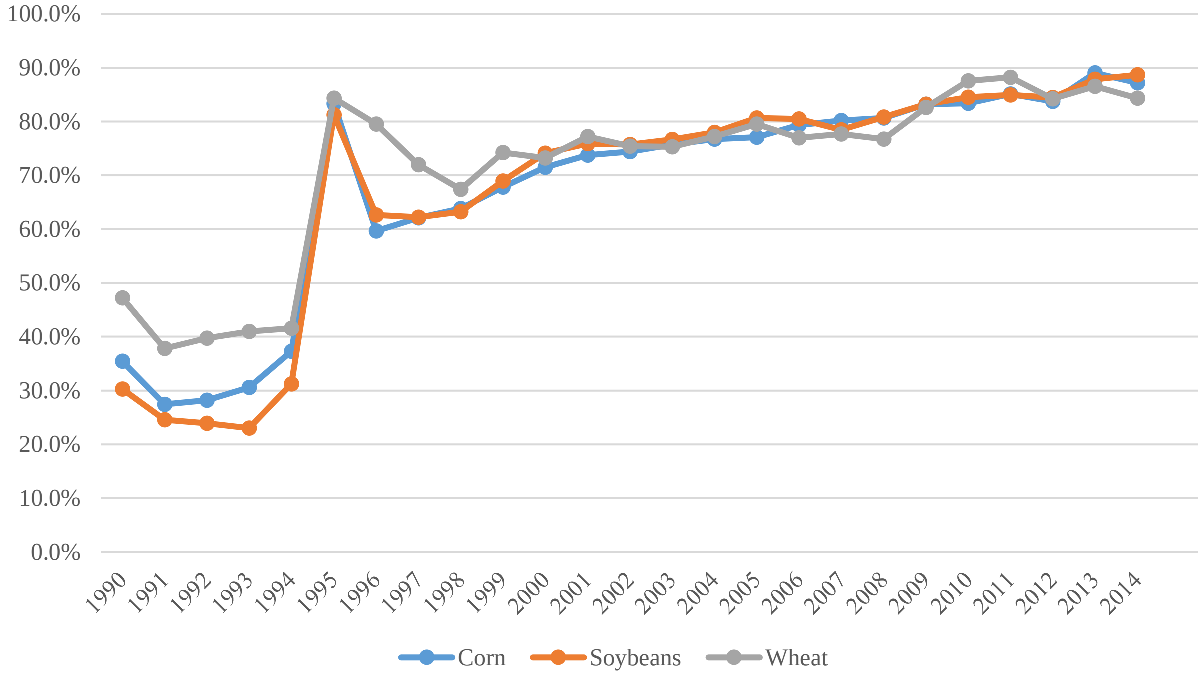
Note: (a) Average annual precipitation (mm) during the top 10 wettest days in a year for 1971-2000. (b) Trend in the sum of precipitation during the top 10 wettest days in a year for 1901-2000, expressed in a percent per decade; A red circle means the stations showed a significant increase through time; a blue circle indicates a statistically significant decrease. A plus symbol indicates that the trend was not significant. The source is NOAA Technical Report NESDIS 142-3 (2013).

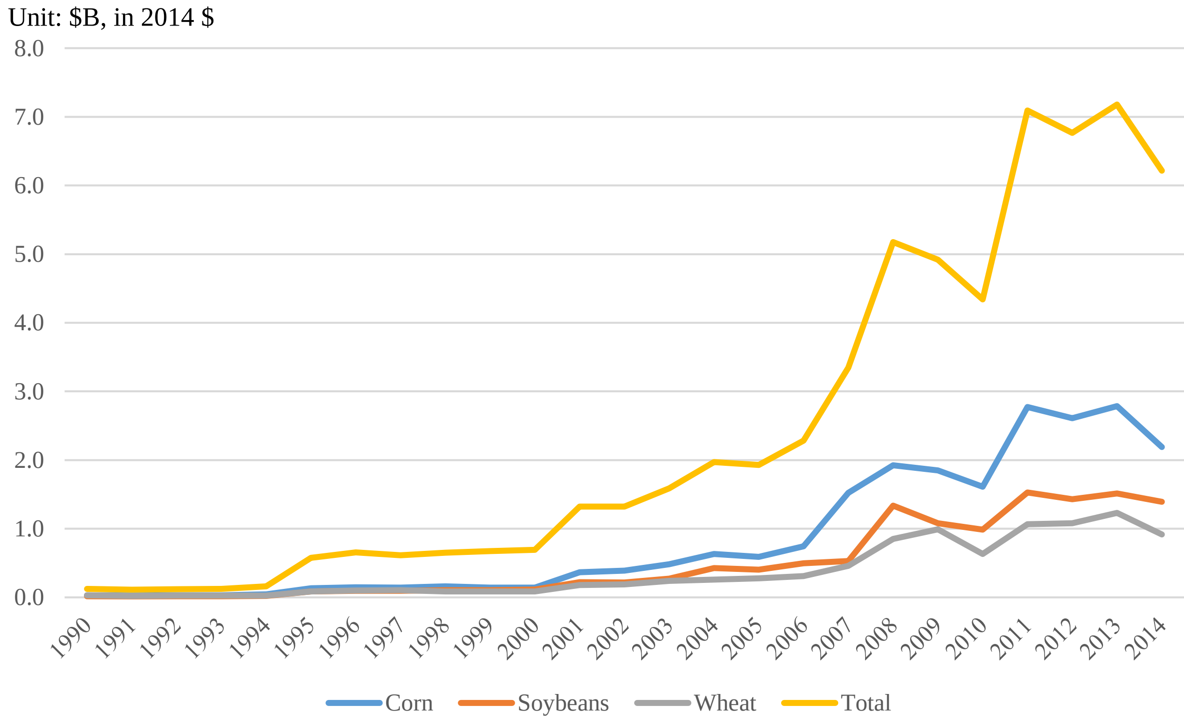
Figure 2.1. Changes in precipitation in the Midwest



Source: Arritt, R., J. Miranowski, A. Daniel, B. Gelder, J. McFadden, T. Sines and J.-H. Sung, 2015: Attribution of changes in precipitation intensity over the central United States. Presented at "Third Annual Meeting of the NSF-DOE-USDA Earth System Modeling (EaSM) activity", Bethesda, MD, 31 August - 2 September 2015.

Figure 2.2. The Changes in Soybean Acreage from 1950 to 2010





Source: NASS Quick stats and Risk Management Agency (RMA)

Figure 2.3. Changes in Shares of acres covered by federal crop insurance (above) and crop insurance subsidies (below)

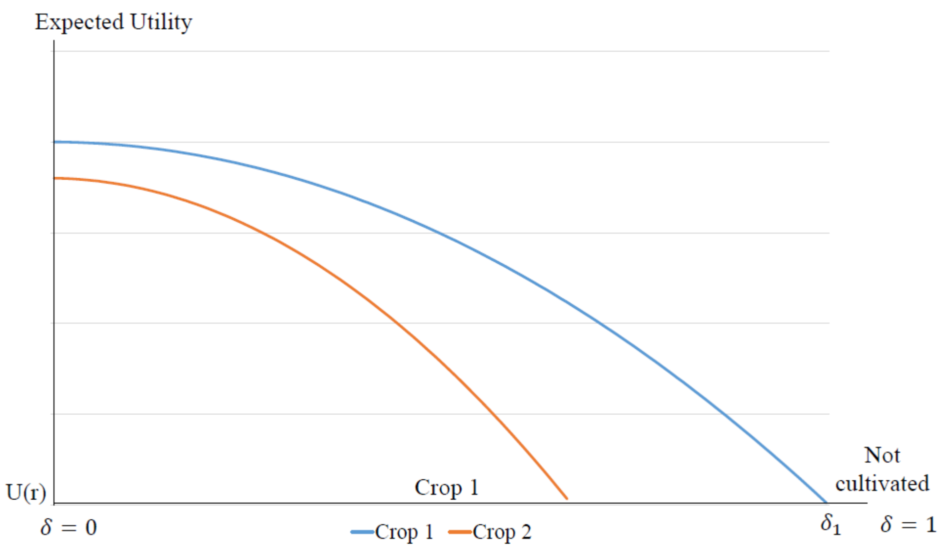


Figure 2.4. Land allocation when Crop 1 is more profitable and less sensitive to the risk

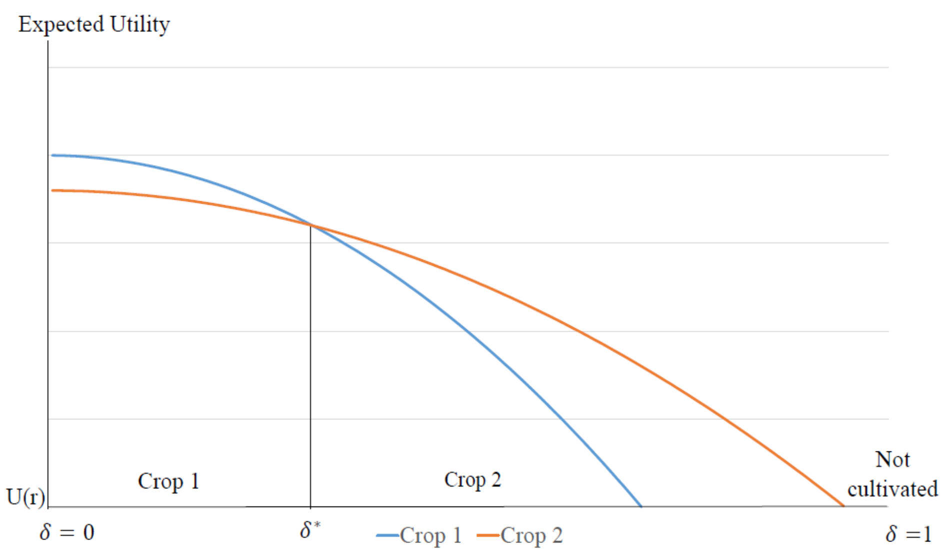


Figure 2.5. Land allocation when Crop1 is beneficial only when the risk level is low

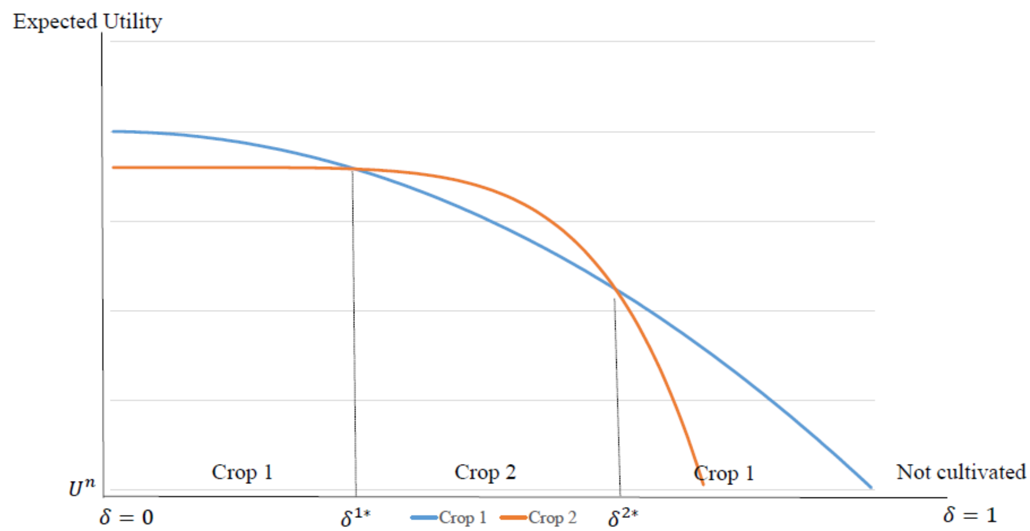


Figure 2.6. Land allocation when Crop2 has larger changes in its curvature than Crop 1

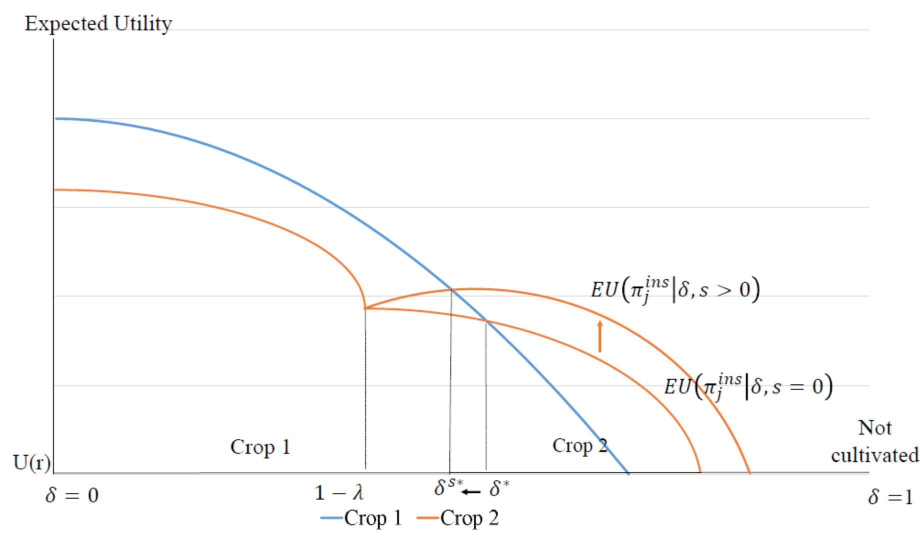


Figure 2.7. Changes in land allocation after buying crop insurance for Crop 2

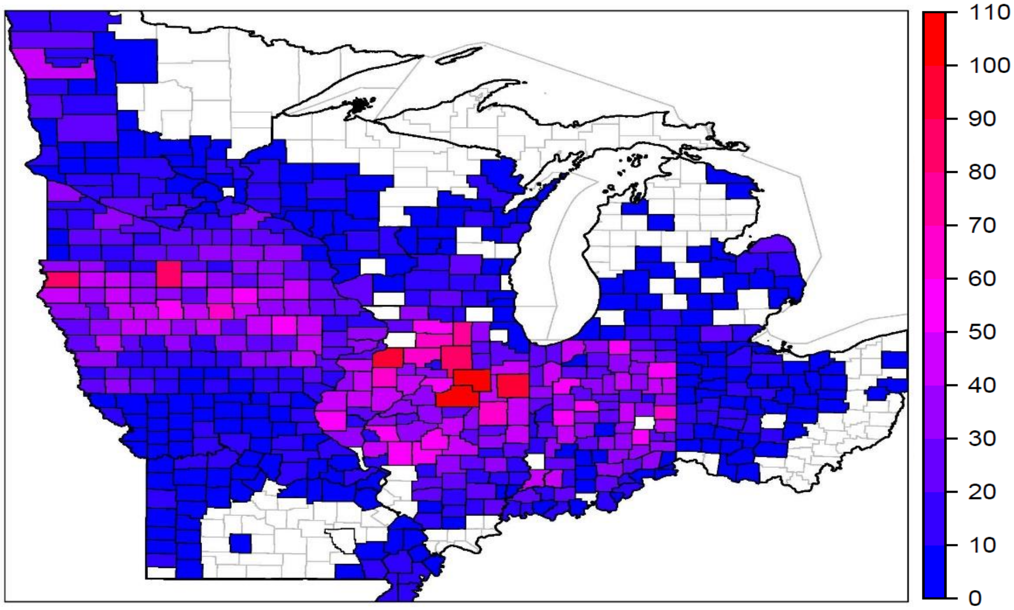


Figure 2.8. The regional distribution of observations (# per county)

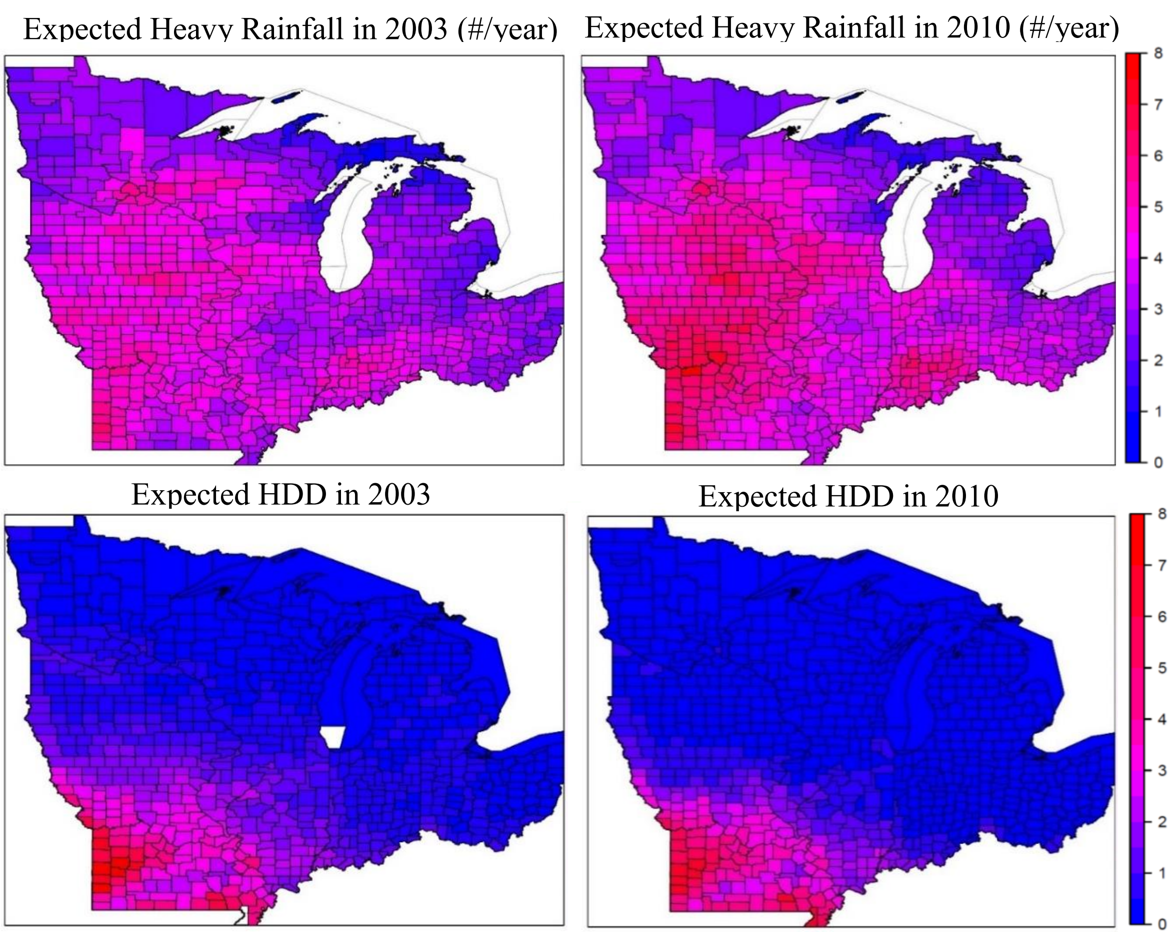


Figure 2.9. The Changes in Expected Weather conditions

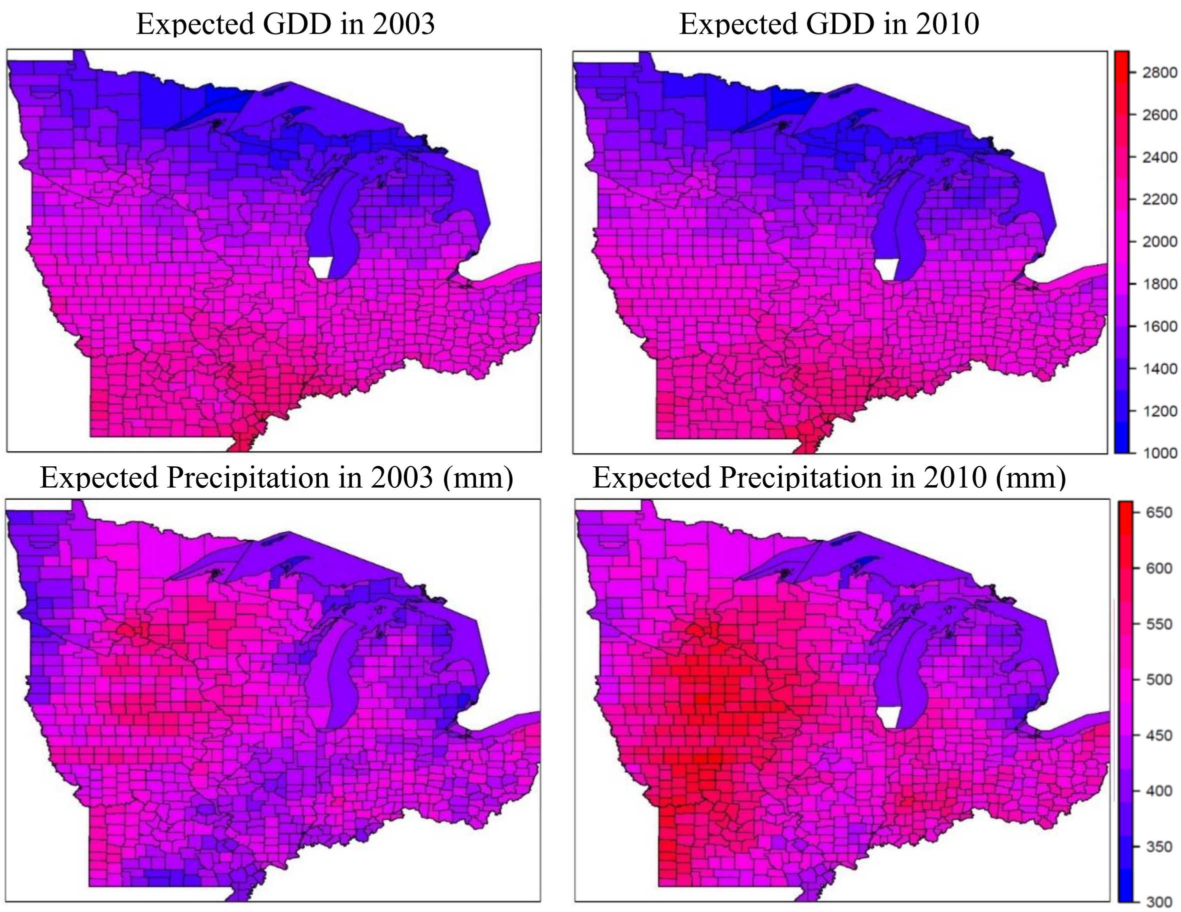


Figure 2.9. The Changes in Expected Weather conditions (Continue)

Table 2.1. Summary Statistics

Variables	Definition	Mean	Std.Dev
Harvested Acreage			
Corn	Corn grain (acres)	491.41	645.55
Soy	Soybean (acres)	411.14	495.51
Wheat	Wheat grain (acres)	25.84	137.66
Land	Total land (acres)	1065.56	1161.44
Expected Price			
P_{corn}	Corn grain ($/bu)	3.99	1.35
P_{soy}	Soybeans ($/bu)	8.81	3.11
P_{wheat}	Wheat grain ($/bu)	4.80	2.05
Variance of Output Price			
Var(corn)	Variance of corn prices	1.00	0.93
Var(soybeans)	Variance of soybean prices	5.44	3.47
Var(wheat)	Variance of wheat prices	0.90	0.96
Farm Characteristics			
Age	Operator age	54.41	11.23
Off-farm income	Previous year off-farm income ($1,000)	52.29	84.98
Equity	Equity ($1,000)	1981.1	2659.1
Debt-ratio	debt-ratio	0.15	0.19
Ins_c	Insurance for corn	0.67	0.47
Ins_s	Insurance for soybeans	0.66	0.47
Ins_w	Insurance for wheat	0.10	0.30
# of Observations	10056		

Table 2.1 (Continued)

Variables	Definition	Mean	Std.Dev
Soil and Land Characteristics			
OM	Organic matter (%)	1.90	1.08
Slope	Slope (%)	2.57	2.15
Ksat	Hydraulic Conductivity (m/second)	6.29	6.11
AWC	Available Water Capacity (in./in.)	0.12	0.06
K-factor	K factor	0.19	0.10
Dept	Depth to water table (cm)	32.64	15.54
Climate and Weather Events			
GDD	GDD for corn	1978.43	185.35
	GDD for soybeans	1796.66	166.35
	GDD for wheat	371.00	301.93
HDD	HDD for corn	1.08	0.95
	HDD for soybeans	1.08	0.95
	HDD for wheat	0.06	0.20
PRE	Precipitation for corn	499.79	45.61
	Precipitation for soybeans	420.65	41.06
	Precipitation for wheat	138.78	79.56
I_PRE	Intensive Precipitation for corn	4.23	0.84
	Intensive Precipitation for soybeans	3.58	0.77
	Intensive Precipitation for wheat	1.11	0.70
Early_PRE	Precipitation during April and May	196.91	70.87

Table 2.2. Estimates of Crop Selection and Crop Insurance Selection

	Corn		Corn Insurance		Soybeans		Soybean Insurance		Wheat		Wheat Insurance	
P_{corn}	0.550**	(0.265)	-0.342	(0.207)	-0.130	(0.258)	0.170	(0.197)	-0.318	(0.240)	2.255***	(0.589)
P_{soy}	-0.108	(0.137)	0.385***	(0.091)	-0.178	(0.113)	0.313***	(0.094)	0.236	(0.146)	0.727**	(0.325)
P_{wheat}	-0.088	(0.063)	0.024	(0.056)	-0.064	(0.064)	-0.001	(0.055)	-0.598***	(0.091)	-0.316	(0.347)
Var(P_{corn})	1.017	(4.185)	7.146**	(3.072)	-7.129*	(3.814)	10.194***	(3.123)	-5.535	(4.312)	38.321***	(10.534)
Var(P_{soy})	-0.113	(1.050)	-1.779**	(0.768)	1.727*	(0.954)	-2.499***	(0.782)	1.549	(1.086)	-9.463***	(2.631)
Var(P_{wheat})	-0.482***	(0.165)	-0.066	(0.151)	0.286	(0.194)	-0.207	(0.152)	-0.855***	(0.191)	-0.381	(0.567)
Early_PRE	-0.002***	(0.000)	-0.001*	(0.000)	0.001***	(0.000)	-0.001***	(0.000)	-		-	-
I_PRE	0.090	(0.058)	0.236***	(0.047)	-0.040	(0.063)	0.250***	(0.051)	-0.092	(0.123)	0.004	(0.248)
GDD	0.001***	(0.000)	0.000	(0.000)	0.002***	(0.000)	-0.001**	(0.000)	0.002	(0.001)	-0.003	(0.002)
HDD	-0.130***	(0.054)	-0.065	(0.042)	-0.246***	(0.054)	0.074*	(0.042)	-1.405***	(0.337)	0.040	(0.732)
PRE	0.002**	(0.001)	-0.004***	(0.001)	-0.001	(0.001)	-0.004***	(0.001)	-0.015***	(0.002)	-0.001	(0.007)
OM	-0.020	(0.051)	0.235***	(0.040)	0.065	(0.053)	0.173***	(0.038)	-0.120**	(0.047)	0.095	(0.097)
Slope	0.004	(0.013)	-0.043***	(0.010)	-0.070***	(0.011)	-0.005	(0.011)	-0.014	(0.012)	-0.027	(0.026)
Ksat	-0.003	(0.004)	-0.006*	(0.003)	-0.015***	(0.003)	-0.003	(0.003)	-0.004***	(0.004)	-0.004	(0.007)
AWC	7.611***	(2.220)	-8.431***	(1.698)	4.484**	(2.273)	-6.499***	(1.618)	-3.904	(2.000)	-6.488	(4.364)
Kffact	-4.803***	(0.912)	3.251***	(0.688)	-1.737*	(0.910)	2.317***	(0.658)	3.057***	(0.760)	2.244	(1.943)
Depth	-0.001	(0.001)	0.003**	(0.001)	-0.0003	(0.001)	0.003**	(0.001)	-0.001	(0.001)	-0.001	(0.003)
Age	-0.011***	(0.002)	-	-	0.0002	(0.002)	-	-	0.005***	(0.002)	-	-
Off income	-0.001***	(0.000)	-	-	-0.001***	(0.000)	-	-	-0.001***	(0.000)	-	-
Constant	-1.930**	(0.897)	1.298*	(0.726)	-2.019**	(0.833)	2.129***	(0.731)	0.755	(0.722)	-0.701	(1.529)
Debt Ratio	-	-	1.341***	(0.129)	-	-	1.413***	(0.126)	-	-	1.733***	(0.324)
Equity	-	-	0.086***	(0.017)	-	-	0.066***	(0.014)	-	-	0.076**	(0.031)
ρ	-	-	-0.570***	(0.206)	-	-	-0.557**	(0.249)	-	-	-0.245	(0.422)
Year dummies and state dummies			Yes				Yes				Yes	
McFaddens' Pseudo R-squared			0.1253				0.1021				0.2423	
Wald Statistic			383.33***				421.97***				135.11***	

Note: *** significant at 1% level. ** significant at 5% level. * significant at 1% level. ( ) standard errors of estimates. For corn and corn insurance selection equations, 1934 iterations among 2000 iterations succeeded in converging the optimal. For soybean and soybean insurance selection equations 1981 iterations among 2000 iterations succeeded in converging the optimal. Lastly, for wheat and wheat insurance selection equations 1819 iterations among 2000 iterations succeeded in converging the optimal.

Table 2.3. Estimates of Acreage Equations

	Corn Acreage		Soybeans Acreage		Wheat Acreage	
	Estimates	(Std. Error)	Estimates	(Std. Error)	Estimates	(Std. Error)
P_{corn}	294.36	(306.44)	47.05	(284.63)	138.64	(565.35)
P_{soy}	58.68	(162.13)	-80.24	(157.25)	-89.84	(221.80)
P_{wheat}	-99.84	(119.85)	-103.61	(148.18)	456.81***	(140.42)
$Var(P_{corn})$	3501.80	(4730.29)	-3728.23	(5111.83)	3337.82	(10085.27)
$Var(P_{soy})$	-905.31	(1203.30)	842.63	(1312.53)	-888.52	(2670.61)
$Var(P_{wheat})$	-90.71	(331.72)	421.50	(587.61)	557.85	(1202.55)
Early_PRE	0.20	(0.49)	0.89**	(0.45)	-	-
I_PRE	-201.29***	(0.004)	-343.87***	(78.66)	-142.34	(221.62)
GDD	-0.27	(0.28)	0.77	(0.48)	2.68**	(1.35)
HDD	115.50	(71.87)	-46.84	(82.50)	565.68	(1107.38)
PRE	2.52*	(1.41)	5.95***	(1.50)	4.15	(4.35)
OM	-278.34***	(61.63)	-211.58***	(53.05)	21.51	(42.05)
Slope	64.69***	(14.50)	43.69***	(16.85)	-28.48	(33.19)
Ksat	4.18	(3.74)	5.88	(4.09)	4.18	(3.81)
AWC	7393.19***	(2342.15)	7828.45****	(2234.80)	1770.45	(2115.88)
Kffact	-3066.77***	(991.47)	-3233.46***	(977.76)	-1170.12	(977.47)
Depth	-0.50	(1.42)	-1.45	(1.44)	0.41	(1.43)
λ_{corn}	-136.62	(163.38)	-229.07*	(121.46)	42.53	(95.16)
λ_{soy}	-448.44**	(222.46)	103.81	(225.54)	-104.76	(190.59)
λ_{wheat}	-32.32	(41.83)	-124.00***	(34.90)	118.38	(190.59)
Constant	-106.03	(592.64)	-3721.90***	(1434.45)	-2766.28***	(1009.20)
Year and State dummies	Yes		Yes		Yes	

Note: Standard errors are from about 1,891 bootstrap runs. *** significant at 1% level. ** significant at 5% level. * significant at 1% level. ( ) standard errors of estimates.

Table 2.3 (Continued)

	Corn Acreage		Soybeans Acreage		Wheat Acreage	
	Estimates	(Std. Error)	Estimates	(Std. Error)	Estimates	(Std. Error)
Ins×P_{corn}	-440.90	(515.65)	-340.70	(440.75)	-1212.34	(1660.85)
Ins×P_{soy}	-211.73	(249.21)	-106.79	(219.24)	29.45	(612.16)
Ins×P_{wheat}	204.66	(156.01)	242.45	(169.17)	-837.24***	(286.16)
Ins×Var(P_{corn})	-7576.23	(7426.96)	-1729.54	(6900.96)	-19191.9	(27811.3)
Ins×Var(P_{soy})	1921.18	(1875.71)	477.89	(1761.41)	4887.43	(7141.12)
Ins×Var(P_{wheat})	-47.28	(405.94)	-260.60	(662.29)	-	-
Ins×Early_PRE	0.20	(0.63)	0.17	(0.51)	-	-
Ins×I_PRE	176.45*	(92.43)	292.98***	(89.84)	242.37	(542.91)
Ins×GDD	-0.09	(0.24)	-0.66	(0.72)	-4.76	(3.10)
Ins×HDD	-68.56	(37.57)	54.54	(121.44)	-1021.28	(1501.40)
Ins×PRE	-1.70	(0.94)	-5.20***	(1.72)	-11.72	(11.02)
Ins×OM	237.25***	(86.13)	181.92***	(69.38)	-39.77	(87.73)
Ins×Slope	-86.52***	(9.11)	-72.14***	(24.89)	74.78	(96.52)
Ins×Ksat	4.61	(7.37)	-5.33	(4.90)	-6.81	(9.78)
Ins×AWC	-4566.24	(3506.71)	-6191.58**	(2938.64)	-4200.57	(4715.45)
Ins×Kffact	2101.03	(1561.42)	2930.75**	(1360.35)	3018.29	(1858.51)
Ins×Depth	-1.70	(1.97)	-0.79	(1.74)	-1.39	(3.85)
Ins	1169.86	(1584.32)	4694.94***	(1810.46)	6304.20***	(2274.48)
Year and State dummies	Yes		Yes		Yes	
Adjusted R-squared	0.3617		0.3998		0.1725	
Wald Statistics	91.43***		107.30***		37.13***	

Note: Standard errors are from about 1,891 bootstrap runs. *** significant at 1% level. ** significant at 5% level. * significant at 1% level. ( ) standard errors of estimates. The interaction term between crop insurance dummies and variance of wheat prices in an equation for wheat acreage is dropped because of collinearity.

Table 2.4. The Average Acreage Response Elasticity of Climate Variables

	Corn	Soybeans	Wheat
GDD	1.710 (0.925)*	3.554*** (1.201)	2.634** (1.164)
HDD	-0.118 (0.925)	-0.591*** (0.213)	-0.001 (0.001)
Precipitation	-0.791 (1.033)	-2.937*** (0.861)	-2.198 (1.413)
Intensive rainfall	0.245 (0.290)	-0.048 (0.289)	-0.612 (0.433)
Insurance	5.158*** (0.607)	10.770*** (1.359)	80.595 (-)

Note: Standard errors are from about 1,891 bootstrap runs. *** significant at 1% level. ** significant at 5% level. * significant at 1% level. ( ) standard errors of estimates. Since outliers in each iteration, the variance of the elasticity becomes large. To exclude the effects of outliers, the values which are higher than 95% quantile and lower than 5% quantile are thrown out. (-) means variance estimates based on the bootstrapping method based on probability weights are unreasonable large because of outliers.

Table 2.5. The Effects of Crop Insurance on Average Acreage Response Elasticity

	Corn	Soybeans	Wheat
Without crop insurance			
GDD	-0.550 (2.126)	5.755 (4.776)	8.298* (4.234)
HDD	0.211 (0.303)	-0.624 (0.412)	-0.0001 (0.001)
Precipitation	3.817 (3.082)	11.061*** (3.867)	5.053 (5.272)
Intensive rainfall	-3.623*** (1.202)	-6.478*** (1.606)	-1.349 (1.998)
After purchasing crop insurance			
GDD	2.279 (2.173)	-2.118 (4.956)	-5.495 (3.744)
HDD	-0.324 (0.244)	-0.043 (0.387)	-0.0003 (0.001)
Precipitation	-4.733* (2.657)	-14.125*** (3.582)	-6.984 (4.416)
Intensive rainfall	3.966*** (1.185)	6.309*** (1.601)	-0.706 (1.732)

Note: Standard errors are from about 1,891 bootstrap runs. *** significant at 1% level. ** significant at 5% level. * significant at 1% level. ( ) standard errors of estimates. Since outliers in each iteration, the variance of the elasticity becomes large. To exclude the effects of outliers, the values which are higher than 95% quantile and lower than 5% quantile are thrown out.

Table 2.6. Summary Statistics: Iowa, Illinois, and Indiana in 2010

Variables	Definition	Iowa	Illinois	Indiana
	Harvested Acreage			
Corn	Corn grain (acres)	455.31	571.06	516.21
Soy	Soybean (acres)	345.87	370.16	468.97
Wheat	Wheat grain (acres)	0.28	3.995	10.76
	Climate and Weather Events			
GDD	GDD for corn	1916.33	2113.03	2064.81
	GDD for soybeans	1722.63	1874.73	1796.95
	GDD for wheat	237.87	276.23	284.73
HDD	HDD for corn	0.45	0.94	0.38
	HDD for soybeans	0.45	0.94	0.38
	HDD for wheat	0.00	0.00	0.00
PRE	Precipitation for corn	575.07	503.62	530.61
	Precipitation for soybeans	477.23	408.24	410.56
	Precipitation for wheat	115.33	121.55	120.11
I_PRE	Intensive Precipitation for corn	5.33	4.38	4.56
	Intensive Precipitation for soybeans	4.51	3.54	3.49
	Intensive Precipitation for wheat	1.00	0.96	1.07
Early_PRE	Precipitation during April and May	179.16	219.32	212.75

Note: The estimates mean the simple average among observations in each state.

Appendix A: proofs regarding the conceptual model

1. **WTS: $\partial EU(\pi_j|\delta)/\partial\delta < 0$ and $\partial^2 EU(\pi_j|\delta)/\partial\delta^2 < 0$**

Proof.

$$\partial EU(\pi \mid \delta)/\partial\delta =$$

$$\int_{-\mu}^{\mu}\int_{-P}^{P} U_\pi(\pi(\epsilon,\theta)\mid\delta)(P+\theta)\epsilon dF(\theta\mid\epsilon)dG(\epsilon) = \int_{-\mu}^{\mu}\epsilon E_\theta[U_\pi(\pi(\epsilon,\theta)\mid\delta)(P+\theta)]dG(\epsilon) =$$

$$\int_{0}^{\mu}\epsilon E_\theta[U_\pi(\pi(\epsilon,\theta)\mid\delta)(P+\theta)]dG(\epsilon) + \int_{-\mu}^{0}\epsilon E_\theta[U_\pi(\pi(\epsilon,\theta)\mid\delta)(P+\theta)]dG(\epsilon) =$$

$$< \int_{0}^{\mu}\epsilon E[U_\pi(\pi(0,\theta)\mid\delta)(P+\theta)]dG(\epsilon) + \int_{-\mu}^{0}\epsilon E[U_\pi\pi(0,\theta)(P+\theta)]dG(\epsilon) =$$

$$E[U_\pi(\pi(0,\theta)\mid\delta)(P+\theta)]\int_{-\mu}^{\mu}\epsilon dG(\epsilon) = 0$$

The inequality holds because $U_\pi(\pi(\epsilon,\theta)|\delta) < U_\pi(\pi(0,\theta)|\delta)$ when $\epsilon > 0$, and $U_\pi(\pi(\epsilon,\theta)|\delta) > U_\pi(\pi(0,\theta)|\delta)$ when $\epsilon < 0$. Also $U_{\pi\pi} < 0$, we can show that

$$\partial^2 EU(\pi\mid\delta)/\partial\delta^2 = \int_{-\mu}^{\mu}\int_{-P}^{P} U_{\pi\pi}(\pi(\epsilon,\theta)\mid\delta)(P+\theta)^2\epsilon^2 dF(\theta\mid\epsilon)dF(\epsilon) < 0$$

2. **Taylor expansion of $\partial EU(\pi_j|\delta)/\partial\delta$**

Based on Isik (2002), we can derive the below equation.

$$\partial EU(\pi\mid\delta)/\partial\delta \approx E\{[U_\pi(\bar\pi\mid\delta) + U_{\pi\pi}(\bar\pi\mid\delta)(\mu\theta+\delta\epsilon\theta+P\delta\epsilon)][P+\theta]\epsilon\mid\delta\}$$

$$= U_\pi(\bar\pi\mid\delta)E\{[P+\theta]\epsilon - \phi(\delta)[\mu\theta+\delta\epsilon\theta+P\delta\epsilon][P+\theta]\epsilon\mid\delta\}$$

$$= U_\pi(\bar\pi\mid\delta)\{-\phi(\delta)E[(\mu\theta+\delta\epsilon\theta+P\delta\epsilon)(P+\theta)\epsilon]\mid\delta\}$$

$$= U_\pi(\bar\pi\mid\delta)\{-\phi(\delta)[P\mu\sigma_\theta^2 + \delta\sigma_\theta^2\sigma_\epsilon^2]\}$$

where $\bar\pi = \mu P$ and $\phi = -U_{\pi\pi}(\bar\pi)/U_\pi(\bar\pi)$ means the Arrow-Pratt measure of absolute risk aversion. If we assume $\bar\pi$ is same between Crop 1 and Crop 2, the relative sizes of $\partial EU(\pi_j|\delta)/\partial\delta$ are determined by the variances of ε and θ of each crop.

3. **WTS: $\partial EU(\pi_j^{ins}|\delta)/\partial\delta$ can be positive**.

Proof. Before proving the hypothesis, we have to show some properties regarding expected indemnity.

$EU(\pi^{ins}|\delta)$ and $\partial EU(\pi^{ins}|\delta)/\partial\delta$ are as follows

$$EU(\pi^{ins}\mid\delta) = \begin{matrix} EU[\lambda\mu P + (\mu+\delta\epsilon)\theta - c - (1-s)v(\delta)] = EU[\pi_{lower}] \text{if } \epsilon \le \varphi \\ EU[(\mu+\delta\epsilon)(P+\theta) - c - (1-s)v(\delta)] = EU[\pi_{upper}] \text{if } \epsilon > \varphi \end{matrix}$$

$$\partial EU(\pi^{ins}\mid\delta)/\partial\delta = \int_{-P}^{P}\int_{-\mu}^{\varphi} U_\pi(\pi_{lower}(\epsilon,\theta)\mid\delta)[\theta\epsilon - (1-s)\frac{\partial v(\delta)}{\partial\delta}]dG(\epsilon)dF(\theta) +$$

$$\int_{-P}^{P}\int_{\varphi}^{\mu} U_\pi(\pi_{upper}(\epsilon,\theta)\mid\delta)[(P+\theta)\epsilon - (1-s)\frac{\partial v(\delta)}{\partial\delta}]dG(\epsilon)dF(\theta)$$

Claim 1: $\frac{\partial v(\delta)}{\partial \delta} > 0$

Let $\varphi = \frac{\lambda\mu-\mu}{\delta}$, then we know that only where $\epsilon < \varphi < 0$, the indemnity is paid.

$$v(\delta) = \int_{-\mu}^{\varphi} (\lambda\mu P - (\mu + \delta\epsilon)P)dG(\epsilon)$$

$$\frac{\partial v(\delta)}{\partial \delta} = -\{\frac{\varphi}{\delta}[\lambda\mu P - (\mu+\delta\varphi)P]g(\varphi) + \int_{-\mu}^{\varphi}(P+\theta)\epsilon dG(\epsilon)\} = -P\int_{-\mu}^{\varphi}\epsilon dG(\epsilon) > 0$$

Claim 2: $\partial EU(\pi^{ins}|\delta)/\partial\delta\,|_{s=1 or\ 0,\lambda=0} > 0$.

When s = 1 or 0 and λ = 0, $\varphi = -\mu$, $v(\delta) = 0$. Then,

$$\partial EU(\pi^{ins} \mid \delta)/\partial\delta\,|_{s=1 or\,0,\lambda=0} = \int_{-P}^{P}\int_{-\mu}^{\mu} U_\pi(\pi(\epsilon,\theta)\mid\delta)(P+\theta)\epsilon dG(\epsilon\mid\theta)dF(\theta)$$

$$= \partial EU(\pi\mid\delta)/\partial\delta < 0$$

Claim 3: $\partial EU(\pi^{ins}|\delta)/\partial\delta\,|_{s=1,\lambda=1} > 0$. When s = 1 and λ = 1, $\varphi = 0$. Firstly, we can easily show the below inequality.

$$\int_{-P}^{P}\int_{-\mu}^{0} U_\pi(\pi_{lower}(\epsilon,\theta)\mid\delta)\theta\epsilon dG(\epsilon)dF(\theta) =$$

$$\int_{-\mu}^{0}\epsilon[\int_{-P}^{0} U_\pi(\pi_{lower}(\epsilon,\theta)\mid\delta)\theta dF(\theta) + \int_{0}^{P} U_\pi(\pi_{lower}(\epsilon,\theta)\mid\delta)\theta dF(\theta)]dG(\epsilon) > 0$$

Based on the upper inequality, we can prove that

$$\partial EU(\pi^{ins}\mid\delta)/\partial\delta\,|_{s=1,\lambda=1} =$$

$$\int_{-P}^{P}\int_{-\mu}^{0} U_\pi(\pi_{lower}(\epsilon,\theta)\mid\delta)\theta\epsilon dG(\epsilon)dF(\theta) + \int_{-P}^{P}\int_{0}^{\mu} U_\pi(\pi_{upper}(\epsilon,\theta)\mid\delta)(P+\theta)\epsilon dG(\epsilon\mid\theta)dF(\theta) > 0$$

Claim 4: $\partial EU(\pi^{ins}|\delta)/\partial\delta\,|_{s=0} < 0$.

Let $\hat{\epsilon} = \int_{-\mu}^{\varphi} -\epsilon > 0$, $\tilde{\varepsilon} = \frac{P}{P+\theta}\int_{-\mu}^{\varphi} -\epsilon > 0$, then we can know that $\epsilon < \hat{\epsilon} \leftrightarrow p\epsilon - \frac{\partial v(\delta)}{\partial\delta} < 0$, $\epsilon < \tilde{\varepsilon} \leftrightarrow (P+\theta)\epsilon - \frac{\partial v(\delta)}{\partial\delta} < 0$, and $\pi_{upper}(\tilde{\varepsilon},\theta) = \mu(P+\theta) + \delta\hat{\epsilon}P - c - (1-s)v(\delta) > P\lambda\mu + \mu\theta + \delta\widehat{\theta\epsilon}P/(\theta+P) - c - (1-s)v(\delta) = \pi_{lower}(\tilde{\varepsilon},\theta)$. Based on these results, we can show that

$$\partial EU(\pi^{ins}\mid\delta)/\partial\delta\,|_{s=0} =$$

$$\int_{-P}^{P}\int_{-\mu}^{\varphi} U_\pi(\pi_{lower}(\epsilon,\theta)\mid\delta)[\theta\epsilon - \frac{\partial v(\delta)}{\partial\delta}]dG(\epsilon)dF(\theta) +$$

$$\int_{-P}^{P}\int_{\varphi}^{\mu} U_\pi(\pi_{upper}(\epsilon,\theta)\mid\delta)[(P+\theta)\epsilon - \frac{\partial v(\delta)}{\partial\delta}]dG(\epsilon)dF(\theta)$$

$$< \int_{-P}^{P} U_\pi(\pi_{lower}(\tilde{\varepsilon},\theta)\mid\delta)\int_{-\mu}^{\varphi}[\theta\epsilon - \frac{\partial v(\delta)}{\partial\delta}]dG(\epsilon)dF(\theta) +$$

$$\int_{-P}^{P} U_\pi(\pi_{upper}(\tilde{\varepsilon},\theta)\mid\delta)\int_{\varphi}^{\mu}[(P+\theta)\epsilon - \frac{\partial v(\delta)}{\partial\delta}]dG(\epsilon)dF(\theta) =$$

$$\int_{-P}^{P} U_\pi(\pi_{lower}(\tilde{\varepsilon},\theta)\,|\,\delta)\int_{-\mu}^{\varphi} \theta\epsilon dG(\epsilon)dF(\theta) - \frac{\partial v(\delta)}{\partial \delta}\int_{-P}^{P} U_\pi(\pi_{lower}(\tilde{\varepsilon},\theta)\,|\,\delta)\int_{-\mu}^{\varphi} dG(\epsilon)dF(\theta) +$$
$$\int_{-P}^{P} U_\pi(\pi_{upper}(\tilde{\varepsilon},\theta)\,|\,\delta)\int_{\varphi}^{\mu} (P+\theta)\epsilon dG(\epsilon)dF(\theta)$$
$$-\frac{\partial v(\delta)}{\partial \delta}\int_{-P}^{P} U_\pi(\pi_{upper}(\tilde{\varepsilon},\theta)\,|\,\delta)\int_{\varphi}^{\mu} dG(\epsilon)dF(\theta) <$$
$$\int_{-P}^{P} U_\pi(\pi_{lower}(\tilde{\varepsilon},\theta)\,|\,\delta)\theta\int_{-\mu}^{\mu} \epsilon dG(\epsilon)dF(\theta) + \int_{-P}^{P} U_\pi(\pi_{upper}(\tilde{\varepsilon},\theta)\,|\,\delta)\int_{\varphi}^{\mu} P\epsilon dG(\epsilon)dF(\theta) -$$
$$\frac{\partial v(\delta)}{\partial \delta}[\int_{-P}^{P} U_\pi(\pi_{lower}(\tilde{\varepsilon},\theta)\,|\,\delta)\int_{-\mu}^{\varphi} dG(\epsilon)dF(\theta) + \int_{-P}^{P} U_\pi(\pi_{upper}(\tilde{\varepsilon},\theta)\,|\,\delta)\int_{\varphi}^{\mu} dG(\epsilon)dF(\theta)] <$$
$$\int_{-P}^{P} U_\pi(\pi_{upper}(\tilde{\varepsilon},\theta)\,|\,\delta)\int_{\varphi}^{\mu} P\epsilon dG(\epsilon)dF(\theta) - \frac{\partial v(\delta)}{\partial \delta}\int_{-P}^{P} U_\pi(\pi_{upper}(\tilde{\varepsilon},\theta)\,|\,\delta)dF(\theta) = 0$$

The first inequality is holds because $\theta\epsilon - \frac{\partial v(\delta)}{\partial \delta} < 0$ when $\epsilon < 0 < \hat{\epsilon}$ for all θ. Also, we show that

$$\int_{-P}^{P}\int_{\varphi}^{\tilde{\varepsilon}} U_\pi(\pi_{upper}(\epsilon,\theta)\,|\,\delta)[(P+\theta)\epsilon - \frac{\partial v(\delta)}{\partial \delta}]dG(\epsilon)dF(\theta) +$$
$$\int_{-P}^{P}\int_{\tilde{\varepsilon}}^{\mu} U_\pi(\pi_{upper}(\epsilon,\theta)\,|\,\delta)[(P+\theta)\epsilon - \frac{\partial v(\delta)}{\partial \delta}]dG(\epsilon)dF(\theta) <$$
$$\int_{-P}^{P} U_\pi(\pi_{upper}(\tilde{\varepsilon},\theta)\,|\,\delta)\int_{\varphi}^{\mu}[(P+\theta)\epsilon - \frac{\partial v(\delta)}{\partial \delta}]dG(\epsilon)dF(\theta)$$

The second and third inequality holds because $U_\pi(\pi_{lower}(\tilde{\varepsilon},\theta)\,|\,\delta) > U_\pi(\pi_{upper}(\tilde{\varepsilon},\theta)\,|\,\delta)$ for all θ, and we can show that

$$\int_{-P}^{P} U_\pi(\pi_{lower}(\tilde{\varepsilon},\theta)\,|\,\delta)\int_{-\mu}^{\varphi} \theta\epsilon dG(\epsilon)dF(\theta) + \int_{-P}^{P} U_\pi(\pi_{upper}(\tilde{\varepsilon},\theta)\,|\,\delta)\int_{\varphi}^{\mu} \theta\epsilon dG(\epsilon)dF(\theta) <$$
$$\int_{-P}^{P} U_\pi(\pi_{lower}(\tilde{\varepsilon},\theta)\,|\,\delta)\int_{-\mu}^{\mu} \theta\epsilon dG(\epsilon)dF(\theta)$$

The last equality is based on the fact that $-P\int_{-\mu}^{\varphi}\epsilon dG(\epsilon) = P\int_{\varphi}^{\mu}\epsilon dG(\epsilon) = \frac{\partial v(\delta)}{\partial \delta}$

Since $\partial EU(\pi^{ins}|\delta)/\partial\delta$ is a continuous function of λ, by intermediate theorem, we can know that there exists a unique λ^* such that $\partial EU(\pi^{ins}|\delta)/\partial\delta > 0$ when $s = 1$ and $\lambda > \lambda^*$. Also, because $\frac{\partial EU(\pi^{ins}|\delta)}{\partial\delta}|_{s=0} < 0$ and $\frac{\partial EU(\pi^{ins}|\delta)}{\partial\delta}$ is continuous function of s, there exists $(\hat{\lambda}, \hat{s})$ such that $\frac{\partial EU(\pi^{ins}|\delta)}{\partial\delta}|_{\lambda>\hat{\lambda}, s>\hat{s}} > 0$ by the intermediate value theorem (Miao, Hennessy, & Feng 2016).

Appendix B: How to derive empirical model

Fishe, Trost, and Lurie (1981) shows that

$$E(\epsilon_{ij} \mid \tau_{ij}^* > 0, \omega_{ij}^* > 0) = \sigma_{jj}^{\tau} M_{12} + \sigma_{jj}^{\omega} M_{21}$$
$$E(\epsilon_{ij} \mid \tau_{ij}^* > 0, \omega_{ij}^* \le 0) = \sigma_{jj}^{\tau} M_{34} + \sigma_{jj}^{\omega} M_{43} \qquad (13)$$

where $M_{lk} = (1-\rho^2)^{-1}[P_l - \rho P_k]$ for $l, k \in [1, \dots, 4]$, and

$$P_1 = \int_{-S_{ij}\eta_j}^{\infty} \int_{-Z_{ij}\gamma_j}^{\infty} e_{ij} dF(e_{ij}, v_{ij}) / F(-Z_{ij}\gamma_j, -S_{ij}\eta_j, \rho_j)$$

$$P_2 = \int_{-S_{ij}\eta_j}^{\infty} \int_{-Z_{ij}\gamma_j}^{\infty} v_{ij} dF(e_{ij}, v_{ij}) / F(-Z_{ij}\gamma_j, -S_{ij}\eta_j, \rho_j)$$

$$P_3 = \int_{-\infty}^{-S_{ij}\eta_j} \int_{-Z_{ij}\gamma_j}^{\infty} e_{ij} dF(e_{ij}, v_{ij}) / F(Z_{ij}\gamma_j, -S_{ij}\eta_j, -\rho_j)$$

$$P_4 = \int_{-\infty}^{-S_{ij}\eta_j} \int_{-Z_{ij}\gamma_j}^{\infty} v_{ij} dF(e_{ij}, v_{ij}) / F(Z_{ij}\gamma_j, -S_{ij}\eta_j, -\rho_j)$$

Based on normality assumptions,

$$\int_{-S_{ij}\eta_j}^{\infty} \int_{-Z_{ij}\gamma_j}^{\infty} e_{ij} dF(e_{ij}, v_{ij}) = \int_{-S_{ij}\eta_j}^{\infty} \int_{-Z_{ij}\gamma_j}^{\infty} e_{ij} f(e_{ij} \mid v_{ij}) f(v_{ij}) de_{ij} dv_{ij} =$$

$$\int_{-S_{ij}\eta_j}^{\infty} \int_{-Z_{ij}\gamma_j}^{\infty} -\frac{\partial f(e_{ij} \mid v_{ij})}{\partial e_{ij}} (1-\rho^2) f(v_{ij}) de_{ij} dv_{ij} + \int_{-S_{ij}\eta_j}^{\infty} \int_{-Z_{ij}\gamma_j}^{\infty} \rho v_{ij} f(e_{ij} \mid v_{ij}) f(v_{ij}) de_{ij} dv_{ij}$$

The second equality holds because

$$\frac{\partial f(e_{ij} \mid v_{ij})}{\partial e_{ij}} = \frac{1}{\sqrt{2\pi}\sqrt{1-\rho^2}} \exp\left(\frac{-(e_{ij} - \rho v_{ij})^2}{2(1-\rho^2)}\right)\left(\frac{\rho v_{ij} - e_{ij}}{(1-\rho^2)}\right).$$

Also, we can verify that the last term of the above equation is ρP_2. The first term becomes

$$\int_{-S_{ij}\eta_j}^{\infty} \frac{\partial}{\partial e_{ij}} \int_{-Z_{ij}\gamma_j}^{\infty} -f(e_{ij} \mid v_{ij})(1-\rho^2) f(v_{ij}) de_{ij} dv_{ij} = \int_{-S_{ij}\eta_j}^{\infty} f(-Z_{ij}\gamma_j \mid v_{ij})(1-\rho^2) f(v_{ij}) dv_{ij}$$

$$= \int_{-S_{ij}\eta_j}^{\infty} \frac{(1-\rho^2)}{2\pi\sqrt{1-\rho^2}} \exp\left(\frac{-(v_{ij} + \rho Z_{ij}\gamma_j)^2}{2(1-\rho^2)}\right) \exp\left(\frac{-(Z_{ij}\gamma_j)^2}{2}\right) dv_{ij}$$

$$= \phi(Z_{ij}\gamma_j)\Phi\left(\frac{S_{ij}\eta_j - \rho Z_{ij}\gamma_j}{\sqrt{1-\rho^2}}\right)(1-\rho^2)$$

With the similar way, we can derive below relationships between P_l for $l \in [1, \dots, 4]$.

$$
\begin{aligned}
P_1 &= \phi(Z_{ij}\gamma_j)\Phi\left(\frac{S_{ij}\eta_j - \rho Z_{ij}\gamma_j}{\sqrt{1-\rho^2}}\right)(1-\rho^2) + \rho P_2 \\
P_2 &= \phi(S_{ij}\eta_j)\Phi\left(\frac{Z_{ij}\gamma_j - \rho S_{ij}\eta_j}{\sqrt{1-\rho^2}}\right)(1-\rho^2) + \rho P_1 \\
P_3 &= \phi(Z_{ij}\gamma_j)\Phi\left(\frac{-S_{ij}\eta_j + \rho Z_{ij}\gamma_j}{\sqrt{1-\rho^2}}\right)(1-\rho^2) + \rho P_4 \\
P_4 &= -\phi(S_{ij}\eta_j)\Phi\left(\frac{Z_{ij}\gamma_j - \rho S_{ij}\eta_j}{\sqrt{1-\rho^2}}\right)(1-\rho^2) + \rho P_3
\end{aligned} \tag{14}
$$

When we enter Equation (14) into Equation (13), then we can get Equation (8). Lastly, since we assume $e_{ij} \perp e_{ik}$, $v_{ij} \perp v_{ik}$, and $e_{ij} \perp v_{ik}$ for $j \neq k$, we can control for the correlation between e_{ij} and ε_{ik} by adding correction terms in Equation (7) (Lacroix and Thomas 2011). To derive the Equation (9), put Equation (8) into Equation (7) as follows.

$$
\begin{aligned}
& E(A_{ij}^* \mid X_{ij}, S_{ij}, Z_{ij}) = P_1 X_{ij}\alpha_j + (P_1+P_2)[X_{ij}\beta_j + \sum_{j\neq k}^{4}\sigma_{jk}^{\tau}\lambda_{ik}] + \\
& \sigma_{jj}^{\tau}\phi(Z_{ij}\gamma_j)\Phi(S_{ij}^*) + \sigma_{jj}^{\omega}\phi(S_{ij}\eta_j)\Phi(Z_{ij}^*) + \sigma_{jj}^{\tau}\phi(Z_{ij}\gamma_j)\Phi(-S_{ij}^*) - \sigma_{jj}^{\omega}\phi(S_{ij}\eta_j)\Phi(Z_{ij}^*) = \\
& P_1 X_{ij}\alpha_j + (P_1+P_2)[X_{ij}\beta_j + \sum_{j\neq k}^{4}\sigma_{jk}^{\tau}\lambda_{ik}] + \sigma_{jj}^{\tau}\phi(Z_{ij}\gamma_j) = \\
& P_1 X_{ij}\alpha_j + (P_1+P_2)[X_{ij}\beta_j + \sum_{j\neq k}^{4}\sigma_{jk}^{\tau}\lambda_{ik} + \frac{\sigma_{jj}^{\tau}\phi(Z_{ij}\gamma_j)}{(P_1+P_2)}] = \\
& \Phi(Z_{ij}\gamma_j)[X_{ij}\beta_j + \sum_{k=1}^{4}\sigma_{jk}^{\tau}\lambda_{ik}] + \Phi_2(Z_{ij}\gamma_j, S_{ij}\eta_j; \rho_j)X_{ij}\alpha_j
\end{aligned}
$$

The second equality holds because $\Phi(-S_{ij}^*) = 1 - \Phi(S_{ij}^*)$. Also, the last quality is based on the fact that $P_1 + P_2 = P(\tau_{ij}^* > 0, \omega_{ij}^* > 0 | Z_{ij}, S_{ij}) + P(\tau_{ij}^* > 0, \omega_{ij}^* \leq 0 | Z_{ij}, S_{ij}) = P(\tau_{ij}^* > 0 | Z_{ij})$.

Appendix C: Climate Variables

To calculate GDD and HDD, we consider below four cases, and HDD is only calculated at case 3 and case 4.

- Case 1: tmin $\geq$ lower, GDD=M-lower and HDD=0

- Case 2: tmin < lower and tmax $\leq$ upper,

  GDD=(M-lower)/(π/2-θ)+Wcos(θ)/π and HDD=0

  where θ=arcsin((lower-M)/W)

- Case 3: tmin $\geq$ lower and tmax > upper

  GDD=M-lower-(M-upper)($\pi/2-\tau$)+Wcos(τ)/π

  HDD=(M-upper)($\pi/2-\tau$)+Wcos(τ)/π where τ=arcsin((upper-M)/W)

- Case 4: tmin < lower and tmax > upper

  GDD=(M-lower)/(π/2-θ)+Wcos(θ)/π-(M-upper)($\pi/2-\tau$)+Wcos(τ)/π

  HDD=(M-upper)($\pi/2-\tau$)+Wcos(τ)/π

where “upper” and “lower” mean the upper threshold and the lower threshold, respectively. The upper threshold is 34℃, and the lower threshold is 8℃ (Ritchie & NeSmith, 1991). “tmax” is a daily maximum temperature, and “tmin” is a daily minimum temperature. Lastly, M = (tmax+ tmin)/2 and W=(tmax-tmin)/2.

CHAPTER 3

ECONOMIC AND ENVIRONMENTAL IMPLICATIONS OF BIOTECHNOLOGY AND INFORMATION TECHNOLOGY

Jae-hoon Sung and John A. Miranowski

Abstract

Technology adoption has significant effects on corn yield and nutrient management for corn production. Over the last decade, the adoption of genetically modified (GM) corn and information technologies has increased. We analyze the effects of GM corn, pest scouting, and yield monitoring on corn yield and nutrient management of Midwest farmers. We incorporate a nonlinear endogenous regression approach to control for self-selection bias, and the Agricultural Resource Management Survey is used for estimation. We find that GM corn and its combination with pest scouting increase corn yield and nitrogen use. Also, the effects of GM corn and/or pest scouting depend on soil productivity. Last, the relationship between yield monitoring and pest scouting is complementary in increasing corn yield and nitrogen use.

3.1 Introduction

Identifying the effects of technology adoption on corn yield and nutrient management is important to understand the economic and environmental implications of technology adoption. Gains in corn yield as a result of technology adoption can increase profitability by increasing corn yield (revenue) and further exceeding production costs or by maintaining corn yield (revenue) and further reducing production costs. If profitability improves through the adoption of technology that reduces nitrogen use per bushel of corn – that is, improved nitrogen use efficiency (NUE) – nitrogen pollution from runoff, leaching, and volatilization in corn fields can be reduced.[1]

This study investigates the economic and environmental implications of the adoption of genetically modified (GM) corn and information technologies in the context of corn yield and nutrient management. The adoption of GM corn and information technologies has increased over time and the adoption of GM corn increased fairly rapidly after the introduction of commercial GM corn in 1996. In 2013, the proportion of GM corn to total corn acreage reached 88% (Fernandez-Cornejo et al. 2014). The adoption of information and precision agricultural technologies progressed at a slower pace. Pest scouting, for example, is the most widely adopted information technology. In 2014, weed scouting and insect scouting were used on 94% and 90% of Iowa corn acreage, respectively (NASS quick stat). The adoption of yield monitor, which is the first stage in the adoption of precision agriculture, increased to roughly 70% of Midwest corn acreage in 2010 (see Figure 3.1).

The increased adoption of GM corn and information technologies reflects the profitability of adopting these technologies, as shown by gains in corn yield and NUE (Schimmelpfennig & Ebel 2011; Fernandez-Cornejo et al. 2014). GM corn adopters can increase corn yield by

[1] We define NUE as nitrogen applied per bushel of corn yield (pound of nitrogen per one bushel of corn).

decreasing yield loss from pests. GM corn enables adopters to suppress pest populations more efficiently than farmers who use conventional varieties. Herbicide-tolerant (HT) corn also allows farmers to rely heavily on glyphosate, thereby reducing the use of more environmentally detrimental herbicides. Insect-resistant (Bt) corn produces a toxic protein that targets insects damaging the plant above and below ground. In addition, the Bt trait facilitates efficient water and nutrient uptake of the plant through an improved corn root system (Miranowski, Rosburg, & Aukayanagul 2011) and the HT trait reduces weed competition for water and nutrients for the plant.

Information technologies may have positive effects on corn yield and NUE. Pest scouting provides information on pest infestation, pesticide performance, and pest resistance during the growing season. Farmers who adopt pest scouting can more effectively control pest infestation in their fields and minimize damage to corn yield. Furthermore, we can consider pest scouting as an indicator of general crop management. High adoption of weed scouting, insect scouting, and scouting for diseases suggests that most of the pest scouting adopters adopt the three technologies at the same time (NASS quick stat). Also, pest scouting is closely related to nutrient, soil, and water management.[2]

Yield monitor generates field-level information regarding corn yield distribution, soil conditions, and results of crop management practices during the previous year. Farmers may use this information when determining the most profitable crop management system for each corn field prior to planting season. In addition, yield monitor may encourage farmers to apply nitrogen based on corn yield distribution within and among fields and potentially improve NUE. Thus,

[2] For example, our data show that more than 82% of soil testing adopters also adopted pest scouting and irrigated farms are more likely to use soil testing and pest scouting at the same time. In addition, nitrogen use and tillage systems are important factors of integrated pest management (Evans et al. 2003a; Evans et al. 2003b; Horowitz, Ebel, & Ueda 2010).

farmers may have an incentive to increase nitrogen use on certain areas of fields or fields with higher yield potential but reduce applications on more marginal areas.

This study also investigates the relationship among GM corn, pest scouting, and yield monitoring in improving corn yield and nutrient management. It is desirable to analyze the effects of adopting these technologies jointly to correctly measure the effects of GM corn and information technologies on crop management. Technology adoption decisions are made simultaneously, and the effects of one technology depend on its combination with another. For example, suppose farmers who adopt GM corn are more likely to adopt pest scouting. If pest scouting is not considered, comparing corn yield across fields will overestimate the yield effects of GM corn when pest scouting has positive effects on corn yield.

In this study, we seek to answer the following specific three research questions: (1) Does the adoption of GM corn and pest scouting increase corn yield, nitrogen use, and NUE? (2) Is the relationship between GM corn and pest scouting complementary in improving corn yield and nutrient management? (3) How does information from yield monitor alter corn yield and nutrient management of farmers who adopt GM corn and/or pest scouting? To answer these questions, we construct and estimate equations for corn yield, nitrogen use, and NUE based on the technology adoption status of individual farmers. An endogenous switching regression approach is applied to control for the effects of unobserved factors in technology adoption. We use extensive field-level information based on Agricultural Resource Management Survey (ARMS) data for our estimation. Results show that adopting GM corn and information technologies increases corn yield and nitrogen use but has insignificant effects on NUE. We also find that the effects of adopting GM corn and/or pest scouting on corn yield and nitrogen use are larger for fields having low soil productivity.

The study is organized as follows. Section 2 reviews relevant literature. Section 3 explains the effects of technology adoption on corn yield and nutrient management by using a simple conceptual model. Section 4 provides the model specifications and related assumptions. Section 5 explains the implications of selected variables and the construction of field-level data. Section 6 discusses the results and economic implications. Section 7 provides the conclusions. References, summary statistics, and estimation results are shown at the end of the paper. The last section is the Appendix, which includes results of robustness checks and supplementary tables.

3.2 Literature review

An extensive body of agricultural economics literature has analyzed the relationship between GM crops and agricultural production.[3] Fernandez et al. (2014) summarize extensive empirical studies on implications of adopting GM crops with respect to yield, pesticide use, and net return. Bt and stacked trait seeds are shown to increase crop yields and net return while simultaneously decreasing insecticide use. HT corn is a cost-reducing technology. Farmers receive monetary and non-monetary benefits, such as reduced time and cost of weed management, by adopting HT corn. However, the effects of HT seeds on crop yields and herbicide use have not yet been addressed (Nolan & Santos 2012).

Compared with the yield effects of GM corn, the effects of GM corn adoption on nutrient management are less well known. In addition, scouting has been examined to measure its effects only on pest management (Carson 1970; Miranowski, Ernst, & Cummings 1974; Yee & Ferguson 1996; Mishra, Nimon, & El-Osta 2005). Literature on yield monitor has focused on general information about precision agriculture, including yield monitor, yield and soil maps, and variable-rate technology and their adoption rates (Griffin & Lowenberg-DeBoer 2005; Schimmelpfennig

[3] Fernandez-Cornejo et al. (2014), Bennet et al. (2013), and Qaim (2009) summarize the effects of GM corn adoption on agricultural production, adopters' welfare, regional environment conditions, and consumer demand.

& Ebel 2011). Only Miranowski, Rosburg, & Aukayangul (2011) discuss the implications of GM crop development on NUE. They argue that increased corn yield will decrease the amount of land and nitrogen required to produce the same amount of corn in 2009 by 17 to 27 million acres and by 0.6 to 1.4 million metric tons of nitrogen in 2030.

Previous literature has emphasized the self-selection problem in measuring the effects of adopting agricultural technologies. Qaim (2009) and Nolan & Santos (2012) argue that the lack of field-level or farm-level information can cause selectivity bias. Shi et al. (2013) explain that the quality of germplasm between conventional corn and GM corn is systematically different and show that this unobserved difference can be a source of selectivity bias. To overcome this problem, an endogenous switching regression has been used to analyze the effects of agricultural technology adoption on economic outcomes of crop management practices (Fuglie & Bosch 1995; Wu & Babcock 1998; Khanna 2001). In particular, Lee (1983) suggests an approach to formulating a polychotomous choice problem with mixed continuous and discrete dependent variables. Based on this approach, endogenous switching regression models can be incorporated to evaluate the effects of alternative combinations of technologies (Wu & Babcock 1998). However, previous literature does not always consider nonnegative corn yield and nitrogen use despite nitrogen use and corn yield always being greater than or equal to zero. Terza (1998) shows how to extend an endogenous switching regression approach to models having an exponential functional form. In this study, we merge Lee (1983) and Terza (1998) to construct a polychotomous choice selectivity model with an exponential functional form. The advantages of our approach are its consideration of selectivity bias in technology adoption and its guarantee of nonnegative outcome variables. Moreover, this approach allows us to evaluate the effects of adopting alternative combinations of technologies and the effects of adoption of an individual technology at the same time.

Insufficient empirical evidence regarding the effects of GM corn, information technologies on corn yield, and nutrient management may be an obstacle to understanding the costs and benefits of adopting the technologies. We expect that our empirical study will contribute to filling this gap. In addition, our results are based on extensive field-level data covering the 13 major corn-producing states. Moreover, by using weights in field-level data, we can generalize our results in a statistically reliable manner. Thus, our results should be more general and credible than those of previous studies.

3.3 Conceptual model

Consider a risk-neutral farmer who uses nitrogen (x_{nit}) and a vector of other agricultural inputs ($\boldsymbol{x}$) to grow corn. We assume that nitrogen is essential in corn production, and the effect of technology adoption on corn production can be captured by incorporating a function $h(\boldsymbol{z})$ in the production function. Also, we assume that the effects of technology adoption depend on given environmental conditions and characteristics of the farmer ($\boldsymbol{z}$), such as soil productivity and human capital. We thus define the production function as $y = f(x_{nit}, \boldsymbol{x}, \varepsilon, h(\mathbf{z}))$, where y is corn yield and ε is a random variable (Koundouri, Nauges, & Tzouvelekas 2006). Assume that $f' > 0$ and $f'' < 0$ for all elements. If we assume only production uncertainty, then the farmer's expected utility maximization problem can be represented as follows:

$$\max_{x_{nit},x} E\{\pi\} = \max_{x_{nit},x} E\{pf(x_{nit}, \mathbf{x}, \varepsilon, h(\mathbf{z})) - r_{nit}x_{nit} - \mathbf{x}'\mathbf{r}\} \quad (1)$$

where p means a corn price. r_{nit} and r mean a nitrogen price and a vector of other input prices, respectively. Then, we can derive the first-order condition for nitrogen use as Equation (2).

$$\frac{r_{nit}}{p} = E\{\frac{\partial f(x_{nit}, \mathbf{x}, \varepsilon, h(\mathbf{z}))}{\partial x_{nit}}\} \quad (2)$$

To illustrate the effects of technology adoption on nitrogen use, assume that the farmer's decisions on technology adoption can be modeled by a binary choice: adopting new technology ($h_1(\boldsymbol{z})$) and using conventional technology ($h_0(\boldsymbol{z})$), Also, assume that the equality in Equation (2) holds at $x_{nit} = x_{0,nit}$ before adopting new technology.

From Equation (2), we can show that, when adopting new technology increases the marginal productivity of nitrogen use, $\frac{\partial f(x_{nit}, \boldsymbol{x}, \varepsilon, h_1(\boldsymbol{z}))}{\partial x_{nit}}|_{x_{nit}=x_{0,nit}} > \frac{\partial f(x_{nit}, \boldsymbol{x}, \varepsilon, h_0(\boldsymbol{z}))}{\partial x_{nit}}|_{x_{nit}=x_{0,nit}}$, the farmer will increase nitrogen use up to $x_{1,nit}$ satisfying $\frac{\partial f(x_{nit}, \boldsymbol{x}, \varepsilon, h_1(\boldsymbol{z}))}{\partial x_{nit}}|_{x_{nit}=x_{1,nit}} = \frac{\partial f(x_{nit}, \boldsymbol{x}, \varepsilon, h_0(\boldsymbol{z}))}{\partial x_{nit}}|_{x_{nit}=x_{0,nit}} = \frac{r_{nit}}{p}$. Also, when technology adoption changes the marginal productivity of agricultural inputs, the optimal input use is changed, and this change may affect corn yield indirectly. Thus, we can express yield gains resulting from technology adoption as $\Delta y\ (\varepsilon, \boldsymbol{z}) = f\left(x_{1,nit}, \boldsymbol{x_1}, \varepsilon, h_1(\boldsymbol{z})\right) - f\left(x_{0,nit}, \boldsymbol{x_0}, \varepsilon, h_0(\boldsymbol{z})\right)$. Last, Equation (2) shows that changes in the marginal productivity of nitrogen (or agricultural inputs) resulting from technology adoption may depend on given conditions. Thus, we can infer that yield gains resulting from technology adoption depend on $\boldsymbol{z}$, and $\Delta y\ (\varepsilon, \boldsymbol{z_1})$ differs from $\Delta y\ (\varepsilon, \boldsymbol{z_0})$ when $\boldsymbol{z_1} \neq \boldsymbol{z_0}$.

From the conceptual approach, we can answer our research questions with a simple optimization problem. The model shows that technology adoption can increase nitrogen use and corn yield simultaneously when technology adoption increases the marginal productivity of nitrogen use. In the next section, we attempt to find empirical evidence to test our research hypotheses.

3.4 Empirical model and estimation

To evaluate the effect of technology adoption, we must account for two features of corn yield and nutrient management. First, we cannot observe the extent to which technology adopters use nitrogen or increase corn yield without adopting technology. Second, decisions regarding technology adoption are voluntary. Unobserved individual conditions may simultaneously affect corn yield (nutrient management) and farmers' decisions regarding technology adoption. For instance, pest scouting is more beneficial in high pest pressure environments. Thus, comparison between corn yield of pest scouting adopters in high pest pressure environments and corn yield of non-adopters in low pest pressure environments leads a downward bias in the effects of pest scouting on corn yield. Technology adoption, thus, can be non-random, and corn yield and nutrient management of farmers who adopt technology differs systematically from corn yield and nutrient management of randomly selected farmers with the same individual characteristics.

To account for these features, we apply a polychotomous choice selectivity model (Lee 1983) to conceptualize farmers' incentives regarding technology adoption and simultaneously control for the self-selection problem. A polychotomous choice selectivity model of technology adoption consists of two parts. The first part analyzes farmers' decisions on technology adoption. The second part estimates the effects of technology adoption on corn yield and nutrient management, conditional on technology adoption status.

3.4.1 Decision regarding technology adoption

Suppose farmer *i* can choose from *M* possible combinations of GM corn and information technologies. Let $U_{i,j}$ represent farmer *i*'s expected utility from adopting combination j, and $I_{i,j}$ be an index representing farmer *i*'s decision on adopting combination j. Then, the farmer's observable choice among *M* combinations can be represented by $I_{i,j} = 1$ if $U_{i,j} = \max\{U_{i,1}, \dots, U_{i,M}\}$. We assume that $U_{i,j}$ is a linear function of observed explanatory variables (Z_i):

$$U_{i,j} = Z_i^{'}\gamma_j + \varepsilon_{i,j} \tag{3}$$

where γ_j is the vector of parameters, and $\varepsilon_{i,j}$ is independent and identically distributed according to the type I extreme value distribution.[4]

3.4.2 Corn yield, nitrogen use, and NUE

Since technology adoption can alter the productivity of agricultural inputs and farmers' knowledge of their field conditions, farmers' responses to given exogenous conditions may depend on their technology adoption status (Kaminski, Kan, & Fleischer 2012). We thus specify equations representing farmer *i*'s corn yield, nitrogen use, and NUE based on his technology adoption status. Based on this approach, the differences in size and direction of coefficients corresponding to each explanatory variable among the equations can be interpreted as slope changes caused by technology adoption.[5]

To control for non-negativity of our outcome variables (*Y*), we use a log transformation and apply ordinary least squares (OLS) for estimation. However, a log transformation does not account for observations whose outcome variables equal zero.[6] In addition, when the error term is heteroscedastic, the estimate of the expected outcome variables, $E(Y|X)$, based on a log transformation can be biased (Manning & Mullahy 2001; Wooldridge 2010, pp. 740). To overcome these disadvantages, this study incorporates the exponential functional form as Equation (4).

$$Y_{i,j} = \exp(X_i^{'}\beta_j + e_{i,j}) \text{ if } I_{i,j} = 1 \text{ for } j = 1, \ldots, M \tag{4}$$

where $Y_{i.}$ is one of the outcome variables conditional on farmer *i*'s technology adoption. The expected values of Equation (5) are as follow:

[4] We assume no dependency among $\varepsilon_{i,j}$ for simplicity. We can generalize this assumption by using a multinomial probit model. However, a mutinomal probit model is more difficult to estimate than a multinomial logit model.
[5] Another way to capture slope changes resulting from technology adoption is to include interaction terms between technology adoption and explanatory variables. However, this approach makes the model too large and would generate problems regarding multicollineality.
[6] In our data set, 4% of observations did not apply nitrogen for corn production.

$$E(Y_{i,j} \mid I_{i,j}=1)=\exp(X_i^{'}\beta_j)E(\exp(e_{i,j}) \mid I_{i,j}=1) \text{ for } j=1,..,M \tag{5}$$

3.4.3 Nonlinear regression with endogenous switching

To account for the correlation between Equation (3) and Equation (4) caused by omitted variables, we transform $\varepsilon_{i,j}$ as $\varepsilon_{i,j}^{*}=\Phi^{-1}(F(\varepsilon_{i,j}))$ where Φ is a cumulative density function of the standard normal distribution and F is the marginal distribution of $\varepsilon_{i,j}$ (Lee 1983). This transformation makes $\varepsilon_{i,j}^{*}$ follow the independent standard normal distribution. Based on this transformation, we assume that $(\varepsilon_{i,j}^{*}, e_{i,j})$ follows bivariate normal distribution with a mean of zero and the following covariance matrix:

$$Cov(\varepsilon_{i,j}^{*}, e_{i,j})=\begin{bmatrix} 1 & \sigma_{\varepsilon e}^{j} \\ \sigma_{\varepsilon e}^{j} & \sigma_j^2 \end{bmatrix} \tag{6}$$

where $Var(e_{i,j})=\sigma_j^2$, $Cov(\varepsilon_{i,j}^{*}, e_{i,j})=\sigma_{\varepsilon e}^{j}$ for $j=1, \ldots, M$. Also, the independence assumption regarding $\varepsilon_{i,j}$ implies that $Cov(\varepsilon_{i,j}^{*}, e_{i,M})=\sigma_{\varepsilon e}^{M}$ for $j=1,\ldots, M$. With the covariance matrix in Equation (6), Terza (1998) shows that the conditional expectation of $e_{i,j}$ is as follows:

$$E(\exp(e_{i,j}) \mid I_{i,j}=1)=\exp(\frac{\sigma_j^2}{2})\frac{\Phi(\Phi^{-1}(F(Z_i\gamma_j))-\sigma_{\varepsilon e}^{j})}{F(Z_i\gamma_j)} \tag{7}$$

As a result, the following equation is estimated for all combinations separately:

$$Y_{i,j}=\exp(X_i^{'}\beta_j+\frac{\sigma_j^2}{2})\frac{\Phi(\Phi^{-1}(F(Z_i\gamma_j))-\sigma_{\varepsilon e}^{j})}{F(Z_i\gamma_j)}+\xi_{i,j} \text{ if } I_{i,j}=1 \tag{8}$$

where $\xi_{i,j}=Y_{i,j}-E(Y_{i,j})$ for j=1, …, M. The latter term in Equation (8) is a correction term accounting for self-selection. Selectivity bias is tested for $\sigma_{\varepsilon e}^{j}=0$ for j=1, …, M. If $\sigma_{\varepsilon e}^{j}=0$ is rejected, there is self-selection bias in adopting combination j.

One advantage of this approach is that we can examine the average treatment effect of combination j on farmers who adopt combination j (Wu & Babcock 1998). Suppose at least one technology is included in combination $j < M$, and no technology is contained in combination *M*. For farmer *i* with characteristics *(X, Z)* who has used combination $j < M$, the expected change in *Y* for farmer *i* due to the adoption of combination *j* can be calculated by Equation (9).

$$\Delta Y_{j,M}^{i} = E(Y_{i,j} \mid I_{i,j} = 1) - E(Y_{i,M} \mid I_{i,j} = 1) =$$
$$\exp(X_i^{'}\beta_j + \frac{\sigma_j^2}{2})\frac{\Phi(\Phi^{-1}(F(Z_i\gamma_j)) - \sigma_{\varepsilon e}^{j})}{F(Z_i\gamma_j)} - \exp(X_i^{'}\beta_M + \frac{\sigma_M^2}{2})\frac{\Phi(\Phi^{-1}(F(Z_i\gamma_j)) - \sigma_{\varepsilon e}^{M})}{F(Z_i\gamma_j)} \quad (9)$$

The first term of Equation (9) means the expected value of *Y* for farmer *i*, and the latter term indicates the expected value of *Y* when farmer *i* does not adopt any technology (combination *M*). To calculate the expected change in *Y* for adopters of combination *j*, we use the weighted average of $\Delta Y_{j,M}^{i}$ for fields whose operators adopted combination *j*, with sampling weights in our data.

3.4.4 Estimation

Terza (2009) and Wooldridge (2010, pp. 724-748, 2014) suggest a two-step method for estimating a nonlinear endogenous switching regression model. The first step is to estimate Equation (3) by using a multinomial logit model to obtain consistent estimates of γ_j. Second, we estimate Equation (8) with a Poisson quasi-maximum likelihood estimator (QMLE). Gourieroux, Monfort, and Trognon (1984) show that a QMLE based on a linear exponential family (LEF) generates consistent estimates when the conditional mean function is correctly specified and its range is identical to the range of the chosen LEF density. The conditional mean function based on an exponential functional form such as Equation (5) is nonnegative and has no upper bound, which coincides with the range of Poisson distribution. Thus, we can estimate Equation (5) consistently by using the Poisson QMLE provided the conditional expectation in Equation (5) is correctly specified. In particular, since the consistency of the Poisson QMLE does not depend on the Poisson distributional assumption, we can apply the Poisson QMLE even when dependent variables are not count variables (Wooldridge 2010, pp. 727-728).

Variance estimates from the two-step method are not consistent because variance estimates generated from the second-step do not take into account the variation of first-step estimates. Also, our data set is non-random, which indicates that sampling design should be taken into account for inference (Dubman 2000). Although the United States Department of Agriculture (USDA) provides replicate weights for delete-a-group jackknife estimators, the number of replicate weights has changed since 2008. Goodwin, Mishra, and Ortalo-Magné (2003) suggest that a jackknife procedure may not be appropriate when using only a subset of the data. We adopt a bootstrapping method based on probability weights (Goodwin & Mishra 2005). That is, we generate 1,000 bootstrap samples based on probability weights and estimate Equations (3), (8), and (9) 1,000 times. The mean and variance of the replicated estimates are used as estimates of parameters and their variances (Goodwin, Mishra, & Ortalo-Magné 2003; Goodwin & Mishra 2005).[7]

3.4.5 Identification

One disadvantage of the two-step approach is identification of parameters in the second step. When variables affecting technology adoption and outcomes variables (Y) are identical, problems regarding multicollinearity can arise during the estimation. For identification, we impose at least one exclusion restriction on Z (Terza, Basu, & Rathouz 2008; Terza 2009; Wooldridge 2014). That is, we include variables which are not included in X and satisfy conditions of instrument variables in Z, in addition to X. To follow the restriction, we use the multi-state GM corn prices, off-farm work hours per year of an operator and his or her spouse, and farmers'

[7] This approach is based on the assumption that the sampling scheme of the data and population of samples are constant for 2001, 2005, and 2010 ARMS data.

financial status.[8] Since GM corn can lower labor requirements for chemical management, a high degree of commitment to off-farm work increases farmers' incentive to adopt GM corn (Gould, Saupe, & Klemme 1989; Fernandez-Cornejo 2007; Fernandez-Cornejo et al. 2014). We include farmers' total debt and equity to control for their financial status. Credit constraints impede technology adoption (Feder et al. 1985; Fernandez-Cornejo 2007); however, the effects of farmers' financial status are not determined. Large farms are more likely to have high levels of debt and equity (Ifft, Novini, & Patrick 2014; Ifft, Kuethe, & Morehart 2015). Since large farms can spread the cost of technology adoption, they are more likely to adopt new technologies (Schimmelpfennig & Ebel 2011).[9] Last, we assume that GM corn prices, farmers' off-farm work, and financial status influence farmers' technology adoption but not necessarily corn yield and nutrient management.

3.5 Data and model specification

We use ARMS Phase II and Phase III version 2 (2001, 2005, and 2010) data for this study. The ARMS Phase II and Phase III version 2 data contain different but complementary information regarding farmers' corn-growing operations. The ARMS Phase II data include information about one specific cornfield, such as corn yield and crop management practices for the field. The ARMS Phase III version 2 data contain farmers' financial status and socioeconomic characteristics. We

[8] For the multi-state GM corn prices, we calculate the average values of ratios between field-level total cost per unit of purchased GM corn and that of conventional corn varieties over multiple states. Also, we only use the total cost of GM herbicide-resistant seed variety because of lack of observations having information about the cost of Bt corn. We separate the 13 states into three regions based on USDA farm production regions. Region 1 (Corn Belt) is Iowa, Illinois, Indiana, Missouri, and Ohio. Region 2 (Lake States) is Michigan, Minnesota, and Wisconsin. Region 3 (Northern Plains) is Colorado, Kansas, Nebraska, North Dakota, and South Dakota. However, we do not take into account the cost of pest scouting for our analysis due to lack of observations having cost information regarding pest scouting.

[9] From Table 2.2, we can verify that total debt, equity, and off-farm work hours vary among groups. Adopters of GM corn and/or pest scouting have higher total debt and equity than other groups. Specifically, total debt and equity of GM corn and pest scouting adopters are more than two times higher than those of non-adopters. Table 2.2 also shows that off-work hours of non-adopters are much higher (by 150 hours per year) than off-farm work hours of other groups. This result is opposite to our expectation. However, Table 2.2 also shows that the field size of non-adopters is smaller than that of technology adopters on average. Thus, we can imagine that the difference in off-work hours between non-adopters and adopters is correlated with the difference in field size between the two groups.

merge two data sets and link production practices of farmers to their individual characteristics. In addition to the rich information in the ARMS data, we incorporate sampling weights accounting for sampling design to generalize our results (Dubman 2000). However, since the ARMS data are repeated cross-sectional data, it may be difficult to control for the unobserved heterogeneity of each field even though we use field-level information in the data.[10] Also, to merge multiple-year surveys, we assume that the sampling design and population density of samples are invariant across survey years.

We select 2,062 fields of corn grain harvested in 13 states in 2001, 2005, and 2010 based on three criteria.[11] We exclude fields for organic corn and fields operated by retired farmers and only include fields operated by mainstream farms (Goodwin & Mishra 2005). In addition, we exclude fields in which manure was applied because the heterogeneous nitrogen content in manure makes it difficult to measure actual nitrogen use for corn production. Last, about 4% of observations did not apply nitrogen for corn production, and we exclude them when we estimate equations for NUE.

Summary Statistics

Table 3.1 reports definitions and summary statistics of the variables used in the analysis. About 73% of famers adopted pest scouting, but less than 40% adopted yield monitor.[12] Less than 50% of farmers planted GM corn. Figure 3.1 shows changes in the proportion of corn acreage in

[10] In addition, missing information and spurious information make a nontrivial proportion of observations useless. For example, to clear our final data, we exclude observations whose corn acreage is larger than the total cropland. We also drop observations having negative land values or negative values of total production.

[11] States included in this study are Colorado, Illinois, Iowa, Indiana, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin.

[12] In the category of GM corn, we include HT corn, Bt corn, and GM corn stacked traits at the same time. However, this approach does not account for the effects of GM corn stacked traits such as Bt and HT. Also, aggregating the various effects of GM corn may render the effects of GM corn on corn yield and nitrogen management statistically insignificant. To test the effects of the aggregation among GM traits, we only use Bt corn and check the robustness of our results (see Appendix A).

which farmers adopted a corresponding technology over three survey years. All estimates in Figure 3.1 are weighted by ARMS weights in calculating proportions; hence, the estimates can be considered as representative proportions of the study area. Figure 3.1 indicates that the adoption of GM corn, pest scouting, and yield monitor have increased over time. In particular, the adoption of GM corn and yield monitor increased considerably in 2005 and 2010.

For estimation, we categorize the technologies as GM corn, yield monitor, and pest scouting. However, we assume that adopting yield monitor is a given condition when farmers make decisions regarding nutrient management practices and adoptions of GM corn and/or pest scouting. Yield monitor has become standard equipment on recent models of farm machinery, especially combines (Schimmelpfennig & Ebel 2011). We can imagine that farmers' decisions on yield monitor adoption are less likely to be related to their decisions on nutrient management practices during the growing season. In addition, yield monitor is a durable good. The status of yield monitor adoption is not affected by other factors when farmers have already adopted yield monitor for harvesting corn during previous years. We thus specify our empirical model based on farmers' decisions regarding GM corn and pest scouting adoption. In the case of yield monitor, we include a dummy variable representing adoptions of yield monitor in all equations.

Table 3.2 reports summary statistics based on the technology adoption status of farmers.[13] To begin with, the table indicates that corn yield and nitrogen use of adopters of GM corn and pest scouting are higher than corn yield and nitrogen use of non-adopters: The differences in corn yield and nitrogen use between the two groups are approximately 24 bushels/acre and 17 pounds/acre,

[13] We include tables in the Appendix showing corn yield, nitrogen use, NUE, and number of observations corresponding to combinations of two technologies in 2001, 2005, and 2010 (see Table A-3.3). From the table, we can verify that variations exist in corn yield, nitrogen use, and compositions of technology adopters over the three survey years However, we do not check the robustness of our results based on each survey year because of lack of non-adopters in 2005 and 2010.

respectively. Also, the table shows that corn yield and nitrogen use of GM corn adopters are larger than corn yield and nitrogen use of non-adopters by approximately 15 bushels/acre and 14 pounds/acre, respectively. However, from Table 3.2, we can verify that there is no difference in corn yield, nitrogen use, and NUE between pest scouting adopters and non-adopters. Also, NUE among the four groups are almost identical. This implies that farmers adopting GM corn (and pest scouting) use nitrogen more intensively to increase corn yield.

However, differences in outcome variables can be attributed to many factors. To be specific, Table 3.2 indicates that the proportion of irrigated fields among fields of GM corn and pest scouting adopters is about 21%, which is the largest proportion among the four groups. In addition, from the table, we can verify that adopters of GM corn and pest scouting are more likely to apply nitrogen during the previous fall and grow corn continuously than other groups. Last, the field size of adopters of GM corn and pest scouting is larger than the field size of non-adopters by about 26 acres on average. In sum, a simple comparison among the average values of outcome variables may mislead about the economic and environmental implications of technology adoption. In this study, we control for farmers' crop management practices, characteristics of farmers, and environmental conditions during the growing season to identify the effects of technology adoption on corn yield and nutrient management.

3.5.1 Determinants of corn yield, nitrogen use, and NUE

Crop management practices and characteristics of farms or fields

We include farmers' management practices in equations for corn yield, nitrogen use, and NUE: nitrogen application timing, continuous corn production, and irrigation. We include a dummy variable for nitrogen application during the previous fall in equations for nitrogen use and NUE. Fall nitrogen applications have a risk of nitrogen loss from the soil during the winter; thus, farmers applying nitrogen in the fall may try to compensate for nitrogen loss by applying more nitrogen. Continuous corn production increases nitrogen use but decreases corn yield. Continuous corn production requires more nitrogen use than corn production following soybeans because the available soil nutrient is reduced after corn production. In addition, continuous corn production results in a yield reduction compared to corn production following soybeans, referred to as the continuous corn yield penalty (Gentry, Ruffo, & Below 2013). Irrigation can reduce yield loss from drought, and irrigated corn fields generally have higher seeding rates than dryland corn fields. Also, irrigation can facilitate efficient uptake of corn for chemical inputs. For example, irrigation systems can be used to apply agricultural chemicals with water, called chemigation. Irrigated farms thus may have higher corn yield and more incentive to increase nitrogen use to optimize corn yield than non-irrigated farms.

As characteristics of fields or farmers, we include field size and variables representing farmers' human capital. Field size is used to control for scale effects on corn yield and nutrient management. The existence of farm machinery, such as center-pivot irrigation systems, can lead to economies of scale. However, the empirical evidence regarding the scale effects on input productivity remain inconsistent (Khanna 2001). For example, increasing the scale of production may make field management difficult and increase the uncertainty regarding productivity within a field and among fields. Human capital is a key factor determining farmers' ability to use the technologies appropriately. In this study, years of farming experience and a dummy variable representing college education are incorporated to control for the effects of human capital on corn yield and nutrient management (Stefanou & Saxena 1988).

To control for policies supporting conservation plans, we include a dummy with a value of one for fields under an existing conservation program contract.[14] If conservation plans decrease soil and nutrient loss from corn fields to water bodies, participation in a conservation program may increase the productivity of corn fields. However, participation in a conservation program contract may also indicate that fields are highly erodible.

Last, we use year dummies and regional dummies to control for unobserved year-specific events and systematic regional differences. One source of yearly variation is biofuel policies. The Energy Policy Act of 2005 introduced the Renewable Fuel Standard (RFS) and established quantitative mandates for the minimum amount of biofuel to be included in US transportation fuel. Also, the Energy Independence and Security Act (EISA) of 2007 expanded these quantitative mandates considerably. Quantitative mandates of biofuel policies affect changes in demand for agricultural outputs and composition of agricultural production (Moschini, Cui, & Lapan 2012). In addition, we also use year dummies to control for changes in corn prices and nitrogen prices. Our data set has little spatial variation in output and input prices.[15] Specifically, our study includes three USDA farm production regions which are used to construct multistate-level nitrogen prices in NASS. Thus, in each year, only three values of nitrogen prices are available for estimation. Also, since expected corn prices are less than national loan rates in 2005, expected corn prices for that year are almost identical across states.

Environmental variables

[14] The programs include the Environmental Quality Incentive Program (EQIP), Conservation Security or Conservation Stewardship Program (CSP), Conservation Reserve Program (CRP), and other federal, state, local, and non-government sources.

[15] To test the effects of omitting corn prices on our results, we include corn prices and check the robustness of our results (see Appendix A). For expected output prices, state-level futures prices are constructed by adjusting regional differences in farm-gate prices (Barr et al. 2011) and national loan rates. Chicago Board of Trade (CBOT) corn futures prices are used.

To control for time invariant soil quality, the National Commodity Crop Productivity Index - Corn and Soybeans (NCCPI-CS), representative slope, sand percentage, silt percentage, available water storage within crop root zone depths (RZAWS), T factor, and soil organic carbon (SOC) are included. The NCCPI-CS is used for physical and chemical properties of soil, landscape, and climate conditions to construct a national-level common soil quality index. The NCCPI-CS is only for dryland agriculture and represents time-inherent soil productivity (Dobos, Sinclair, & Robotham 2012). We use percentage of silt and percentage of sand to account for soil texture. RZAWS is the total amount of water stored in the soil within crops' root zones for crop development. Thus, we can say that the region having insufficient RZAWS is vulnerable to drought. T factor is a measure of the maximum amount of soil erosion which is sustainable without significant loss of soil productivity. SOC represents the carbon component of soil organic matter. SOC is positively correlated to nutrient holding capacity and stability of soil by providing a food source for micro-organisms in soil. Except for RZAWS, SOC, and NCCPI, soil data contain multiple values according to soil zone; hence, we calculate the weighted averages over the zones located within 30cm depth. The Gridded Soil Survey Geographic (gSSURGO) database is used to construct soil variables. [16]

To account for weather conditions during the growing season, we include growing degree days (GDD), extreme heat degree days (HDD), and total precipitation during the growing season. GDD measures accumulated exposure to heat over the growing season and can be interpreted as beneficial heat. GDD is defined by the area under the temperature curve within a day that falls between two temperature thresholds (8ºC and 34ºC). HDD can be interpreted as harmful heat for crop development. HDD is defined by the area under the temperature curve within a day that is

[16] gSSURGO data use a depth of 150cm to approximate the root zone depth. 30cm is the depth corresponding to topsoil that has been plowed or cultivated.

higher than 34ºC. Snyder (1985) is used to calculate GDD and HDD, and the growing season is assumed to be from May to September. To calculate weather variables, daily Parameter-elevation Regression on Independent Slope Model (PRISM) data are used. Last, we construct field-level environmental variables based on the longitude and latitude information of each field in the ARMS Phase II data. To be specific, based on locational information, we create a 300m buffer around each geocode and calculate the average values of environmental conditions within the buffer.[17]

3.6 Empirical results[18]

3.6.1 The effects of technology adoption

Table 3.3 shows empirical evidence of the effects of adopting GM corn and/or pest scouting on corn yield and nutrient management. The estimates indicate the differences between outcome variables of farmers adopting one of the combinations of the two technologies and what these values would have been if adopters had not adopted any technology. First, the results show that adopting GM corn and/or pest scouting increases corn yield, even though the effects of pest scouting on corn yield are statistically insignificant. Specifically, the results show that GM corn increases corn yield by approximately 13.0 bushels/acre on average. Moreover, the results show that GM corn and pest scouting are complementary in increasing corn yield: Adopting GM corn and pest scouting increases corn yield by approximately 26.8 bushels/acre on average. Our results are consistent with studies documenting the yield effects of GM corn (Brookes & Barfoot 2012; Aldana et al. 2012; Nolan & Santos 2012; Fernandez-Cornejo et al. 2014). For example, Aldana et al. (2012) show that Bt corn increases corn yield by 5 bushels/acre-12 bushels/acre. Nolan and Santos (2012) find that the yield effects of Bt corn and stacked-trait Bt corn vary between 6

[17] We use the minimum size of fields in our data and polygons in gSSRUGO data as a radius of buffers. Also, we find little variation in soil variables when the size of buffers changes from 100m to 300m. Last, since the spatial resolution of PRISM is 4km by 4km, the size of buffers less than 1km has ignorable effects on variations in climate variables.
[18] The results regarding determinants of corn yield, nitrogen use, and NUE are in Tables 3.7, 3.8, and 3.9.

bushels/acre and 21 bushels/acre, and the size of the yield effects depends on model specifications and GM traits. Finally, Brookes and Barfoot (2012) report that HT corn increases corn yield in Argentina, Brazil, and the Philippines by 1%-15%.

Second, the results show that adopting GM corn and/or pest scouting increases nitrogen use, even though only the effects of GM corn adoption on nitrogen use are statistically significant. An intuitive explanation is based on our conceptual model. That is, our conceptual model indicates that adopting new technology can increase nitrogen use when it increases marginal productivity of nitrogen use. Thus, increases in nitrogen use as a result of adopting GM corn may reflect increases in the marginal productivity of nitrogen use due to adopting GM corn.[19]

Third, we find that adopters of GM corn and/or pest scouting do not achieve gains in nitrogen use efficiency. Moreover, Table 3.4 indicates that increases in nitrogen use caused by pest scouting adoption are larger than the yield effects, and thus pest scouting increases NUE by 0.3 pounds/one bushel of corn. This result may reflect the interaction between nutrient management and weed management. To be specific, the improvement in early season corn growth with additional nitrogen use results in greater leaf area, biomass, and height, which enhances the competitive ability of corn against weeds (Evans et al. 2003b). Thus, if pest scouting weeds is adopted for weed management, farmers may have an incentive to increase nitrogen use to decrease yield loss due to weed competition.

Table 3.4 shows the effects of adopting GM corn and/or pest scouting on corn yield and nutrient management conditional on soil productivity. The effects of GM corn and/or pest scouting adoption on corn yield and nutrient management depend on soil productivity (Fuglie & Bosch

[19] We explain how GM corn can increase marginal productivity of nitrogen use in Section 1: HT corn and pest scouting can reduce weed competition for water and nutrients for the plant. Also, the Bt traits ensure efficient water and nutrient uptake (Miranowski, Rosburg, & Aukayanagul 2011). Finally, Shi et al. (2013) argue that patented GM traits are inserted into the superior germplasm.

1995; Khanna 2001).[20] To identify the effects of adopting GM corn and/or pest scouting conditional on soil productivity, we separate fields into two groups: fields having NCCPI-CS higher than 0.5 and fields having NCCPI-CS lower than 0.5. Considering that NCCPI-CS is only for dryland fields, we exclude irrigated fields when we estimate our model and calculate Equation (9) for Table 3.4.[21] From Table 3.4, we find that the yield effects of GM corn and/or pest scouting for fields having low soil productivity are statistically significant and larger than those for productive fields. Adopters of GM corn (pest scouting) achieve yield gains of approximately 16.6 bushels/acre (18.6 bushels/acre) by incorporating the technology for fields having NCCPI-CS less than 0.5. Also, the results indicate that adopting GM corn and pest scouting increase corn yield for less productive fields by approximately 31.4 bushels/acre. However, for fields having high NCCPI-CS, the yield effects of pest scouting and its combination with GM corn are insignificant, except for GM corn adoption.

In the case of nutrient management, the results indicate that the effects of adopting GM corn and/or pest scouting on nitrogen use for fields having low soil quality are statistically significant and larger than those for productive fields. However, the results show that the effects of adopting GM corn and/or pest scouting on nitrogen use for productive fields are statistically insignificant. These result may reflect that the effects of adopting GM corn and/or pest scouting on the marginal productivity of nitrogen use in fields having low soil productivity are positive and larger than those in fields having high soil productivity. Thus, farmers may be more likely to increase nitrogen use for fields having low soil productivity.

[20] For example, when corn yield is an increasing and concave function of soil productivity, the yield effects of technology adoption on productive fields may be smaller than the effects of technology adoption on fields having low soil productivity. Conversely, field-level information increases the productivity of nitrogen by decreasing nitrogen use on marginal areas.
[21] To control for the effects of continuous corn production, we also calculate the estimates in Table 3.4 after excluding fields producing corn continuously (see Appendix B). The results show that excluding fields producing corn continuously has modest effects on the results.

Yield monitor generates information regarding corn yield distribution, soil conditions, and results of crop management practices during the previous year. Farmers have used this information to improve the profitability of their crop management systems by comparing corn yield depending on corn variety, agricultural technology, and chemical use. However, the effectiveness of information generated from yield monitor may vary according to its combination with other technology. For example, assume that the variation in corn yield in fields in which GM corn is planted is smaller than the variation in corn yield in fields in which conventional varieties are planted. Then, information on corn yield distribution over the fields may be less useful for farmers planting GM corn than farmers planting conventional varieties.[22]

We measure the effect of yield monitor on corn yield and nutrient management and test the relationship between yield monitoring and other technologies. The estimates in Table 3.5 indicate the marginal effects of yield monitor on corn yield, nitrogen use, and NUE conditional on GM corn and/or pest scouting adoption. From the table, we can verify that adopting yield monitor has positive effects on corn yield and nitrogen use, even though the effects of yield monitor adoption on corn yield and nitrogen use are statistically insignificant when it is used with GM corn. The results show that yield monitor increases corn yield when it is used alone by 8.2 bushels/acre. When yield monitor is incorporated with GM corn and pest scouting, it increases corn yield by 8.9 bushels per acre. Also, we find that the effects of yield monitor combined with pest scouting are larger than those of any other combination of yield monitor and other technology. Yield monitor adoption increases corn yield and nitrogen use of pest scouting adopters by 16.8 bushels/acre and

[22] Previous literature also argues that the value of information increases when the uncertainty regarding farm management increases (Feder 1979; Babcock & Blackmer 1992; Fuglie & Bosch 1995; Koundouri, Nauges, & Tzouvelekas 2006).

14.6 pounds/acre, respectively. This result implies that the effects of adopting yield monitor on corn yield and nutrient management are positively correlated to adopting pest scouting.[23]

3.6.2 Implications

We find that GM corn and its combination with pest scouting have larger effects on corn yield and nitrogen use when these technologies are adopted in fields having low soil productivity. This result indicates that GM corn and information technologies may enable farmers to obtain economic gains from increasing their land use at the extensive margin. This result also shows the importance of GM corn and/or pest scouting adoption in reducing the likelihood of low corn yield that farmers are likely to have in fields having low soil productivity. It is highly likely that fields having low soil productivity have low corn yield. For example, Egli and Hatfield (2014) show the positive relationship between county-level corn yield and NCCPI. Our results indicate that adopting GM corn and/or pest scouting increases corn yield at the lower tail of the yield distribution and decreases the probability of low corn yield.

Our conceptual model indicates that technology adoption may increase nitrogen use when technology adoption increases the marginal productivity of nitrogen use. Given that adopting GM corn and information technologies can increase the marginal productivity of nitrogen use, as explained in Section 1, farmers have an incentive to increase nitrogen use to optimize their input use when they adopt these technologies. The empirical results indicate that GM corn and information technologies increase nitrogen use. Increased nitrogen use can result in increases in nutrient loss to surface and groundwater from corn production (Sawyer 2015). In this sense,

[23] Table 3.6 shows the marginal effects of adopting yield monitor on corn yield and nutrient management depending on soil productivity. The table shows that the differences in estimates between fields having high soil productivity and fields having low soil productivity are ignorable.

benefits from adopting GM corn and information technologies may be limited considering the adverse effects of corn production on regional environmental conditions.

3.7 Conclusion

Genetic improvement and advanced crop management practices have been major contributing factors to corn yield growth in the U.S. after the 1930s (Duvick 2005). During the last decade, adoption of GM corn, pest scouting, and yield monitor increased significantly. However, only a limited number of studies have investigated the economic and environmental implications of adopting these technologies.

This study identifies the effects of adopting GM corn, pest scouting, and yield monitor on corn yield and nutrient management of Midwest farmers. Our findings can be summarized as follows. First, adopting GM corn increases corn yield and nitrogen use by 13 bushels/acre and 16 pounds/acre, respectively. Adopting the combination of GM corn and pest scouting has larger effects on corn yield and nitrogen use than adopting only one technology. Second, the effects of adopting GM corn and/or pest scouting on corn yield and nitrogen use are larger for fields having low soil productivity. Third, the effects of adopting yield monitor on corn yield and nitrogen use are significant when farmers adopt yield monitor and pest scouting at the same time.

A major limitation of this study is based on the structure of the ARMS data. Our data are repeated cross-sectional data and include only three survey years. Thus, we may not be controlling for unobserved characteristics, even though we use field-level information and the endogenous switching regression model. Also, spatial variations in price variables are too small to identify price effects on corn yield and nutrient management. Finally, our results are based on short time periods, and they may be very sensitive to year specific events. However, we do not check the robustness of our results based on each survey year because of the lack of information regarding non-adopters in 2005 and 2010.

References

Aldanaa, U., Barhamb, B., Foltzb, J., & Usechec, P. (2012). Early adoption, experience, and farm performance of GM corn seeds. *Agricultural Economics*, 43, 11-18.

Babcock, B. A., & Blackmer, A. M. (1992). The value of reducing temporal input nonuniformities. *Journal of Agricultural and Resource Economics, 17 (2)*, 335-347.

Bennett, A, B., Chi-Ham, C., Barrows, G., Sexton, S., & Zilberman, D. (2013). Agricultural Biotechnology: Economics, Environment, Ethics, and the Future. *Annual Review of Environmental and Resource, 38 (19),* 1-31

Brookes, G., & Barfoot, P. (2012). *GM crops: global socio-economic and environmental impacts 1996–2010.* PG Economics *Ltd. http://www. pgeconomics. co. uk/page/33/global-impact-2012 [accessed 31 Jan 2013]*.

Carlson, G. A. (1970). A decision theoretic approach to crop disease prediction and control. *American Journal of Agricultural Economics, 52(2),* 216-223.

Dobos, R. R., H.R. Sinclair, Jr., & M. P. Robotham. (2012). *User Guide for the National Commodity Crop Productivity Index (NCCPI) version 2.0.*

Dubman, R. W. (2000). *Variance estimation with USDA's farm costs and returns surveys and agricultural resource management surveys,* (Economic Research Report AGE 00-01). Washington, DC: U.S. Department of Agriculture, Economic Research Service.

Duvick, D. N. (2005). Genetic progress in yield of United States maize (Zea mays L.). *Maydica, 50(3),* 193-202.

Egli, D. B., & Hatfield, J. L. (2014). Yield gaps and yield relationships in central US soybean production systems. *Agronomy Journal, 106(2),* 560-566.

Evans, S. P., Knezevic, S. Z., Lindquist, J. L., Shapiro, C. A., & Blankenship, E. E. (2003a). Nitrogen application influences the critical period for weed control in corn. *Weed Science, 51(3),* 408-417.

Evans, S. P., Knezevic, S. Z., Lindquist, J. L., & Shapiro, C. A. (2003b). Influence of nitrogen and duration of weed interference on corn growth and development. *Weed Science, 51(4),* 546-556.

Feder, G. (1979). Pesticides, information, and pest management under uncertainty. *American Journal of Agricultural Economics, 61(1),* 97-103.

Feder, G., Just, R. E., & Zilberman, D. (1985). Adoption of agricultural innovations in developing countries: A survey. *Economic development and cultural change, 33(2),* 255-298.

Fernandez-Cornejo, J., Wechsler, S., Livingston, M., & Mirchell, L. (2014). *Genetically Engineered Crops in the United States* (Economic Research Report No. 162). Washington, DC: U.S. Department of Agriculture, Economic Research Service.

Fernandez-Cornejo, J. (2007). *Off-Farm Income, Technology Adoption, and Farm Economic Performance* (Economic Research Report No. 36). Washington, DC: U.S. Department of Agriculture, Economic Research Service.

Fuglie, K. O., & Bosch, D. J. (1995). Economic and environmental implications of soil nitrogen testing: A switching-regression analysis. *American Journal of Agricultural Economics, 77(4),* 891-900.

Gentry, L. F., Ruffo, M. L., & Below, F. E. (2013). Identifying factors controlling the continuous corn yield penalty. *Agronomy Journal, 105(2),* 295-303.

Gould, B.W., Saupe, W.E., & Klemme, R.M. (1989). Conservation tillage: The role of farm and operator characteristics and the perception of soil erosion. *Land Economics*, 167-182.

Goodwin, B.K., Mishra, A.K., & Ortalo-Magné, F.N. (2003). What's wrong with our models of agricultural land values?" *American Journal of Agricultural Economics, 85(1),* 744-752.

Goodwin, B. K., & Mishra, A. K. (2005). "Another look at decoupling: Additional evidence on the production effects of direct payments." *American Journal of Agricultural Economics, 87(5),* 1200-1210.

Griffin, T. W., & Lowenberg-DeBoer, J. (2005). Worldwide adoption and profitability of precision agriculture Implications for Brazil. *Revista de Politica Agricola*, *14 (4)*, 20-37.

Gourieroux, C., Monfort, A., & Trognon, A. (1984). Pseudo Maximum Likelihood Methods: Theory. *Econometrica*, 52(3), 681-700.

Horowitz, J., Eble, R., & Ueda, K. (2010). *No-Till" Farming Is a Growing Practice*. (Economic Information Bulletin No. 70). Washington, DC, U.S. Department of Agriculture, Economic Research Service.

Ifft, J. E., A. Novini, & K. Patrick. (2014). *Debt Use By U.S Farm Businesses, 1992-2011*, (Economic Information Bulletin No. 122). Washington, DC, U.S. Department of Agriculture, Economic Research Service.

Ifft, J. E., T. Kuethe, & M. Morehart. (2015). "Does federal crop insurance lead to higher farm debt use? Evidence from the Agricultural Resource Management Survey (ARMS)." *Agricultural Finance Review 75(3),* 349-367.

Kaminski, J., Kan, I., & Fleischer, A. (2013). A structural land-use analysis of agricultural adaptation to climate change: a proactive approach. *American Journal of Agricultural Economics, 95(1),* 70-93.

Khanna, M. (2001). Sequential adoption of site-specific technologies and its implications for nitrogen productivity: A double selectivity model. *American Journal of Agricultural Economics, 83(1),* 35-51.

Koundouri, P., Nauges, C., & Tzouvelekas, V. (2006). Technology adoption under production uncertainty: theory and application to irrigation technology. *American Journal of Agricultural Economics, 88(3),* 657-670.

Lambert, D., Sullivan, P., Claassen, R., & Foreman, L. (2006). *Conservation-compatible practices and programs: Who participates?* (Economic Research Report No. 14). Washington, DC: U.S. Department of Agriculture, Economic Research Service.

Lee, L. F. (1983). Generalized econometric models with selectivity. *Econometrica 51*, 507-512.

Manning, W. G., & Mullahy, J. (2001). Estimating log models: to transform or not to transform? *Journal of health economics*, 20(4), 461-494.

Miranowski, J.A., Ernst, U. F.W., & Cummings, F. H. (1974). *Crop insurance and information technologies to control use of pesticides* (EPA 600/5-74-018). Washington, DC: Environmental Protection Agency.

Miranowski, J. A., Rosburg, A., & Aukayanagul, J. (2011). US Maize Yield Growth Implications for Ethanol and Greenhouse Gas Emissions. *AgBioForum, 14(3),* 120–132

Mishra, A.K., Nimon, R.W., & El-Osta, H. S. (2005). Is moral hazard good for the environment? Revenue insurance and chemical input use. *Journal of Environmental Management, 74(1),* 11-20.

Moschini, G., Cui, J., & Lapan, H. (2012). Economics of biofuels: an overview of policies, impacts and prospects. *Bio-based and Applied Economics*, 1(3), 269-296.

Nolan, E., & Santos, P. (2012). The contribution of genetic modification to changes in corn yield in the United States. *American journal of agricultural economics, 94(5),* 1171-1188.

PRISM Climate Group. 2004. PRISM AN81m Data. Website. url: http://prism.oregonstate.edu.

Qaim, M. (2009). The Economics of Genetically Modified Crops. *Annual Review of Resource Economics, 1,* 665-693

Sawyer, J. E. (2015). *Nitrogen use in Iowa corn production.* Ames, IA: Iowa State University Extension and Outreach.

Schimmelpfennig, D., & Ebel, R., (2011). *On the Doorstep of the Information Age* (Economic Information Bulletin No. 80). Washington, DC: U.S. Department of Agriculture, Economic Research Service.

Shi, G., Chavas, J. P., Lauer, J., & Nolan, E. (2013). An Analysis of Selectivity in the Productivity Evaluation of Biotechnology: An Application to Corn. *American Journal of Agricultural Economics, 95(3)*, 739-754.

Snyder, R. L. (1985). Hand calculating degree days. *Agricultural and forest meteorology, 35(1),* 353-358.

Stefanou, S. E., & Saxena, S. (1998). Education, Experience, and Allocative Efficiency: A Dual Approach. *American Journal of Agricultural Economics, 70(2),* 338-345.

Terza, J.V., Basu, A, & Rathouz, P. J. (2008). Two-stage residual inclusion estimation: addressing endogeneity in health econometric modeling. *Journal of Health Economics, 27(3)*, 531-543.

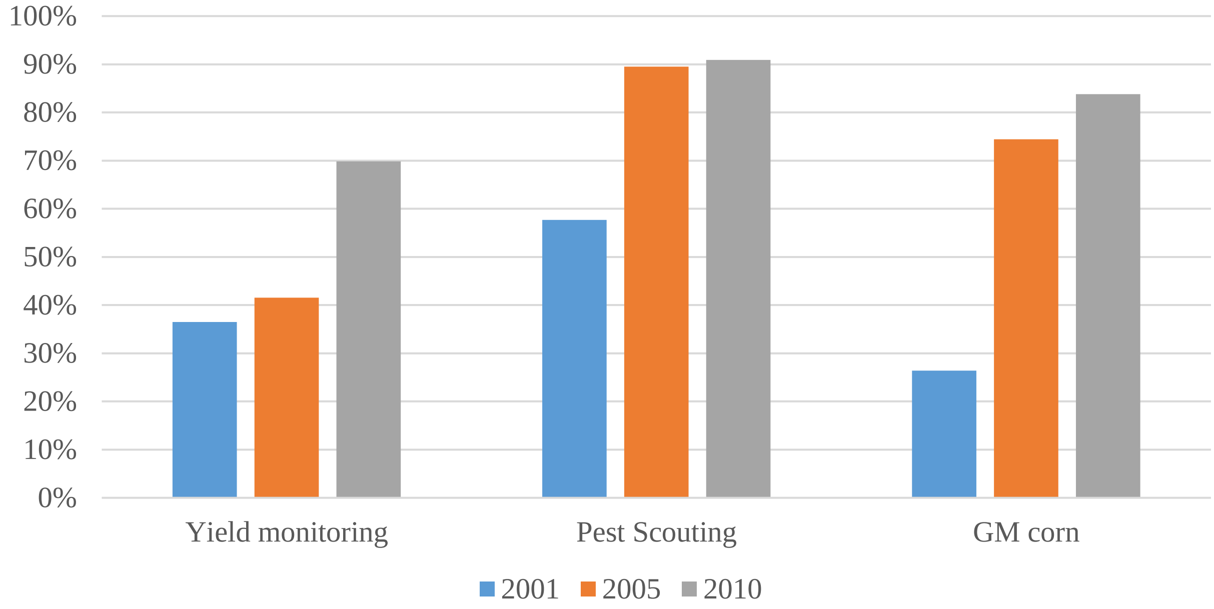
Terza, J.V. (2009). Parametric nonlinear regression with endogenous switching. *Econometric Reviews, 28(6),* 555-580.

Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data (2d ed.).* Cambridge, MA: MIT Press.

Wooldridge, J. M. (2014). Quasi-maximum likelihood estimation and testing for nonlinear models with endogenous explanatory variables. *Journal of Econometrics, 182(1),* 226-234.

Wu, J., & Babcock, B. A. (1998). The choice of tillage, rotation, and soil testing practices: economics and environmental implications. *American Journal of Agricultural Economics, 80(3),* 494-511.

Yee, J., & Ferguson, W. (1996). Sample selection model assessing professional scouting programs and pesticide use in cotton production. *Agribusiness, 12(3),* 291-300.



Note: Estimates on the percentages of acres are based on weighted sum. The weights are calibrated so that the sum of planted acres for corn based on the survey data matches the NASS published estimates of planted corn acreage for each survey year.

Figure 3.1. Corn acreage adopting GM corn or information technologies

Table 3.1. Summary statistics

Variable	Mean	St.dev	Definition
			Dependent Variables
Nlb	134.13	65.41	Nitrogen application rate (pounds/acre)
Yield	143.12	43.59	Corn yield (bushel/acre)
NUE	1.01	0.69	Nitrogen use efficiency (lb/bushel)
			Technology adoption
Pest scouting	0.73	0.45	Scouting for pests adopted in field (1=yes, 0=no)
Yield monitor	0.40	0.49	Yield monitoring adopted in field (1=yes, 0=no)
GM	0.54	0.50	GM corn used (1=yes, 0=no)
			Practices
Irrigation	0.12	0.33	Field irrigated (1=yes, 0=no)
Fall_Nit	0.30	0.46	Nitrogen applied during the previous fall (1=yes, 0=no)
CC rotation	0.17	0.37	Continuous corn production (1=yes, 0=no)
			Characteristics of corn fields and operators
Off-work	455.8	853.3	Off-work hours per year (operator and operators' spouse)
Total debt	290.8	528.3	Total debt ($1,000)
Equity	73.48	490.0	Equity ($1,000)
Tenure	28.89	12.63	Number of years farmer has operated the field
College	0.24	0.43	Farm operator graduated college (1=yes, 0=no)
Conservation	0.07	0.25	Conservation program contract (1=yes, 0=no)
Field area	0.62	0.55	The size of corn field (100 acre)
			Prices and environmental conditions
P_{GM}	1.20	0.07	Total cost of HT corn seeds/ total cost of conventional seeds ($/approximately 80,000 Kernel Bag)
NCCPI	0.55	0.21	NCCPI-Corn and Soybeans
RZAWS	2.34	0.57	Available water storage within the root-zone depth (100 mm)
T-factor	4.52	0.65	Soil loss tolerance (in tons per acre).
SOC	6.64	3.38	Soil organic carbon (1000 g C/m^2)
Slope	2.79	4.17	Representative slope (%)
% silt	50.86	15.71	Percent silt
% sand	24.57	19.05	Percent sand
GDD	18.88	2.95	Growing degree days during growing seasons (100 GDD)
HDD	2.67	5.64	Extreme heat degree days during growing seasons
Precipitation	4.81	1.83	Total precipitation days during growing seasons (100 mm)
Number of observations			2062

Note: Soil variables are the weighted averages over soil zones within 30cm depth.

Table 3.2. Summary Statistics depending on technology adoption status

Variable	GM corn and pest scouting		Pest scouting		GM corn		Non-adopter	
	Mean	(St.dev)	Mean	(St.dev)	Mean	(St.dev)	Mean	(St.dev)
Nlb	143.7	(60.75)	122.0	(69.79)	140.2	(62.40)	126.6	(66.95)
Yield	154.2	(42.08)	133.0	(44.00)	145.6	(39.44)	130.3	(41.67)
NUE	1.03	(0.69)	0.98	(0.73)	1.01	(0.48)	1.03	(0.65)
Yield monitor	0.51	(0.50)	0.35	(0.48)	0.32	(0.47)	0.27	(0.44)
Irrigation	0.15	(0.36)	0.12	(0.33)	0.08	(0.27)	0.08	(0.27)
Fall_Nit	0.35	(0.48)	0.27	(0.45)	0.24	(0.43)	0.24	(0.43)
CC rotation	0.21	(0.41)	0.15	(0.36)	0.11	(0.32)	0.12	(0.33)
Off-work	424.4	(830.9)	431.5	(837.1)	425.2	(831.2)	594.2	(935.1)
Total debt	375.2	(633.5)	250.3	(468.2)	249.2	(391.5)	168.0	(325.1)
Equity	97.24	(597.3)	78.45	(418.3)	65.21	(418.0)	9.56	(292.8)
Tenure	29.45	(12.24)	28.32	(12.84)	30.65	(12.46)	27.33	(13.16)
College	0.27	(0.44)	0.25	(0.43)	0.22	(0.41)	0.15	(0.36)
Conservation	0.09	(0.28)	0.07	(0.25)	0.06	(0.23)	0.03	(0.17)
Field area	0.72	(0.57)	0.61	(0.58)	0.52	(0.49)	0.46	(0.41)
P_{GM}	1.22	(0.07)	1.20	(0.07)	1.20	(0.06)	1.17	(0.05)
NCCPI	0.57	(0.21)	0.52	(0.22)	0.57	(0.18)	0.54	(0.19)
RZAWS	2.39	(0.57)	2.31	(0.58)	2.35	(0.51)	2.24	(0.61)
T-factor	4.56	(0.65)	4.53	(0.66)	4.57	(0.56)	4.39	(0.70)
SOC	6.92	(3.84)	6.34	(2.78)	6.66	(2.71)	6.39	(3.35)
Slope	3.51	(3.68)	4.01	(4.39)	3.31	(3.42)	4.40	(5.15)
% silt	51.05	(15.81)	50.62	(16.35)	49.37	(14.59)	51.62	(15.03)
% sand	24.12	(19.09)	25.54	(20.23)	26.42	(18.17)	23.07	(17.28)
GDD	19.31	(2.71)	18.60	(3.06)	19.00	(2.69)	18.15	(3.26)
HDD	2.78	(5.82)	3.14	(6.44)	2.10	(4.80)	1.94	(3.85)
Precipitation	5.14	(1.85)	4.70	(1.88)	4.70	(1.76)	4.18	(1.51)
# of observations	905		595		206		356	

Note: Soil variables are the weighted averages over soil zones within 30cm depth.

Table 3.3. The effects of GM corn and/or pest scouting adoption

	Yield (bushel/acre)	Nitrogen use (pounds/acre)	NUE (lb/bushel)
GM corn and pest scouting	26.87 (15.95)*	52.26 (44.60)	0.39 (0.28)
Pest scouting	8.52 (9.75)	32.63 (21.06)	0.26 (0.14)*
GM corn	13.01 (5.68)**	16.43 (9.11)*	-0.04 (0.10)

Note: *** significant at 1% level. ** significant at 5% level. * significant at 10% level. ( ) standard errors of estimates. Estimates and their standard errors are from about 1,000 bootstrap runs.

Table 3.4. The effects of technology adoption based on soil quality: non-irrigated

	Soil productivity	Yield (bushel/acre)	Nitrogen use (pounds/acre)	NUE (lb/bushel)
GM corn and pest scouting	Low	31.39 (14.26)**	67.14 (25.52)***	0.50 (0.23)**
	High	27.81 (19.55)	46.98 (48.51)	0.37 (0.33)
Pest scouting	Low	18.55 (8.00)**	33.30 (11.47)***	0.16 (0.13)
	High	6.54 (12.35)	32.03 (24.22)	0.32 (0.16)*
GM corn	Low	16.58 (7.20)**	31.42 (12.15)***	0.04 (0.17)
	High	11.20 (6.35)*	12.01 (10.25)	-0.07 (0.11)

Note: *** significant at 1% level. ** significant at 5% level. * significant at 10% level. ( ) standard errors of estimates. Estimates and their standard errors are from about 1,000 bootstrap runs. NCCPI-CS is used as the measure of soil productivity. Fields having low soil productivity mean fields having NCCPI-CS less than 0.5. Fields having high soil productivity mean fields having NCCPI-CS larger than 0.5.

Table 3.5. Marginal effects of yield monitor adoption

	Yield (bushel/acre)	Nitrogen use (pounds/acre)	NUE (lb/bushel)
GM corn and pest scouting	8.86 (2.25)***	3.73 (3.63)	-0.06 (0.04)
Pest scouting	16.78 (4.61)***	14.60 (6.81)**	-0.13 (0.09)
GM corn	9.88 (7.20)	11.31 (11.28)	-0.01 (0.11)
Non-adopter	8.22 (4.45)*	2.79 (9.34)	-0.04 (0.08)

Note: *** significant at 1% level. ** significant at 5% level. * significant at 10% level. ( ) standard errors of estimates. Estimates and their standard errors are from about 1,000 bootstrap runs.

Table 3.6. Marginal effects of yield monitor adoption: non-irrigated

	Soil productivity	Yield (bushel/acre)	Nitrogen use (pounds/acre)	NUE (lb/bushel)
GM corn and pest scouting	Low	8.26 (2.09)***	3.69 (3.59)	-0.08 (0.05)
	High	8.79 (2.24)***	3.70 (3.60)	-0.07 (0.05)
Pest scouting	Low	14.89 (4.19)***	13.15 (6.24)**	-0.11 (0.09)
	High	17.69 (4.86)***	15.12 (7.03)**	-0.11 (0.10)
GM corn	Low	8.45 (6.21)	10.82 (10.78)	-0.05 (0.15)
	High	10.00 (7.32)	11.36 (11.31)	-0.04 (0.13)
Non-adopter	Low	7.30 (4.01)*	2.81 (9.13)	-0.02 (0.10)
	High	8.76 (4.78)*	2.92 (9.66)	-0.02 (0.09)

Note: *** significant at 1% level. ** significant at 5% level. * significant at 10% level. ( ) standard errors of estimates. Estimates and their standard errors are from about 1,000 bootstrap runs. NCCPI-CS is used as the measure of soil productivity. Fields having low soil productivity mean fields having NCCPI-CS less than 0.5. Fields having high soil productivity mean fields having NCCPI-CS larger than 0.5.

Table 3.7. Estimates regarding corn yield

Technologies	Non-adopters		GM corn		Pest scouting		Both technologies	
Yield monitor	0.060	(0.032)*	0.072	(0.053)	0.112	(0.029)***	0.059	(0.016)***
Continuous corn	-0.046	(0.066)	-0.105	(0.078)	-0.065	(0.042)	-0.064	(0.020)***
Irrigation	0.443	(0.086)***	0.445	(0.098)***	0.557	(0.075)***	0.435	(0.035)***
Field area	0.121	(0.059)**	0.053	(0.047)	0.052	(0.035)	0.025	(0.016)
College	-0.029	(0.044)	-0.053	(0.046)	-0.070	(0.034)**	-0.008	(0.017)
Experience	-0.001	(0.001)	-0.002	(0.001)	0.001	(0.001)	-0.001	(0.001)*
Conservation	0.038	(0.104)	-0.144	(0.085)*	-0.008	(0.054)	0.008	(0.027)
GDD	0.005	(0.011)	-0.029	(0.013)**	-0.005	(0.009)	-0.017	(0.005)***
HDD	-0.040	(0.013)***	-0.006	(0.007)	-0.010	(0.006)*	-0.015	(0.005)***
Precipitation	0.062	(0.014)***	-0.016	(0.018)	0.001	(0.011)	0.004	(0.006)
NCCPI	0.432	(0.140)***	-0.279	(0.198)	0.184	(0.118)	0.143	(0.064)**
% sand	0.003	(0.003)	0.005	(0.004)	-0.001	(0.003)	0.001	(0.002)
% silt	0.007	(0.003)**	0.005	(0.004)	0.001	(0.003)	0.002	(0.002)
SOC	0.013	(0.008)	0.007	(0.010)	0.011	(0.007)	-0.008	(0.004)*
Slope	0.007	(0.003)*	-0.003	(0.008)	0.004	(0.003)	-0.001	(0.002)
RZAWS	-0.849	(0.349)**	0.860	(0.703)	-0.227	(0.361)	0.341	(0.211)
T-factor	0.057	(0.033)*	0.011	(0.055)	0.025	(0.028)	0.023	(0.015)
Constant	3.588	(0.340)***	4.433	(0.464)***	4.920	(0.372)***	5.007	(0.210)***
$\sigma_{\varepsilon e}^{j}$	-0.094	(0.086)	-0.150	(0.190)*	0.200	(0.078)**	0.078	(0.054)
Year and regional dummies	Yes		Yes		Yes		Yes	
Wald Statistics	211.62***		194.47***		218.95***		341.31***	
R-squared	0.358		0.413		0.295		0.315	
# of convergence	987		987		987		987	

Note: *** significant at 1% level. ** significant at 5% level. * significant at 10% level. ( ) standard errors of estimates. Estimates and their standard errors are from about 1,000 bootstrap runs. R-squared is the squared correlation coefficients between actual corn yield and predicted corn yield (Wooldridge 2010, pp 731~732). R-squared and Wald Statistics are based on whole samples and ARMS weights. Units of environmental variables are in Table 3.1.

Table 3.8. Estimates regarding nitrogen use

Technologies	Non-adopters		GM corn		Pest scouting		Both technologies	
Yield monitor	0.020	(0.075)	0.088	(0.086)	0.094	(0.042)**	0.027	(0.026)
Continuous corn	-0.028	(0.116)	-0.013	(0.130)	0.000	(0.072)	0.031	(0.031)
Irrigation	0.486	(0.147)***	0.563	(0.183)***	0.313	(0.107)***	0.262	(0.056)***
Field area	-0.147	(0.142)	0.018	(0.093)	-0.021	(0.052)	0.064	(0.026)**
Fall_Nit	0.053	(0.085)	0.150	(0.113)	0.037	(0.037)	0.007	(0.029)
College	-0.009	(0.092)	0.097	(0.084)	-0.118	(0.048)**	-0.001	(0.029)
Experience	0.001	(0.002)	0.000	(0.002)	-0.001	(0.002)	-0.002	(0.001)**
Conservation	0.014	(0.132)	-0.111	(0.133)	0.013	(0.061)	0.011	(0.035)
GDD	0.042	(0.020)***	0.027	(0.024)	0.020	(0.014)	0.033	(0.009)***
HDD	-0.047	(0.017)***	-0.014	(0.010)	-0.002	(0.007)	-0.010	(0.006)*
Precipitation	0.004	(0.026)	-0.027	(0.028)	-0.008	(0.563)	-0.015	(0.008)*
NCCPI	0.312	(4.959)	0.181	(2.490)	0.515	(8.486)	-0.292	(6.008)
% sand	-0.004	(0.065)	0.020	(0.254)	-0.003	(0.066)	-0.005	(0.112)
% silt	-0.001	(0.025)	0.029	(0.353)	-0.001	(0.017)	-0.009	(0.154)
SOC	0.011	(0.375)	0.033	(0.516)	0.001	(0.170)	-0.000	(0.022)
Slope	-0.014	(0.201)	-0.004	(0.117)	-0.001	(0.031)	0.004	(0.002)
RZAWS	-1.178	(0.656)***	-2.771	(0.046)***	-1.262	(0.488)***	0.169	(0.385)
T-factor	-0.009	(0.059)	0.084	(0.080)	0.033	(0.035)	-0.027	(0.024)
Constant	4.140	(0.573) ***	4.284	(0.859)***	4.820	(0.556)***	4.882	(0.356)***
$\sigma_{\varepsilon e}^{j}$	-0.237	(0.250)	0.089	(0.179)	0.122	(0.112)	0.097	(0.082)
Year and regional dummies		Yes		Yes		Yes		Yes
Wald Statistics		138.58***		110.78***		68.79***		76.41***
R-squared		0.144		0.331		0.188		0.078
# of convergence		991		991		991		991

Note: *** significant at 1% level. ** significant at 5% level. * significant at 10% level. ( ) standard errors of estimates. Estimates and their standard errors are from about 1,000 bootstrap runs. R-squared is the squared correlation coefficients between actual nitrogen use and predicted nitrogen use (Wooldridge 2010, pp 731~732). R-squared and Wald Statistics are based on whole samples. Units of environmental variables are in Table 3.1.

Table 3.9. Estimates regarding NUE

Technologies	Non-adopters		GM corn		Pest scouting		Both technologies	
Yield monitor	0.040	(0.083)	-0.001	(0.112)	-0.126	(0.091)	-0.055	(0.041)
Continuous corn	-0.067	(0.149)	0.097	(0.164)	0.083	(0.113)	0.033	(0.050)
Irrigation	0.030	(0.164)	0.140	(0.185)	-0.330	(0.154)**	-0.351	(0.111)***
Field area	-0.478	(0.175)***	-0.357	(0.122)***	-0.053	(0.079)	-0.028	(0.046)
Fall_Nit	0.015	(0.115)	0.067	(0.125)	0.016	(0.082)	-0.058	(0.044)
College	-0.108	(0.112)	0.209	(0.092)**	0.026	(0.114)	-0.052	(0.046)
Experience	0.001	(0.003)	0.000	(0.003)	-0.003	(0.003)	0.000	(0.002)
Conservation	0.023	(0.217)	-0.572	(0.234)**	0.148	(0.224)	0.070	(0.063)
GDD	0.048	(0.023)**	0.086	(0.023)***	0.014	(0.021)	0.028	(0.013)**
HDD	-0.011	(0.022)	-0.013	(0.012)	0.014	(0.012)	0.015	(0.009)
Precipitation	-0.067	(0.032)**	-0.005	(0.031)	-0.009	(0.022)	-0.010	(0.013)
NCCPI	-0.082	(0.359)	-0.330	(0.320)	0.002	(0.214)	-0.509	(0.150)***
% sand	-0.006	(0.005)	-0.002	(0.006)	0.000	(0.007)	-0.004	(0.004)
% silt	-0.015	(0.006)**	-0.000	(0.008)	0.002	(0.008)	-0.008	(0.005)*
SOC	-0.020	(0.018)	-0.003	(0.022)	-0.007	(0.014)	-0.011	(0.011)
Slope	-0.011	(0.010)	-0.002	(0.012)	-0.013	(0.008)	-0.004	(0.004)
RZAWS	0.069	(0.832)	-3.699	(1.088)	-1.099	(0.785)	0.201	(0.447)
T-factor	-0.120	(0.060)**	-0.020	(0.038)	0.006	(0.054)	-0.020	(0.038)
Constant	1.097	(0.653)*	-0.915	(0.883)	-0.145	(0.912)	0.680	(0.498)
$\sigma_{\varepsilon e}^{j}$	-0.371	(0.311)	-0.050	(0.229)	-0.267	(0.185)	0.214	(0.126)*
Year and regional dummies		Yes		Yes		Yes		Yes
Wald Statistics		53.25***		104.31***		48.86***		121.02***
R-squared		0.085		0.248		0.056		0.086
# of convergence		1000		1000		1000		1000

Note: *** significant at 1% level. ** significant at 5% level. * significant at 10% level. ( ) standard errors of estimates. Estimates and their standard errors are from about 1,000 bootstrap runs. R-squared is the squared correlation coefficients between actual NUE and predicted NUE (Wooldridge 2010, pp 731~732). R-squared and Wald Statistics are based on whole samples. Units of environmental variables are in Table 3.1.

Appendix A: Robustness checks

To check the robustness of our results, we test the effects of three assumptions on our estimation results. Firstly, to examine the effects of the aggregation among GM traits, we only consider Bt corn and Stacked-trait Bt corn as GM corn and exclude HT corn adopters when estimating models. Second, we include corn prices in our model specification to check the effects of excluding price variables.[24] Third, since irrigation could change farmers' responses to environmental conditions and crop management practices, we estimate our model without irrigated fields to control for the effects of irrigation (Deschênes and Greenstone 2007; Hornbeck and Keskin 2014). Table A-3.1 represents the effects of adopting GM corn and/or pest scouting on corn yield and nutrient management of adopters. Table A-3.2 shows the marginal effects of adopting yield monitor depending on technology adoption status. From two tables, we can verify that the estimates based on the three assumptions are almost identical to estimates in Table 3.3 and Table 3.5.

Table A-3.1. The effects of GM corn and/or pest scouting

	Yield (bushel/acre)	Nitrogen use (pounds/acre)	NUE (lb/bushel)
Including only Bt corn			
GM corn and pest scouting	30.99 (14.45)**	62.99 (15.59)***	0.33 (0.30)
Pest scouting	12.55 (9.59)	41.41 (11.69)***	0.27 (0.16)
GM corn	9.47 (4.76)**	6.41 (10.33)	-0.06 (0.12)
# of convergence	983	984	1000
Including price variables			
GM corn and pest scouting	26.32 (18.15)	63.61 (20.68)***	0.42 (0.23)*
Pest scouting	7.11 (10.64)	35.01 (13.12)***	0.27 (0.13)
GM corn	12.20 (5.96)*	16.22 (8.46)*	-0.05 (0.10)
# of convergence	990	989	1000
Excluding irrigated fields			
GM corn and pest scouting	26.32 (20.99)	61.26 (28.50)**	0.40 (0.31)
Pest scouting	7.77 (12.73)	39.28 (16.54)**	0.29 (0.15)**
GM corn	12.38 (6.18)*	16.70 (8.79)*	-0.05 (0.11)
# of convergence	990	994	1000

Note: *** significant at 1% level. ** significant at 5% level. * significant at 10% level. ( ) standard errors of estimates. Estimates and their standard errors are from about 1,000 bootstrap runs.

[24] Chicago Board of Trade (CBOT) futures prices are used for expected corn prices, and these prices are adjusted to take into account regional differences in farm-gate prices (Barr et al. 2011).

Table A-3.2. Marginal effects of yield monitor adoption

	Yield (bushel/acre)	Nitrogen use (pounds/acre)	NUE (lb/bushel)
Using Bt corn			
GM corn and pest scouting	4.81 (2.69)*	7.34 (4.46)	0.04 (0.05)
Pest scouting	15.40 (4.32)***	8.29 (7.27)	-0.09 (0.09)
GM corn	3.23 (7.84)	14.04 (11.87)	-0.01 (0.10)
Non-adopter	9.15 (4.53)**	5.26 (9.18)	-0.03 (0.08)
Including price variables			
GM corn and pest scouting	8.25 (2.17)***	2.93 (3.97)	-0.07 (0.05)
Pest scouting	14.63 (4.60) ***	13.38 (6.74)**	-0.13 (0.09)
GM corn	8.73 (7.55)	11.64 (12.21)	0.00 (0.12)
Non-adopter	8.46 (4.62)*	5.38 (8.75)	-0.02 (0.09)
Excluding irrigated fields			
GM corn and pest scouting	8.26 (2.12)***	1.99 (3.74)	-0.07 (0.47)
Pest scouting	16.54 (4.74)***	16.02 (6.96)**	-0.11 (0.10)
GM corn	9.02 (8.14)	7.64 (12.89)	-0.04 (0.13)
Non-adopter	9.09 (5.11)*	6.87 (10.13)	-0.02 (0.09)

Note: *** significant at 1% level. ** significant at 5% level. * significant at 10% level. ( ) standard errors of estimates. Estimates and their standard errors are from about 1,000 bootstrap runs.

Appendix B: Supplementary tables

Table A-3.3. Corn yield and nitrogen use in 2001, 2005 and 2010

		Yield (bushels/acre) (St.dev)	Nitrogen use (pounds/acre) (St.dev)	# of observations (%)
2010	GM corn and pest scouting	160.57 (40.01)	140.56 (65.35)	400 (58.82)
	Pest scouting	126.55 (44.02)	90.72 (76.98)	179 (26.32)
	GM corn	153.50 (35.75)	147.03 (56.59)	63 (9.26)
	Non-adopter	140.27 (44.42)	103.72 (78.71)	38 (5.59)
2005	GM corn and pest scouting	150.44 (43.91)	146.99 (57.79)	403 (66.50)
	Pest scouting	128.18 (43.25)	124.69 (63.15)	134 (22.11)
	GM corn	147.09 (44.65)	123.53 (58.61)	53 (8.75)
	Non-adopter	143.13 (48.04)	123.19 (44.67)	16 (2.64)
2001	GM corn and pest scouting	144.94 (38.95)	143.45 (53.08)	102 (13.14)
	Pest scouting	139.38 (43.72)	140.54 (60.66)	282 (36.34)
	GM corn	139.07 (37.71)	145.23 (67.14)	90 (11.60)
	Non-adopter	128.42 (40.81)	129.60 (65.95)	302 (38.92)

Table A-3.4. The effects of technology adoption based on soil quality: non-irrigated and rotation

	Soil productivity	Yield (bushel/acre)	Nitrogen use (pounds/acre)	NUE (lb/bushel)
GM corn and pest scouting	Low	34.07 (13.91)**	65.03 (25.33)**	0.47 (0.22)**
	High	27.89 (18.06)	43.36 (44.51)	0.34 (0.28)
Pest scouting	Low	18.80 (8.12)**	33.16 (11.53)***	0.13 (0.12)
	High	5.54 (12.43)	31.25 (24.17)	0.28 (0.15)**
GM corn	Low	18.63 (7.45)**	33.95 (12.04)***	0.10 (0.15)
	High	11.97 (6.44)*	12.41 (10.55)	-0.08 (0.11)

Note: *** significant at 1% level. ** significant at 5% level. * significant at 10% level. ( ) standard errors of estimates. Estimates and their standard errors are from about 1,000 bootstrap runs. NCCPI-CS is used as the measure of soil productivity. Fields having low soil productivity means fields having NCCPI-CS less than 0.5. Fields having high soil productivity means fields having NCCPI-CS larger than 0.5.

Table A-3.5. Marginal effects of yield monitor adoption: non-irrigated and rotation

	Soil productivity	Yield (bushel/acre)	Nitrogen use (pounds/acre)	NUE (lb/bushel)
GM corn and pest scouting	Low	8.41 (2.16)***	3.74 (3.65)	-0.06 (0.05)
	High	8.69 (2.22)***	3.65 (3.56)	-0.06 (0.05)
Pest scouting	Low	15.09 (4.25)***	13.26 (6.29)**	-0.12 (0.08)
	High	17.96 (4.94)***	15.23 (7.09)**	-0.13 (0.09)
GM corn	Low	8.49 (6.24)	10.71 (10.70)	-0.01 (0.13)
	High	10.02 (7.34)	11.58 (11.32)	-0.01 (0.11)
Non-adopter	Low	7.55 (4.15)*	2.94 (9.44)	-0.04 (0.09)
	High	8.75 (4.78)*	2.91 (9.60)	-0.03 (0.08)

Note: *** significant at 1% level. ** significant at 5% level. * significant at 10% level. ( ) standard errors of estimates. Estimates and their standard errors are from about 1,000 bootstrap runs. NCCPI-CS is used as the measure of soil productivity. Fields having low soil productivity means fields having NCCPI-CS less than 0.5. Fields having high soil productivity means fields having NCCPI-CS larger than 0.5.

CHAPTER 4

FORECASTING FUTURE LAND USE IN THE MIDWEST

Jae-hoon Sung and John A. Miranowski

Abstract

To forecast future land use, researchers need to consider heterogeneous features of projected weather data sets. Also, the land use literature has used different assumptions to construct farmers' expected weather conditions. This study examines the effects of these two uncertainties regarding climate measures on forecasting future land use. Using an out-of-sample forecasting test, we compare the predictive accuracy of 13 linear models depending on five general circulation models (GCMs) and six assumptions regarding expected weather conditions. Our analysis is based on decadal land use data over the Corn Belt, Lake States, and Northern Plains during the last three decades. We find that the forecast land use over three regions and predictive accuracy of models depend on the choice of GCMs and methods of constructing expected weather conditions. However, models consisting of yearly agronomic variables are more stable and have better predictive accuracy than models using monthly climate variables. Last, the best model predicts that the proportion of corn and soybean acreage over the Corn Belt (Lake States) in 2030 will decrease (increase) from 0.43 to 0.41 (0.20 to 0.25).

4.1 Introduction

In designing plans for sustainable agriculture and resource management, accurate estimates of land use change based on various climate scenarios are necessary for decision makers, such as policy developers and farm operators. The typical method of quantifying the potential economic impacts of climate change consists of two steps: Estimate the causal relationship between economic outcomes and climate variables based on historical weather or climate data, and then forecast future impacts by multiplying these estimates by projected changes in climate variables over time. However, in reality, lack of knowledge about climate systems and farmers' response to climate conditions creates uncertainty in forecasting future land use.

This study analyzes the effects of two uncertainties regarding climate measures on forecasting future land use: uncertainty regarding projected weather data sets and uncertainty regarding methods of constructing expected weather conditions. Economists can incorporate various projected weather data sets in forecasting climate impacts on economic outcomes. These data sets are based on general circulation models (GCMs) and emission scenarios. GCMs are numerical models which approximate the fundamental laws of motion for fluids. GCMs also incorporate current scientific and empirical knowledge regarding climate conditions such as sea ice, land surface, and cloud process to improve their representation of climate conditions and their future changes, called parametrizations (Auffhammer, Hsiang, & Schlenker, 2013; Flato et al., 2013, Section 9.1). However, the methods of parametrization vary among GCMs, and the differences in parameterizations are the important reason for the heterogeneous results of GCMs. For example, MIROC-ESM incorporates information on ocean chemistry to account for salinity effects on sea ice formation, but CCSM4 does not include it for its parameterization. [1]

[1] Flato et al. (2013) include a concise summary of components of GCMs included in a Fifth Assessment Report (AR5).

These methods of projecting future weather conditions can also be applied retrospectively to construct historical weather data sets. The advantage of this method is that researchers can use weather data sets with the same GCMs in estimating the causal relationship between economic outcomes and climate and in forecasting climate change impacts. However, the historical weather data sets based on GCMs generally differ from realized station-level weather outcomes, even with the use of bias-correction algorithms to address this problem.

Figures 4.1, 4.2, and 4.3 show differences in three measures representing intensive rainfall events among four GCMs. As the figures show, compared to MIROC-ESM, CCSM4 has more intensive rainfall events and larger variations in the first two measures. However, the literature on climate change argues that GCMs are based on imperfect knowledge of climate systems, and little evidence suggests that any particular GCMs outperform others in describing historical weather outcomes (Gleckler, Taylor, & Doutriaux, 2008; Reichler & Kim, 2008; Pierce et al., 2009). Burke et al. (2015) refer to this limitation of GCMs as climate uncertainty or model uncertainty. They show that estimated climate impacts on economic outcomes such as crop yields, land values, and gross domestic product (GDP) vary widely among GCMs. As a result, estimates of future land use are likely to be affected by the choice of weather data set(s).

The proper derivation of expected weather conditions is worth noting. Weather conditions are considered as stochastic and exogenous input variables in agricultural production from the farmer's point of view. Farmers' decisions on farm management are thus based on their expectations about weather conditions during the growing season. Land use studies have used the average values of observed weather conditions as their climate measures, and the results regarding these climate measures have been interpreted as farmers' responses to expected weather conditions during the growing seasons. However, there is no consensus on how to construct expected weather conditions and which climate measures are more appropriate for inclusion in analysis. For example, in land use studies, the number of years assumed to affect farmers' formulation of expected weather conditions varies from 3 to 30 years. The climate change literature has used 30-year averages, called climate normal, to describe current and future climate conditions. However, the justification for climate normal is controversial. Arguez and Vose (2011) summarize practical issues regarding the definition of climate normal. The main issue is that the definition may not convey accurate information about current and future climate conditions. In particular, Arguez and Vose indicate that climate series have serial autocorrelation, which means that providing greater weights to more recent data is more reliable.

Differences in methods of forming farmers' expectations regarding weather variables also influence the identification of climate effects as well as the interpretation of estimates regarding climate measures. If farmers' decisions are based on long-run averages of weather conditions, then temporal variations in climate measures are smoothed out by the long-run average. Thus, the identification of climate impacts on land use depends more on spatial variations of climate measures. Conversely, if we assume that farmers formulate their expectations in response to short-run weather fluctuations, more temporal variations of climate measures are available to identify climate effects on land use change. However, the meanings of coefficients regarding climate measures are closer to farmers' responses to short-run weather conditions, not to climate. Of course, incorrect assumptions regarding farmers' expectations can misconstrue the actual relationship between climate conditions and farmers' response to them.

In this study, we test two research hypotheses: (i) According to GCMs, forecast land use will change and (ii) the estimated climate change effects on future land use depend on how farmers construct expected weather conditions during the growing season. To test these two hypotheses, we analyze the effects of climate conditions on land use change based on decadal land use data consisting of 25 km × 25 km grids across three regions: Corn Belt, Lake States, and Northern Plains. Specifically, we derive an empirical model representing farmers' land allocation based on climate measures, soil quality, irrigation status, and total cropland, and construct 13 models consisting of different climate measures. Also, we generate 30 scenarios consisting of five GCMs and six assumptions about forming farmers' expectations regarding weather variables. An out-of-sample forecasting test is performed to measure the predictive accuracy of the 13 models for each scenario and each region. We compare the predictive accuracy of the models and their estimates to identify the effects of climate uncertainty and assumptions about forming farmers' expectations regarding weather variables. We forecast land use in 2030 based on the best model of each GCM. The results show that the significance and size of climate effects on land use change depend on the choice of GCMs and methods of forming farmers' expectations regarding weather variables. In addition, the forecast land use in 2030 and predictive accuracy of models vary among the 30 scenarios. However, we find that forecasting results based on models consisting of yearly agronomic variables are more stable and have better predictive accuracy than models consisting of monthly variables. Last, the predicted land use in 2030 shows that corn and soybean acreage will expand to the northwest.

The rest of this paper is organized as follows. In Section 2, we review the previous literature and describe the contributions of this study. Section 3 introduces a simple conceptual model. Section 4 and Section 5 describe the estimation method and our data. Section 6 explains the process of evaluating the empirical model and choosing the best model for prediction. The results and their implications are presented in Section 7. Section 8 discusses conclusions and limitations of this study. The final section contains references, tables, and figures related to the data and estimation results. Last, the Appendix includes the description of decadal land use data, supplementary tables, and figures regarding forecasting results.

4.2 Literature review

In recent years, an increasing number of studies has forecast land use change in response to changes in climate and policies to measure their potential economic effects (Fezzi & Bateman, 2010; Kaminski, Kan, & Fleischer, 2012; Jianhong, McCarl, & Wein, 2013; Miao, Khanna, & Huang, 2016). Fezzi and Bateman (2011) forecast land use change in the United Kingdom resulting from nitrogen tax and zoning to identify the policy effects of new regulations on nitrogen soil balance. Kaminski, Kan, and Fleischer (2012) assume that changes in farmers' land use are affected by climate conditions through the use of available production technologies. Thus, by identifying commodities sensitive to expected climate changes, they derive potentially useful directions for research and development (R&D) to alleviate harmful climate effects more effectively. Mu, McCarl, and Wein (2013) forecast changes in cropland and pastureland based on climate change scenarios. They calculate the economic losses or gains resulting from climate change by multiplying changes in cropland and pastureland by the current value of cropland and pastureland. Miao, Khanna, and Huang (2015) measure the effects of omitting price variables on estimates of climate change effects. To be specific, they estimate the effects of climate change on corn and soybean acreage over counties located east of the 100th meridian with and without input and output prices. They find that omitting price variables results in an overestimation of climate change effects.

However, some common limitations make these forecast land use changes less credible. First, even though recent land use studies employ several GCMs to forecast future land use, they usually incorporate only one weather data set to estimate their empirical models. If the weather data sets used for estimation differ from those used for forecasting, bias is introduced into projected changes in climate variables. In addition, the model having the best predictive accuracy may differ for different GCMs because of climate uncertainty. However, even though one purpose of these studies is to evaluate potential climate change effects, most of them do not perform statistical tests related to forecasting to choose the best models in terms of predictive accuracy.

Reliable estimates regarding the potential impacts of climate change on agricultural production can be used to guide policy makers. For several reasons, we expect our results to contribute to more credible estimates of future land use. First, our study chooses the best model by comparing predictive accuracy over several models. Second, our approach accounts for climate uncertainty and uncertainty related to calculating expected weather conditions in estimating models and forecasting future land use. Last, our study conveys useful information about the effects of uncertainty regarding climate conditions on estimates of future land use.

4.3 Conceptual model

Our conceptual model is drawn from a classical profit maximization problem of risk-neutral farms with land (Chambers & Just, 1989; Fezzi & Bateman, 2011). Fezzi and Bateman (2011) show that the optimal land allocation problem can be represented as:

$$\pi(p,z,L) = \max_{s_1,\dots,s_M} \{\pi(p,z,L,s_1,\dots,s_M) : \sum_{i=1}^{M} s_i = 1\} \tag{1}$$

where p means a price vector, z is the vector of given environmental conditions, L is total land, and $s_i, i = 1, \dots, M$ is the land share allocated to crop i, M denotes the number of crops, and $\pi(p, z, L, s_1, \dots, s_M)$ means the maximum profit conditional on given land shares $(s_1, \dots, s_M)$. From Equation (1), the optimal land allocation $s_i^*(p, z, L)$ is determined at the point where the marginal rent or shadow price of each land use is identical among all crops.

$$\frac{\partial \pi(p,z,L,s_1,...,s_M)}{\partial s_1} = \frac{\partial \pi(p,z,L,s_1,...,s_M)}{\partial s_i} \text{for } i = 2,...,M; \sum_{i=1}^{M} s_i = 1 \quad (2)$$

Previous land use literature uses a dual approach to derive land share equations from Equation (2) and estimate welfare effects of agricultural policies. Since the purpose of this study is to identify the relationship between land use change and climate conditions, we use a simple linear approximation of $s_i^*(p,z,L)$ to construct our empirical model. Consider a farmer who allocates his field *j* to crop *i* at time *t*. His land allocation problem can be specified as Equation (3)

$$s_{ijt} = \beta_i + P_{jt}\beta_{1i} + W_{jt}\beta_{2i} + \beta_{3i}L_{jt} + \alpha_i c_j + \delta_i y90_t + \epsilon_{ijt} \quad (3)$$

where P_{jt} is the vector of output prices, W_{jt} is the vector of given environmental conditions including expected weather measures, variables representing soil quality, and irrigation status. L_{jt} is total cropland, and c_j is unobserved heterogeneity of field *j*. Last, we include a dummy variable having 0 in years earlier than 1996 and 1 after 1996 to control for changes in US farm policy: Federal Agriculture Improvement and Reform (Miao, Khanna, & Huang, 2016).

4.4 Estimation

For estimation, we must account for two features of Equation (3). First, our dependent variables represent mutually exclusive and exhaustive shares of each land use. In addition, the optimal solutions of Equation (2) can be corner solutions, which means the nontrivial proportion of optimal solutions can be 0 or 1. Let X_{jt} be the vector of explanatory variables in Equation (3), $\mathrm{X}_j = \{\mathrm{X}_{j1}, \ldots, \mathrm{X}_{jT}\}$, except for the unobserved heterogeneity (c_j). Then, the features of our model can be described as:

$$s_{ijt} \in [0,1]; \sum_{i=1}^{M} s_{ijt} = 1,\ t = 1,...T,$$

$$\Pr(s_{ijt} = 0 \mid X_j,\ c_j) > 0; \Pr(s_{ijt} = 1 \mid X_j,\ c_j) > 0,\ i = 1,...,M$$

If we assume the strict exogeneity of $\{X_{jt} | t = 1, \ldots T\}$ conditional on c_j, we can conceptualize the above problem as Equation (4) based on Mullahy (2015).[2]

$$
\begin{aligned}
& E(s_{ijt} \mid X_{jt}, c_j) = f_k(X_{jt}; \beta_i, c_j) \in (0,1) \\
& \sum_{i=1}^{M} E(s_{ijt} \mid X_{jt}, c_j) = 1, \\
& \Pr(s_{ijt} = 0 \mid X_{jt}, c_j) \geq 0,\ i = 1, \ldots, M, \\
& \Pr(s_{ijt} = 1 \mid X_{jt}, c_j) \geq 0,\ i = 1, \ldots, M
\end{aligned} \tag{4}
$$

In addition, Mullahy (2015) assumes that the conditional mean of each outcome has a multinomial logit functional form preventing the possibility of predicted shares which are less than 0 or greater than 1.

$$
E(s_{ijt} \mid X_{jt}, c_j) = \frac{\exp(X_{jt}\beta_i + \alpha_i c_j)}{\sum_{m=1}^{M} \exp(X_{jt}\beta_m + \alpha_m c_j)},\ i = 1, \ldots, M \tag{5}
$$

After normalization based on crop *M*, that is, $\beta_M = \alpha_M = \mathbf{0}$, Equation (5) can be rewritten as Equation (6).

$$
\begin{aligned}
& E(s_{ijt} \mid X_{jt}, c_j) = \frac{\exp(X_{jt}\beta_i + \alpha_i c_j)}{1 + \sum_{m=1}^{M-1} \exp(X_{jt}\beta_m + \alpha_m c_j)},\ i = 1, \ldots, M-1 \\
& E(s_{Mjt} \mid X_{jt}, c_j) = \frac{1}{1 + \sum_{m=1}^{M-1} \exp(X_{jt}\beta_m + \alpha_m c_j)}
\end{aligned} \tag{6}
$$

To control for unobserved heterogeneity, we assume that $D(c_j | X_j, w_j) = D(c_j | w_j)$ where $D(c_j | .)$ means the conditional distribution of c_j, and w_j is a vector of redundant and

[2] This assumption rules out including previous land use in our model and the situation in which $X_{.t}$ influences idiosyncratic events affecting future land use. Also, we assume that farmers do not consider the feedback effects of their land use on regional weather conditions during the growing season when they allocate their land.

ignorable variables, but a vector of good proxy variables for c_j. Then, from Wooldridge (2010, pp. 22-24), we derive Equation (7).

$$E_c\left[\frac{\partial E(s_{ijt} \mid X^o_{jt}, c_j)}{\partial X_{jt,q}}\right] = E_w\left[\frac{\partial E(s_{ijt} \mid X^o_{jt}, w_j)}{\partial X_{jt,q}}\right] \tag{7}$$

where E_c and E_w denote the expectation with respect to c_j and w_j. X^o_{jt} is a fixed value of X_{jt}, and $X_{jt,q}$ is one of covariates in X_{jt}. Equation (7) means that we can calculate the average partial effects (APE) of each explanatory variable on land use for crop *i* at time *t* without integration with respect to c_j.[3] We use dummies representing major land resource areas (MLRAs) as w_j (Hendricks, Smith, & Sumner, 2014).[4] After controlling for w_j, we deal with our panel data as repeated cross-sectional data when estimating our model.[5]

For estimation, we incorporate the quasi maximum likelihood estimation (QMLE) method based on likelihood functions of a multinomial logit model to estimate coefficients consistently (Mullahy, 2105).[6]

---

[3] To control for the effects of unobserved heterogeneity in probit models, Mundlak (1978) and Chamberlain (1980) assume that c_j follows the normal distribution. Their estimated coefficients of probit models are scaled by the variance of c_j. Thus, the estimates cannot be used directly to calculate the partial effects of each explanatory variable. Our approach has the same disadvantage – that is, even though we do not assume a specific distribution of c_j and use w_j instead, the estimated coefficient could be affected by the distribution of c_j. However, APE is the intuitive way of summarizing partial effects of explanatory variables for nonlinear models. To be specific, in the case of nonlinear models, the partial effects of each explanatory variable depend on the specific value of X_{jt}, which means APEs are different from individual partial effects, and their directions and sizes are not determined by estimated coefficients alone. Thus, even though we only identify scaled estimates, we can analyze the effects of climate on farmers' land use based on APEs of explanatory variables.

[4] Papke and Wooldridge (2008) and Wooldridge (2010, pp 653-654) recommend using the average values of time variant variables in X_{jt} ($\overline{w}_j$) as w_j to control for the effect of c_j. However, in our study, since climate variables are highly correlated with their averages, we use dummies representing MLRAs instead of $\overline{w}_j$. MLRAs are determined by regional water use, land use, and environmental conditions of specific areas. Thus, even though one MLRA covers a larger area than our observations, its use would alleviate the effects on unobserved heterogeneity (Hendricks, Smith, & Sumner 2014).

[5] Wooldridge (2010, pp 620 and pp 654) recommends this approach to analyze the multinomial or binary logit model for panel data.

[6] Buis (2008) writes a STATA® module for Equation (6), and we use his module for estimation (see http://maartenbuis.nl/software/fmlogit.html).

$$J(\beta) = \sum_{t=1}^{T}\sum_{j=1}^{N}\sum_{i=1}^{M} s_{ijt} \log(E(s_{ijt} \mid X_{jt}, w_j)) \tag{8}$$

To calculate the APE on land use for crop *i* based on Equation (7), we use the average structural function (ASF) approach (Papke & Wooldridge, 2008). To be specific, given consistent estimates $\hat{\theta}_i = (\hat{\beta}_i, \hat{\alpha}_i), i = 1, \ldots, M$, the APE on land use for crop *i* at time *t* can be calculated by taking the derivative or change of Equation (9) with respect to one element of X_{jt}.

$$ASF_{it} = N^{-1}\sum_{j=1}^{N} \frac{\exp(X_{jt}\beta_i + \alpha_i w_j)}{1 + \sum_{m=1}^{M-1}\exp(X_{jt}\beta_m + \alpha_m w_j)} \tag{9}$$

Thus, if $X_{jt,q}$ is a continuous variable, then its APE becomes

$$APE_{it,q} = N^{-1}\sum_{j=1}^{N}\exp(X_{jt}\beta_i + \alpha_i w_j) \times \frac{(1 + \sum_{m=1}^{M-1}\exp(X_{jt}\beta_m + \alpha_m w_j))\beta_{k,q} - \sum_{m=1}^{M-1}\exp(X_{jt}\beta_m + \alpha_m w_j)\beta_{m,q}}{(1 + \sum_{m=1}^{M-1}\exp(X_{jt}\beta_m + \alpha_m w_j))^2} \tag{10}$$

Also, if $X_{jt,q}$ is a discrete variable, then the APE can be represented as

$$APE_{it,q} = \frac{1}{N}\sum_{j=1}^{N}\left(\frac{\exp(X_{jt,-q}\beta_{i,-q} + \beta_{i,q} + \alpha_i w_j)}{1 + \sum_{m=1}^{M-1}\exp(X_{jt,-q}\beta_{m,-q} + \beta_{m,q} + \alpha_m w_j)} - \frac{\exp(X_{jt,-q}\beta_{i,-q} + \alpha_i w_j)}{1 + \sum_{m=1}^{M-1}\exp(X_{jt,-q}\beta_{m,-q} + \alpha_m w_j)}\right) \tag{11}$$

where $\hat{\beta}_{i,-q}$ and $X_{jt,-q}$ are coefficients and covariates, except for $\hat{\beta}_{i,q}$ and $X_{jt,q}$ for $i = 1, \ldots, M$. Due to the adding-up restriction in Equation (4), we know that $\sum_{m=1}^{M} APE_{mt,q} = 0$, which means the APE on land use for crop *M* equals $-\sum_{m=1}^{M-1} APE_{mt,q}$. Finally, we average Equation (10) and Equation (11) across *t* to calculate the effects averaged across time and cross-sectional units.

For inference, we cluster observations by MLRA and year and use a cluster bootstrap with a run of 1,000 for three reasons. First, the variance estimates based on Equation (6) are inconsistent (Mullay, 2015). Second, since some part of unobserved heterogeneity is omitted, arbitrary dependence may exist among the dependent variables, which means that variance estimates should be robust for this correlation (Wooldridge, 2010, pp. 654). Clustering by MLRA and year allows spatial dependence between all areas in the same MLRA and year but assumes independence among MLRAs and years. Finally, to calculate variances for the APEs, the iterative method is also used without specific distributional assumptions.

4.5 Data and model specification

4.5.1 Decadal land cover

The decadal land cover data consist of 25 km × 25 km cells and contain information regarding the irrigation status of each cell and proportion of each of 21 land use classes in each cell. The data include land use change over 21 states in the central United States from the 1940s through the 2000s. Among these land use classes, our study assumes that only five are related to land use change for crop production: corn, soybeans, wheat, other crops, and grassland. We assume that the other land use classes are/will be invariant until 2030. Based on these assumptions, we calculate the area of each of these five land use classes. The dependent variables are the proportion of each of the land use classes to the sum of their areas. Finally, we drop all cells which have not been used for any of these five land use classes during the 2000s and all cells whose area is less than 50% of the area of regular cells. About 200 cells are dropped because of natural boundaries such as seas and lakes. Among 21 states, we analyze land use change over major corn-producing regions: Corn Belt, Lake States, and Northern Plains. Last, we use decadal land use from the 1980s through the 2000s. Total number of cells per decade is about 3,232 and total number of cells overall is 9,696. Tables 4.1, 4.2, and 4.3 show summary statistics regarding land use in the Corn Belt, Lake States, and Northern Plains. The average fractions of three major crops (corn, soybeans, and wheat) differ among the three regions: Corn and soybean acreage account for approximately 43% over the Corn Belt and three decades on average, but the sum of average fractions of corn and soybean acreage in the Lake States and Northern Plains is less than 20%. However, the averages of these three major crops over regions and years may mask heterogeneous historical and regional land use. For example, Figures 4.4 and 4.5 show corn and soybean acreage in the 1950s and 2000s. As is evident, corn and soybean acreage has expanded to the northwest.

4.5.2 Environmental conditions[7]

This study uses the National Aeronautics and Space Administration (NASA) Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) to construct expected weather conditions (Thrasher et al. 2012). This data set comprises 42 climate projections based on 21 Coupled Model Intercomparison Project 5 General Circulation Model (CMIP5 GCM) simulations and two representative concentration pathway (RCP) scenarios (RCP 4.5 and RCP 8.5). It includes daily maximum temperature, daily minimum temperature, and precipitation for each projection. The spatial resolution of the data is 0.25 degrees × 0.25 degrees, and the temporal extent is from 1950 through 2100.[8] We incorporate daily weather information based on four GCMs and their average for our estimation and prediction: CCSM4, MIROC-5, GDFL-CM3, and MIROC-ESM.

[7] Previous studies include price variables to capture yearly price effects on acreage allocation. However, for decadal land use data, the effects of prices may be meaningless. After globalization, the productivity of crop production may be more relevant than output prices to determine decadal land use change. In addition, Hendricks, Smith, and Sumner (2014) show that long-term acreage response elasticity to output prices is much lower than short-term acreage response elasticity to output prices. Lastly, after 1975 the average soybean-corn ratio is 2.52, and there is no trend in this ratio (Zulauf 2013).

[8] More information about the NASA-GDDP data is available on the website of the NASA-GDDP project at http://cds.nccs.nasa.gov/nex-gddp/.

However, we use only one emission scenario (RCP 4.5) because climate change during the next 25 years is predicted to be the same regardless of the emission scenario (McCarl, 2015).

To test the influence of the method for constructing expected weather conditions on forecasting results, we construct expected weather variables based on six scenarios. The first three scenarios assume that information regarding weather conditions can decay at three different rates, 0.925, 0.95, and 0.975, and expected weather conditions are the weighted averages of weather conditions over the previous 30 years.[9] Figure 4.6 shows the weights used to construct the expected weather conditions based on different decay rates. From the figure, we can verify that as the decay rates decrease the years closer to a specific study year have larger weights. The remaining three scenarios assume that farmers' expected weather conditions are the simple average values of weather conditions over the previous 10, 20, and 30 years.

In addition, we set 13 models having different specifications based on five popular weather variables: average temperature, precipitation, growing degree days (GDD), extreme heat degree days (HDD), and intensive rainfall (see Table 4.2). [10] In the case of intensive rainfall, we include three measures: the number of daily rain events above 25.4 mm and above 76.2 mm per year (or month) and the fraction of precipitation (mm) during the 10 wettest days per year (Groisman, Knight, & Karl, 2012; Kunkel et al., 2013). As a result, we construct 30 scenarios based on five GCMs and six ways of constructing farmers' expected weather conditions. Also, we evaluate 13 models per each scenario based on their predictive accuracy. Finally, we choose the best model

[9] We assume that information at time t-1 (I_{t-1}) is less valuable than information (I_t) at time t. To be specific, we assume that $I_t = \delta_t \mathrm{I}_{t-1}$, where δ_t is a decaying rate. Based on this assumption, we construct of farmers' expected weather condition (w_{jt}) as $w_{jt} = \sum_{i=1}^{30} \frac{\delta_{t-i+1}}{\sum_{k=1}^{30} \delta_{t-k+1}} w_{jt-i}$.

[10] Snyder (1985) is used to construct GDD and HDD with an upper bound of 34 ºC and lower bound of 8 ºC.

per each GCM and use it for forecasting. For monthly weather conditions, we include March through September.[11]

Last, to control for soil quality, we include the National Commodity Crop Productivity Index – Overall (NCCPI-all), silt percentage, sand percentage, representative slope, available water storage within crop root zone depths (RZAWS), and soil organic carbon (SOC). The NCCPI-all is used to control for time-invariant and average soil productivity of each cell (Dobos, Sinclair, & Robotham, 2012). Representative slope is the difference in elevation between two points expressed as a percentage of the distance between those points. SOC is the carbon stored in soil organic matter and the main source of energy for soil microorganisms. Soil texture is categorized by sand, silt, and clay based on the size of soil particles. In this study, we include silt percentage and sand percentage to account for soil texture. RZAWS is the maximum amount of available water in the soil within crops' root zones for crop development. Soil variables are based on the Gridded Soil Survey Geographic (gSSURGO) Database. We construct environmental variables corresponding to each cell by averaging soil and climate conditions within each cell.

4.6 Model evaluation and selection

To assess the predictive accuracy of the candidate forecasting models, we must clarify what we want to forecast and which error measures are appropriate for our model selection problem. First, our model specification is designed to estimate conditional means of dependent variables. In addition, single-value point forecasts are useful to identify the effects of uncertainties regarding

[11] Summary statistics for climate measures are given in the Appendix-C. Since the decadal land use data are based on the land use over the last three years of each decade, we construct climate variables based on the 9th year of each decade. For example, for climate variables in 2000s, we use weather conditions before 2009.

climate measures through comparison. We thus focus only on farmers' expected land allocation in 2030 conditional on expected weather conditions, not the distribution of future land use.[12]

Second, we have to choose an appropriate measure of predictive accuracy, called the scoring function. Gneiting (2011) points out the importance of consistency between the scoring function and the distributional feature of a forecaster which researchers want to estimate; he suggests that a scoring function having Bregram form is a consistent measure for mean forecasting (see Equation (12)).

$$S(\hat{y}, y) = \phi(y) - \phi(\hat{y}) - \phi'(\hat{y})(y - \hat{y}) \tag{12}$$

where $\hat{y}$ is the point forecast, and y means the verifying observation. ϕ is the convex function with gradient ϕ'. When we assume that $\phi(\hat{y}) = \hat{y}^2$, then Equation (12) becomes the squared error. However, from Equation (12), we can verify that scoring functions commonly used in the literature such as the absolute error and the relative error are not consistent in forecasting the mean of the predictive distribution. We can then extend Equation (12) to the multivariate case (Gneiting, 2011). That is, we can use the squared Euclidean norm as ϕ and estimate the predictive accuracy of our models.

We use the out-of-sample forecasting test (the holdout or validation estimator) to measure prediction errors and avoid the risk of selecting an over-fitted model specification. The validation estimator is a straightforward measure to estimate out-of-sample prediction errors and assesses forecasting models based on an appropriate scoring function. The advantage of this approach is that it can be applied to a wider range of model selection problems with few assumptions regarding the true underlying model: The training samples and the validation samples follow an identical

[12] Forecasting can be categorized as probability forecasting or point forecasting. The result of probabilistic forecasting is a predictive probability distribution over future quantities, but the result of point forecasting is one feature of a predictive probability distribution (Gneiting & Raftery 2008).

distribution and the training samples are independent of the validation samples (Arlot & Celisse, 2010). To use this approach, we assume that land use in the 2000s is independent of land use in the 1980s and 1990s, but land use in the 1980s, 1990s, and 2000s is identically distributed after controlling for the effects of the explanatory variables we use. We separate observations based on decades and use observations in the 2000s as a validation set. Last, we access forecasting models based on the following scoring function.

$$Score = \sqrt{\frac{1}{N}\sum_{i=1}^{M}\sum_{j=1}^{N}(A_{ijt} - \hat{A}_{ijt})^2} \tag{13}$$

where N is the total number of observations in a test set, and M is the number of crops. A_{ijt} is acreage for crop i in cell j at time t, and $\hat{A}_{ijt}$ is its predicted value.

4.7 Results

4.7.1 Results of out-of-sample forecasting test and land use in 2030

We incorporate the out-of-sample forecasting test to find the model having the most stable and best predictive accuracy for each GCM. Figures 4.7, 4.8, and 4.9 summarize the test results. From the figures, we find that climate uncertainty and methods of forming expected weather conditions have a significant effect on the predictive accuracy of the models. In particular, the results show that, when we use monthly climate variables (from Model M4 to Model M13), the values of the scoring function have large variations within and among GCMs. This result implies that forecasting results based on models having monthly climate measures are sensitive to the choice of GCM and the method of forming expected weather conditions. However, we also find that the simplest models consisting of yearly agronomic climate measures (Model M1 to Model M3) have more stable and better performance in forecasting than models based on monthly climate variables. This result implies that models incorporating yearly agronomic measures generate more robust forecasting results than models based on monthly climate variables.

To show the effects of the choice of GCM and measures of expected weather conditions on forecast future land use, we estimate Model M3 based on 30 scenarios and forecast future land use in the Corn Belt, Lake States, and Northern Plains. Model M3 consists of GDD, HDD, total precipitation during the growing seasons, the fraction of precipitation (mm) during the 10 wettest days per year, irrigation status, and variables representing soil quality. We use Model M3 for three reasons. As we discussed, models based on the simplest specifications have more stable and better performance in prediction. Since future climate conditions are surrounded by lots of uncertainty, using stable models can generate reliable forecasting results. Also, the results of the out-of-sample forecasting test show that Model M3 has better predictive accuracy than Model M1 and Model M2. However, we use different assumptions regarding how to form expected weather conditions among GCMs to increase the predictive accuracy.[13] Last, we maintain consistency in the method of forming expected weather conditions between estimation and forecasting.

Table 4.5 shows the forecast land use over the three regions in 2030 based on different GCMs and assumptions regarding how to form expected weather conditions. To begin with, we verify that variations in forecast land use resulting from changes in GCMs are larger than variations in forecast land use resulting from changes in assumptions regarding how to form expected weather conditions: The standard deviation within a GCM is smaller than the variations of estimates among GCMs in Table 4.5. However, we also find that the standard deviation within a GCM depends on model specifications. Specifically, when Model M7 consisting of monthly

[13] When forecasting results have large variations within a GCM, our approach may be considered as "cherry picking". However, Table 4.11 shows that forecasting results within a GCM is small when we use Model M3 for estimation and prediction. Also, we find that there is no significant difference in forecasting results based on Model M3 when we use only one assumption on expected weather conditions, such as climate normal, for forecasting among GCMs.

climate variables is incorporated to forecast land use in 2030, we find that the standard deviation within a GCM becomes larger than the standard deviation within a GCM based on Model M3 (see Table 4.6). These results imply that the effects of uncertainty regarding farmers' expected weather conditions may depend on model specifications. Also, from the results, we can infer that climate uncertainty and uncertainty regarding farmers' expected weather conditions should be considered at the same time to make forecasting results more credible, especially when we use models based on monthly climate conditions.

From Table 4.5, we also verify that the direction of land use change among GCMs is identical. The table indicates that Model M3 predicts that corn acreage in the Corn Belt will decrease from 23% to 20% on average, but the model predicts that soybean acreage in the Corn Belt will increase from 20% to 21% on average. In the case of the Lake States, the model predicts large increases in corn and soybean acreage: Model M3 predicts that corn acreage in the Lake States will increase from 11% to 17% on average, and it forecasts an increase in soybean acreage in the Lake States from 8% to 9%.

Figure 4.10 shows the regional distribution of corn and soybean acreage in 2030. The figure indicates that the predicted intensity of corn acreage over Illinois and Indiana in 2030 is less than the intensity of corn acreage over the two states in the 2000s. However, the predicted proportion of corn acreage over Minnesota in 2030 is larger than the proportion of corn acreage over Minnesota in the 2000s. Specifically, MIROC-ESM, MIROC5, and averages among GCMs predict large increases in corn acreage in areas close to the border between Iowa and Minnesota. These results reflect the trend in Figure 4.2: Corn and soybean production has expanded to the northwest.[14]

[14] The forecasted land use for wheat, other crop, and grassland are in the Appendix-B.

4.7.2 Acreage response elasticity

To test the effects of uncertainty regarding climate measures on the causal relationship between climate conditions and land use change, we estimate Model M3 and calculate acreage response elasticity based on Equations (10) and (11). Tables 4.7, 4.9, and 4.11 show changes in acreage response elasticity depending on six different assumptions regarding how to construct expected weather conditions. First, from the results, we can verify that the direction of acreage response elasticities to expected weather conditions is consistent over the six assumptions. The results also show that the effects of changes in methods of forming farmers' expectations regarding weather variables on acreage response elasticity are modest. For example, Table 4.7 shows that an increase in HDD of 1% would decrease corn acreage in the Corn Belt by 0.01% regardless of methods of forming farmers' expectations regarding weather variables. Also, the effects of variables representing soil quality and total cropland are robust to methods of forming farmers' expectations regarding weather variables.

Second, the results indicate that the effects of changes in climate and soil quality on corn acreage vary among the three regions. An increase in HDD of 1% increases corn acreage over the Lake States by 0.02% but decreases corn acreage over the Northern Plains by 0.03%. In addition, an increase in the fraction of precipitation during the 10 wettest days per year has negative effects on corn acreage in the Lake States and Northern Plains but positive effects on corn acreage in the Corn Belt.[15] In the case of soil quality, the results indicate that an increase in sand percentage has a positive effect on corn acreage in the Lake States and Northern Plains but a negative effect on corn acreage in the Corn Belt. When RZAWS increases by 1%, then corn acreage in the Lake States decreases by 0.09% but corn acreage in the Northern Plains increases by 0.16%.

[15] The less intuitive results regarding precipitation patterns in the Corn Belt may reflect the effects of farmers' adaptation efforts or agricultural technology development.

Tables 4.8, 4.10, and 4.12 contain acreage response elasticity depending on five GCMs. For estimation, we use 30-year averages when we construct expected weather conditions. From the results, we can verify that the variations in estimates in these tables are larger than the variations in estimates in Tables 4.7, 4.9, and 4.11. In particular, we find that the direction and size of acreage response elasticity based on MIROC-ESM are quite different from those based on another GCM. For example, the effects of intensive rainfall result in different directions with MIROC-ESM and another GCM.

4.8 Conclusion

To measure the effects of climate change or regulations, previous studies have forecast future land use, but most of them have not considered the effects of climate uncertainty and uncertainty regarding farmers' expected weather conditions on estimating and forecasting future land use. However, agricultural production carries great uncertainty regarding environmental conditions during the growing season, and farmers make management decisions based on their expectations about environmental conditions during the growing season. In addition, climate data based on GCMs have large variation in their estimates regarding historical and future climate conditions.

This study analyzes decadal land use change over the Midwest regions to identify the effects of uncertainty regarding climate measures on forecasting future land use. First, we find that climate uncertainty has large effects on acreage response elasticity to expected weather conditions and forecasting results. We also find that forecast land use and acreage response elasticity depend on methods of forming farmers' expectations regarding weather variables, even though the effects of changes in methods of forming farmers' expectations regarding weather variables are smaller than the effects of climate uncertainty. Second, the results show that models including monthly climate variables are sensitive to the choice of GCM and the choice of how to form expected weather conditions. However, the predictive accuracy of models having yearly agronomic variables is more robust to changes in methods of forming farmers' expectations regarding weather variables. Third, our results show heterogeneous responses to climate changes among the three regions and changes in regional distribution of crop production. We find that acreage response elasticity to environmental variables differs among the three regions. Also, forecasting results show that corn and soybean acreage will expand to the northwest. Specifically, the forecasting results based on the best model show that corn and soybean acreage in the Corn Belt will decrease from about 43% to 41% on average. However, the model predicts that corn and soybean acreage in the Lake States will increase from 20% to 25%. Last, we find that corn acreage in areas close to the border between Iowa and Minnesota will increase, even though the intensity of corn acreage in the Corn Belt will decrease slightly.

Our results have certain limitations. The first limitation of our forecasting results is not accounting for the effects of farmers' adaptation and technology development in agriculture. That is, farmers have many adaptation options from self-insurance to adopting biotechnologies, and we can expect that damage from climate change can be partially mitigated through their adaptation efforts (Mendelsohn, Nordhaus, & Shaw, 1994). Also, technology innovation, such as drought-tolerant corn and precision agriculture, can reduce farmers' susceptibility to climate change. Second, the dynamic relationship between regional land use and climate conditions is important in forecasting land use. The interactions between land use and climate conditions are well recognized in climatology (Pielke et al., 2007; Mendelsohn & Dinar, 2009; Groisman, Knight, & Karl, 2012; Anderson et al., 2013). The land surface of the central US is a key factor in determining its climate conditions. Changes in agricultural land use over large areas feed back into the water cycle through changes in transpiration, evaporation, and runoff. These changes, in turn, affect surface energy balances and provide the atmosphere with additional water vapor for precipitation. Conversely, farmers alter their land use in response to changes in climate conditions to maximize their farm operating profit.

References

Anderson, C. J., Anex, R. P., Arritt, R. W., Gelder, B. K., Khanal, S., Herzmann, D. E., & Gassman, P. W. (2013). Regional climate impacts of a biofuels policy projection. *Geophysical Research Letters*, *40*(6), 1217-1222.

Arguez, A., & Vose, R. S. (2011). The definition of the standard WMO climate normal: The key to deriving alternative climate normals. *Bulletin of the American Meteorological Society*, *92*(6), 699.

Arlot, S., & Celisse, A. (2010). A survey of cross-validation procedures for model selection. *Statistics surveys*, *4*, 40-79.

Burke, M., Dykema, J., Lobell, D. B., Miguel, E., & Satyanath, S. (2015). Incorporating climate uncertainty into estimates of climate change impacts. *Review of Economics and Statistics*, *97*(2), 461-471.

Chamberlain, G. (1980). Analysis of Covariance with Qualitative Data. *The Review of Economic Studies*, *47*(1), 225-238.

Chambers, R. G., & Just, R. E. (1989). Estimating multioutput technologies. *American Journal of Agricultural Economics*, *71*(4), 980-995.

Dobos, R. R., H.R. Sinclair, Jr., & Robotham, M. P. (2012). *User Guide for the National Commodity Crop Productivity Index (NCCPI) version 2.0.*.

Fezzi, C., & Bateman, I. J. (2011). Structural agricultural land use modeling for spatial agro-environmental policy analysis. *American Journal of Agricultural Economics*, *93*(4), 1168-1188.

Flato, G., J. Marotzke, B. Abiodun, P. Braconnot, S.C. Chou, W. Collins, P. Cox, F. Driouech, S. Emori, V. Eyring, C. Forest, P. Gleckler, E. Guilyardi, C. Jakob, V. Kattsov, C. Reason & M. Rummukainen, (2013). *Evaluation of Climate Models. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Stocker, T.F., D. Qin, G.-K. Plattner,

M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA

Gleckler, P. J., Taylor, K. E., & Doutriaux, C. (2008). Performance metrics for climate models. *Journal of Geophysical Research (Atmospheres)* 113: D06104.

Gneiting, T. (2011). Making and evaluating point forecasts. *Journal of the American Statistical Association*, *106*(494), 746-762.

Gneiting, T., & Raftery, A. E. (2007). Strictly proper scoring rules, prediction, and estimation. *Journal of the American Statistical Association*, *102*(477), 359-378.

Groisman, P. Y., Knight, R. W., & Karl, T. R. (2012). Changes in intense precipitation over the central United States. *Journal of Hydrometeorology*, *13*(1), 47-66.

Hendricks, N. P., Smith, A., & Sumner, D. A. (2014). Crop Supply Dynamics and the Illusion of Partial Adjustment. *American Journal of Agricultural Economics*, *96*(5), 1469-1491.

Hornbeck, R. (2012). The enduring impact of the American Dust Bowl: Short-and long-run adjustments to environmental catastrophe. *The American Economic Review*, *102*(4), 1477-1507.

Kaminski, J., Kan, I., & Fleischer, A. (2013). A structural land-use analysis of agricultural adaptation to climate change: a proactive approach. *American Journal of Agricultural Economics*, *95*(1), 70-93.

Kunkel, K. K., L. E. Stevens, S. E. Stevens, L. Sun, E. Janssen, D. Wuebbles, S. D. Hillberg, Timlin, M.S., Stoecker, L., Westcott, N.E., Dobson, J. G. (2013). *Regional Climate Trends and Scenarios for the U.S. National Climate Assessment: Part 3. Climate of the Midwest U.S.*. (NOAA Technical Report NESDIS 142-3) National Environmental Satellite, Data and Information Service, US Department of Commerce, NOAA, Washington, USA

McCarl, B. A. (2015). Elaborations on Climate Adaptation in US Agriculture. *Choices*, *30*(2), 1-5.

Miao, R., Khanna, M., & Huang, H. (2016). Responsiveness of crop yield and acreage to prices and climate. *American Journal of Agricultural Economics*, *98*(1), 191-211.

Mu, J. E., McCarl, B. A., & Wein, A. M. (2013). Adaptation to climate change: changes in farmland use and stocking rate in the US. *Mitigation and Adaptation Strategies for Global Change*, *18*(6), 713-730.

Mullahy, J. (2015). Multivariate fractional regression estimation of econometric share models. *Journal of Econometric Methods*, *4*(1), 71-100.

Mundlak, Y. (1978). On the pooling of time series and cross section data. *Econometrica: journal of the Econometric Society 46(1)*, 69-85.

Natural Resources Conservation Service, United States Department of Agriculture. 2013. Description of SSURGO Database. Website. url: http://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/?cid=nrcs142p2_053627.

Papke, L. E., & Wooldridge, J. M. (2008). Panel data methods for fractional response variables with an application to test pass rates. *Journal of Econometrics*, *145*(1), 121-133.

Pielke Sr, R. A., Adegoke, J., Beltrán-Przekurat, A., Hiemstra, C. A., Lin, J., Nair, U. S., Niyogi, D. & Nobis, T. E. (2007). An overview of regional land-use and land-cover impacts on rainfall. *Tellus: Series B*, *59*(3).

Pierce, D. W., Barnett, T. P., Santer, B. D., & Gleckler, P. J. (2009). Selecting global climate models for regional climate change studies. *Proceedings of the National Academy of Sciences*, *106*(21), 8441-8446.

PRISM Climate Group. 2004. PRISM AN81m Data. Website. url: http://prism.oregonstate.edu.

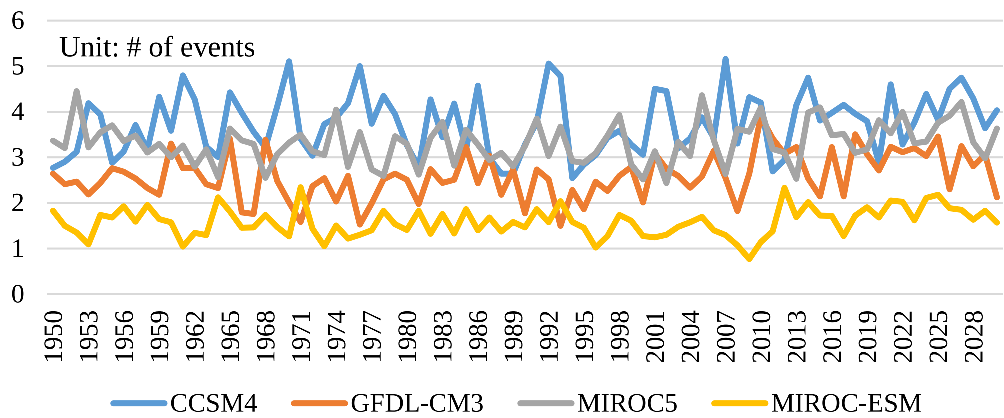
Reichler, T., & Kim, J. (2008). How well do coupled models simulate today's climate?. *Bulletin of the American Meteorological Society*, *89*(3), 303.

Snyder, R. L. (1985). Hand calculating degree days. *Agricultural and forest meteorology*, *35*(1), 353-358.

Thrasher, B., Maurer, E. P., McKellar, C., & Duffy, P. B., 2012: Technical Note: Bias correcting climate model simulated daily temperature extremes with quantile mapping. *Hydrology and Earth System Sciences*, *16*(9), 3309-3314.

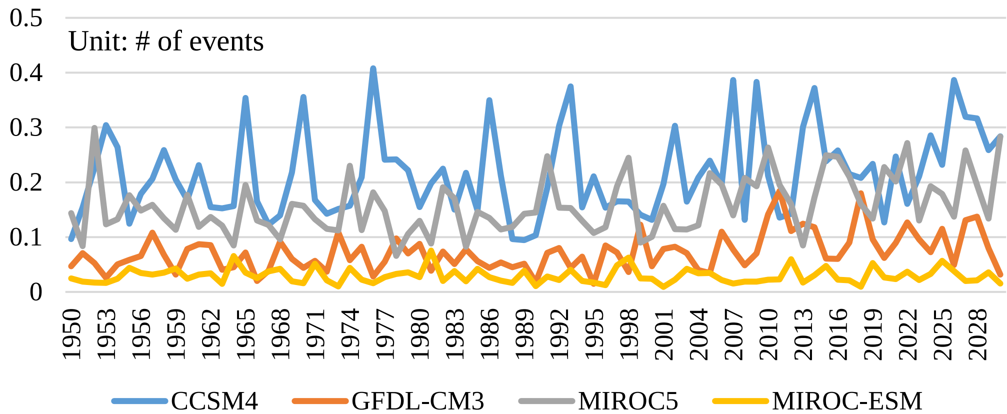
Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data (2d ed.)*. Cambridge, MA: MIT Press.

Zulauf, C. (2013). *Soybean - Corn Price Ratio Since 1975.* Farmdoc daily http://farmdocdaily.illinois.edu/2013/09/soybean-corn-price-ratios-since-1975.html



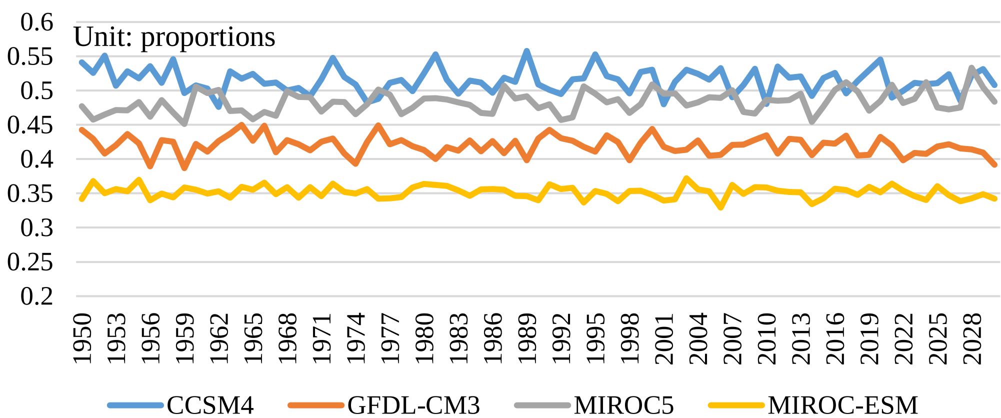
Source: NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) data set.

Figure 4.1. Average number of daily rain events above 25.4 mm per year in the central US



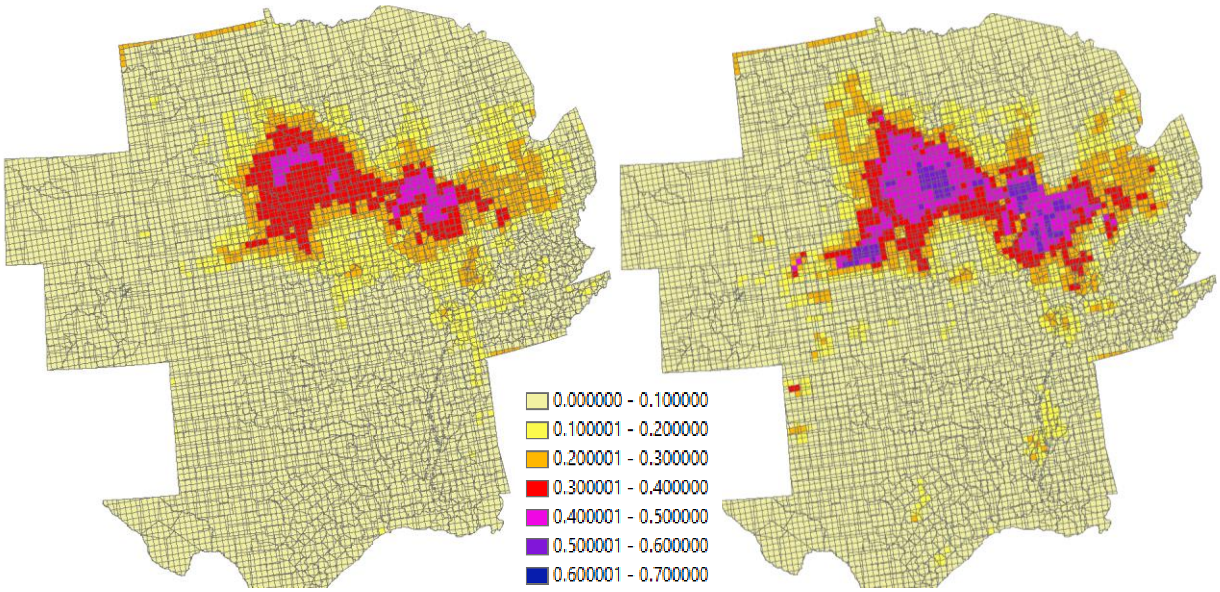
Source: NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) data set.

Figure 4.2. Average number of daily rain events above 76.2 mm per year in the central US



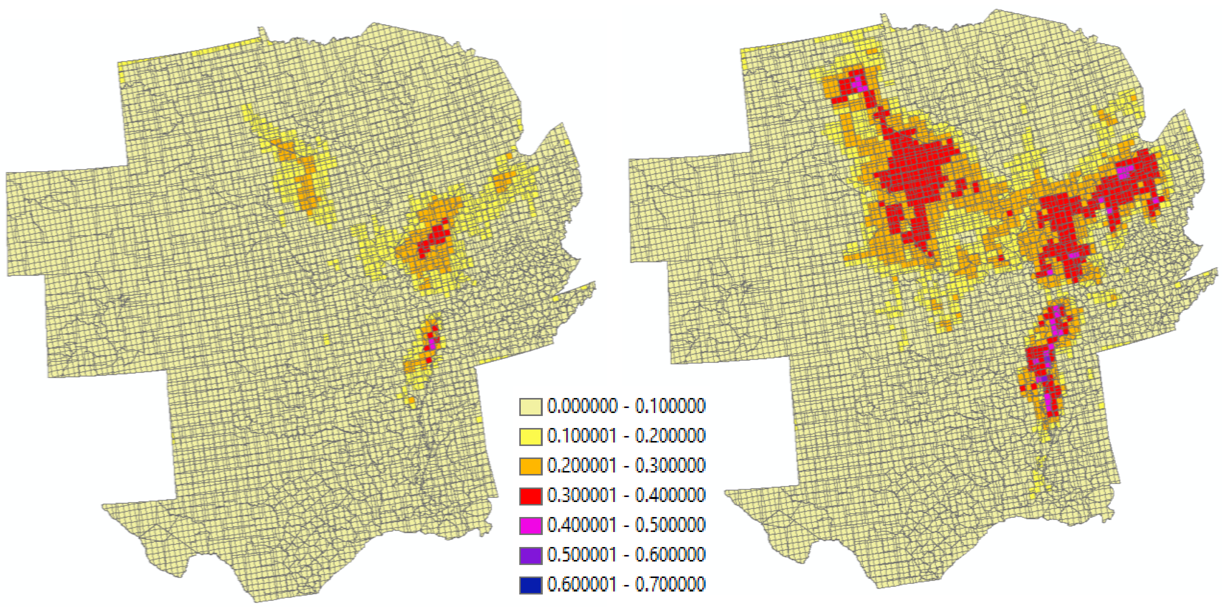
Source: NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) data set.

Figure 4.3. Average proportion of precipitation (mm) during the 10 wettest days per year in the central US



Source: NASS county data down-sampled to 25km grid cells using an area weighting algorithm.

Figure 4.4. Proportions of areas growing corn in 1950s (left) and 2000s (right)



Source: NASS county data down-sampled to 25km grid cells using an area weighting algorithm

Figure 4.5. Proportions of areas growing soybeans in 1950s (left) and 2000s (right)

Table 4.1. Summary statistics regarding land use, prices, and soil quality - Corn Belts

Item	Description	Mean	SD	Min	Max
Corn	Corn acreage/total cropland	0.21	0.15	0.00	0.59
Soybeans	Soybean acreage/total cropland	0.20	0.13	0.00	0.48
Wheat	Wheat acreage/total cropland	0.04	0.04	0.00	0.23
Other crop	Other crops acreage/total cropland	0.01	0.03	0.00	0.46
grassland	Grassland/total cropland	0.39	0.20	0.00	0.94
Total cropland	The sum of acreage allocated to crops and grassland (km^2)	572.05	184.84	0.71	728.88
P_{sc}	soybean price/corn price	2.67	0.30	2.29	3.17
NCCPI	NCCPI-all	0.56	0.16	0.01	0.89
Sand	% of sand	19.28	10.48	4.51	77.44
Silt	% of silt	56.23	9.99	12.84	74.78
Slope	Representative slope (%)	7.29	5.87	0.33	36.93
RZNAWS	available water storages within crop root zone depths (100 mm)	2.05	0.56	0.05	3.20
Soc30	Soil organic carbon (1,000 g C/m^2)	5.56	2.32	1.17	11.90
# of observations		3,282			

Table 4.2. Summary statistics regarding land use, prices, and soil quality - Lake states

Item	Description	Mean	SD	Min	Max
Corn	Corn acreage/total cropland	0.10	0.12	0.00	0.50
Soybeans	Soybean acreage/total cropland	0.07	0.10	0.00	0.42
Wheat	Wheat acreage/total cropland	0.04	0.08	0.00	0.51
Other crop	Other crops acreage/total cropland	0.01	0.04	0.00	0.48
grassland	Grassland/total cropland	0.41	0.27	0.00	0.93
Total cropland	The sum of acreage allocated to crops and grassland (km^2)	420.84	254.81	0.61	709.07
NCCPI	NCCPI-all	0.36	0.18	0.00	0.82
Sand	% of sand	47.66	19.38	7.65	90.00
Silt	% of silt	35.31	15.56	3.95	87.23
Slope	Representative slope (%)	4.96	3.74	0.29	21.87
RZNAWS	available water storages within crop root zone depths (100 mm)	1.93	0.77	0.00	6.48
Soc30	Soil organic carbon (1,000 g C/m2)	8.78	3.02	3.15	28.24
# of observations			2541		

Table 4.3. Summary statistics regarding land use, prices, and soil quality - Northern Plains

Item	Description	Mean	SD	Min	Max
Corn	Corn acreage/total cropland	0.08	0.11	0.00	0.67
Soybeans	Soybean acreage/total cropland	0.06	0.09	0.00	0.43
Wheat	Wheat acreage/total cropland	0.15	0.14	0.00	0.75
Other crop	Other crops acreage/total cropland	0.05	0.06	0.00	0.32
grassland	Grassland/total cropland	0.62	0.24	0.00	1.00
Total cropland	The sum of acreage allocated to crops and grassland (km^2)	607.53	69.49	6.22	661.29
Irrigation	% of irrigated area for crop production in each cell.	0.01	0.06	0.00	0.73
NCCPI	NCCPI-all	0.31	0.14	0.07	0.69
Sand	% of sand	33.83	21.82	5.76	94.14
Silt	% of silt	41.65	14.95	2.61	66.24
Slope	Representative slope (%)	6.66	4.78	0.18	32.33
RZNAWS	available water storages within crop root zone depths (100 mm)	2.06	0.62	0.48	3.20
Soc30	Soil organic carbon (1,000 g C/m^2)	5.13	1.94	1.75	10.17
Irrigation	% of irrigated area for crop production in each cell.	0.04	0.10	0.00	0.73
# of observations		3,873			

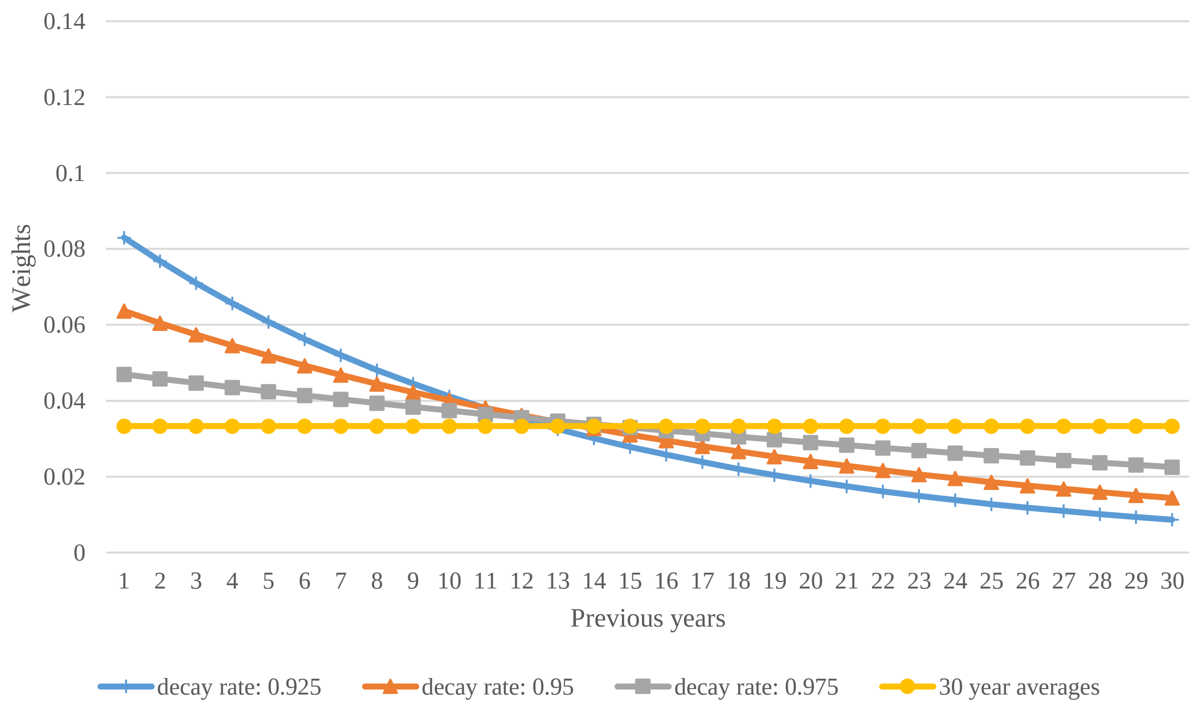
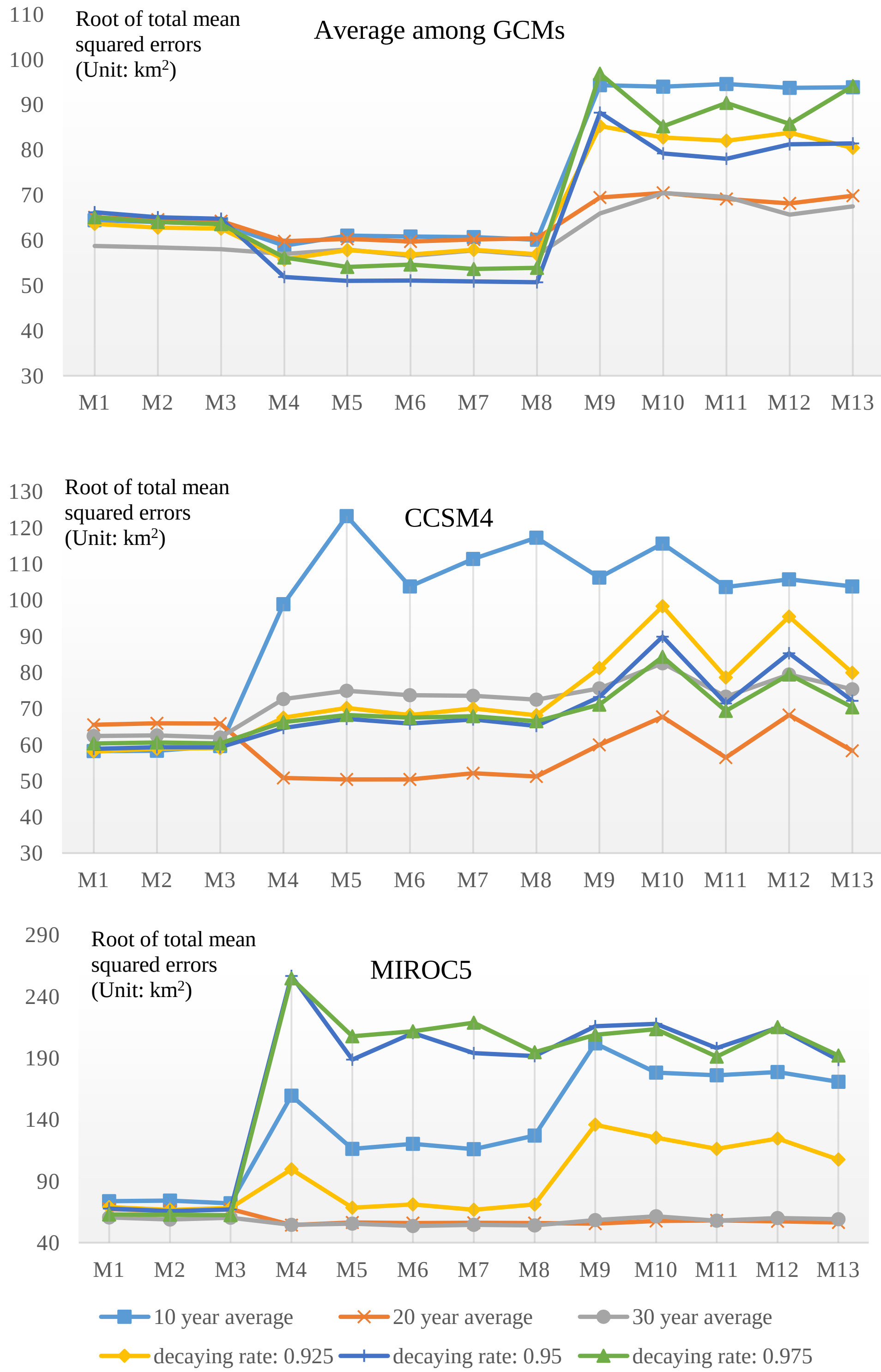


Figure 4.6. Weights used to construct farmers' expected weather conditions

Table 4.4. Explanatory Variables in Each Model Specification

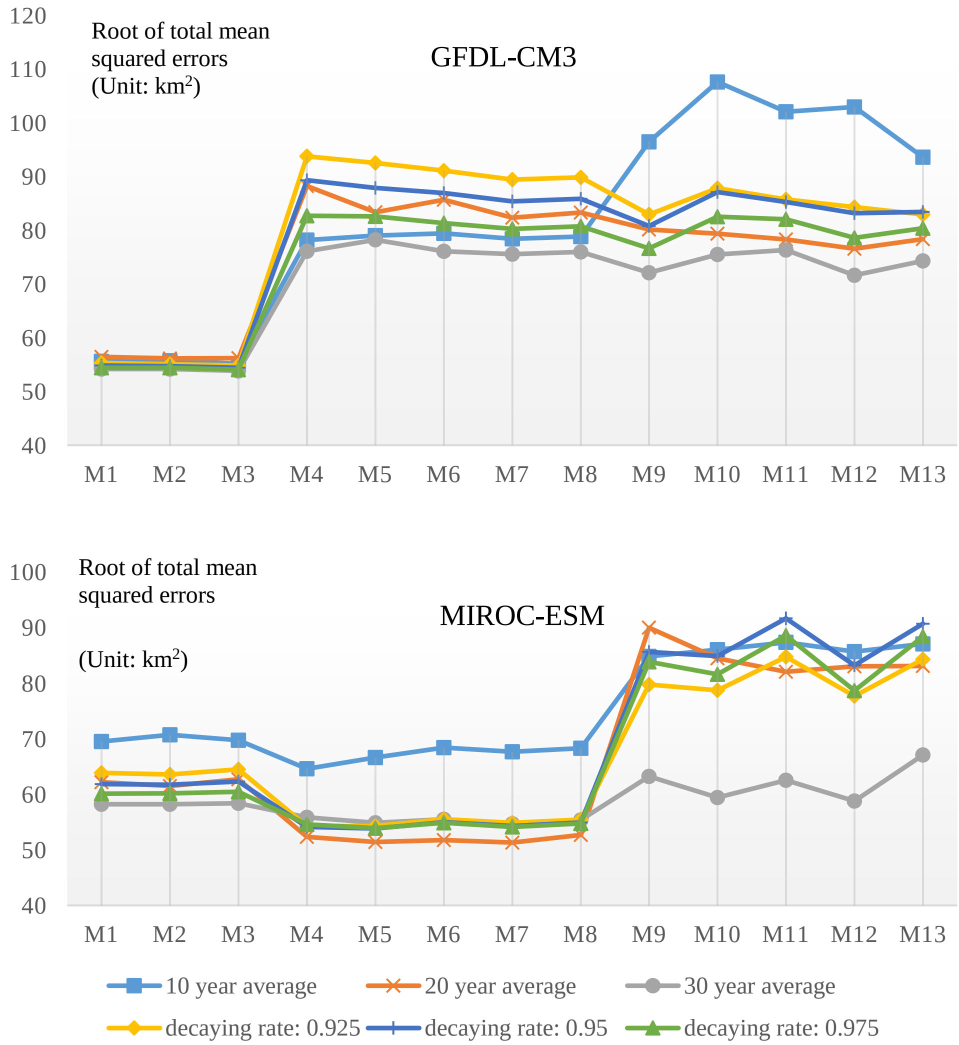
Model	Average temperature		GDD, HDD		Precipitation		Intensive rainfall1	
	monthly	yearly	monthly	yearly	monthly	yearly	monthly	yearly
M1				O		O		O(1)
M2				O		O		O(2)
M3				O		O		O(3)
M4	O				O		O(1)	
M5	O				O		O(2)	
M6	O				O			O (1)
M7	O				O			O (2)
M8	O				O			O (3)
M9			O		O		O (1)	
M10			O		O		O (2)	
M11			O		O			O (1)
M12			O		O			O (2)
M13			O		O			O (3)

Note: ( ) is the measure of intensive rainfalls. (1) is the number of daily rain events above 25.4 mm per year, (2) is the number of daily rain events above 76.2 mm per year, and (3) is the fraction of precipitation (mm) during the ten wettest days per year.



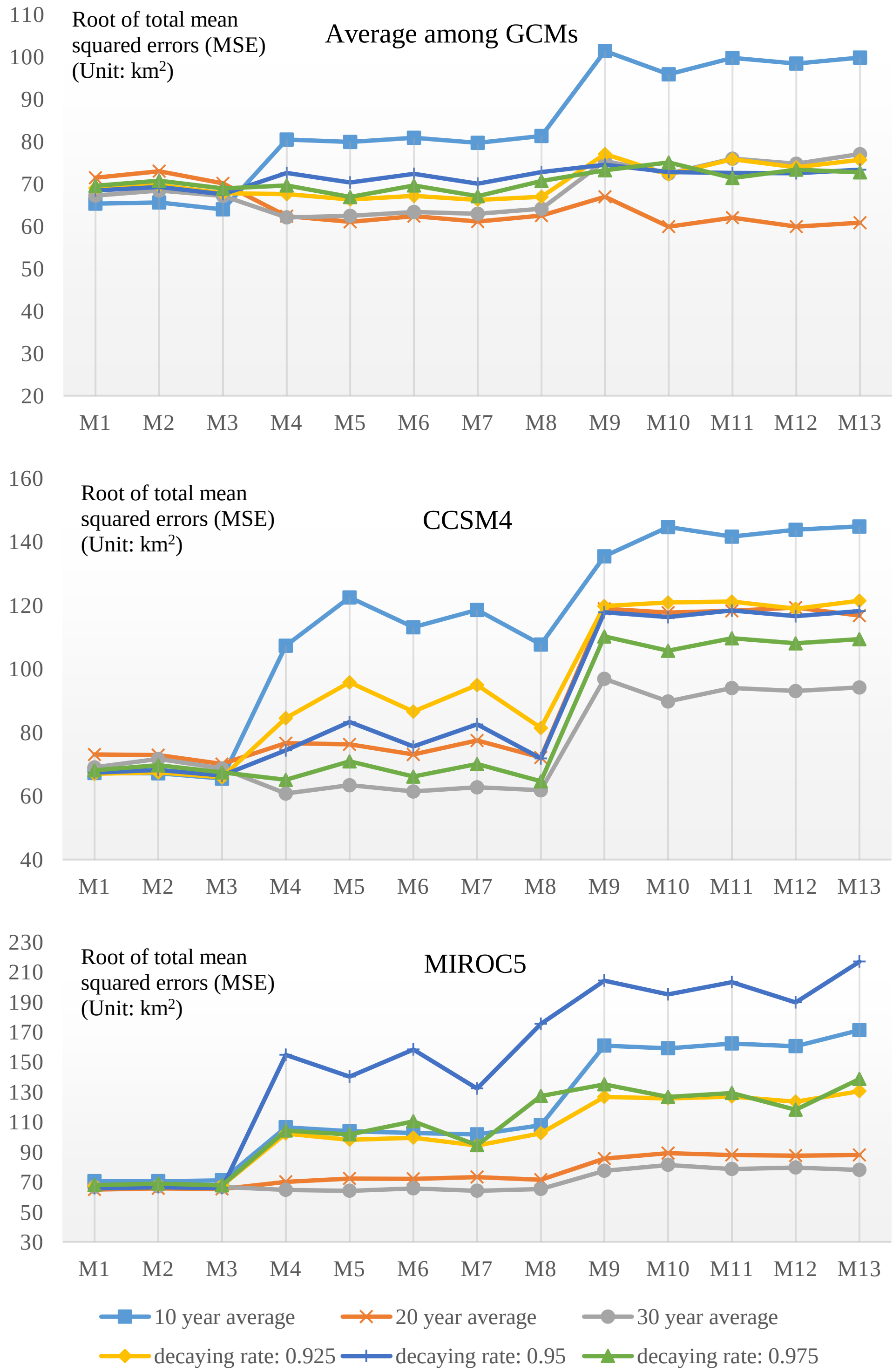
Note: The horizontal axis corresponds to models in Table 4. The vertical axis means values of score function in Equation (13). Each line represents one way of constructing farmers' expected weather conditions, and its variation shows how predictive accuracy varies depending on thirteen models.

Figure 4.7. Results of out-of-sample forecasting test for Corn Belt



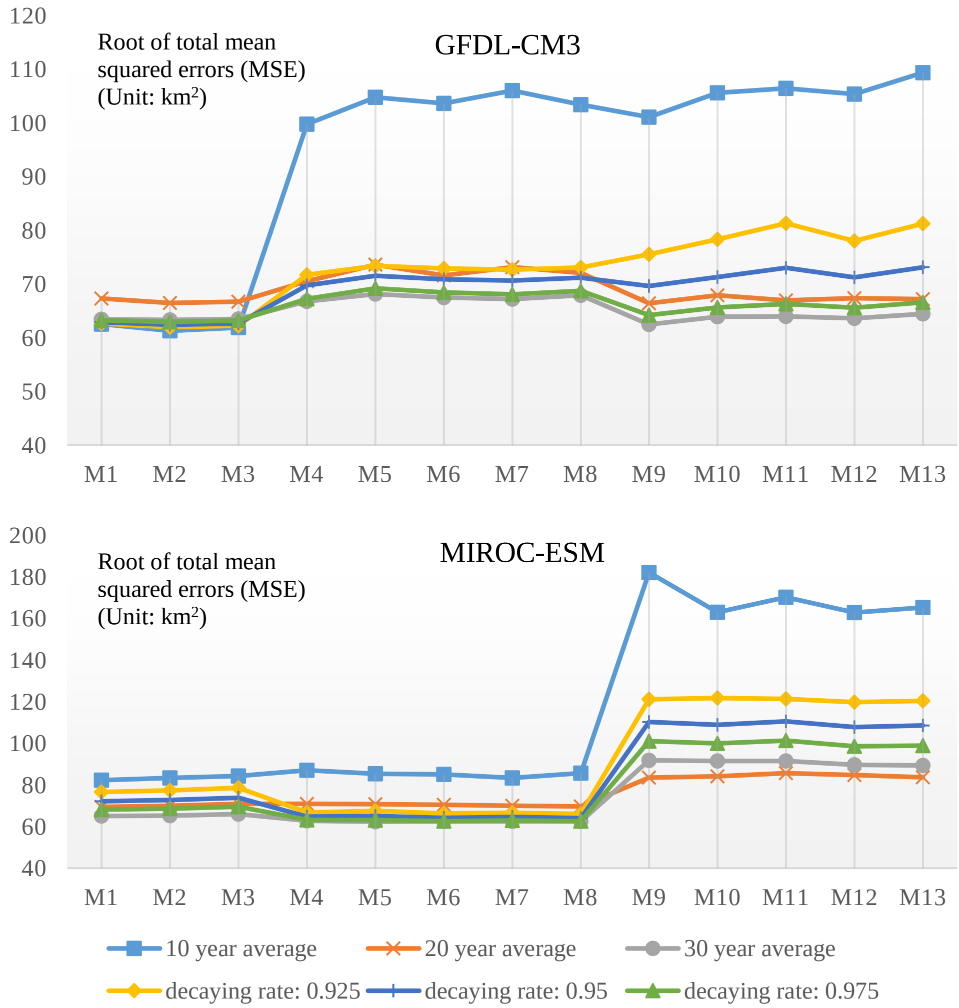
Note: The horizontal axis corresponds to models in Table 4. The vertical axis means values of score function in Equation (13). Each line represents one way of constructing farmers' expected weather conditions, and its variation shows how predictive accuracy varies depending on thirteen models.

Figure 4.7 (Continued)



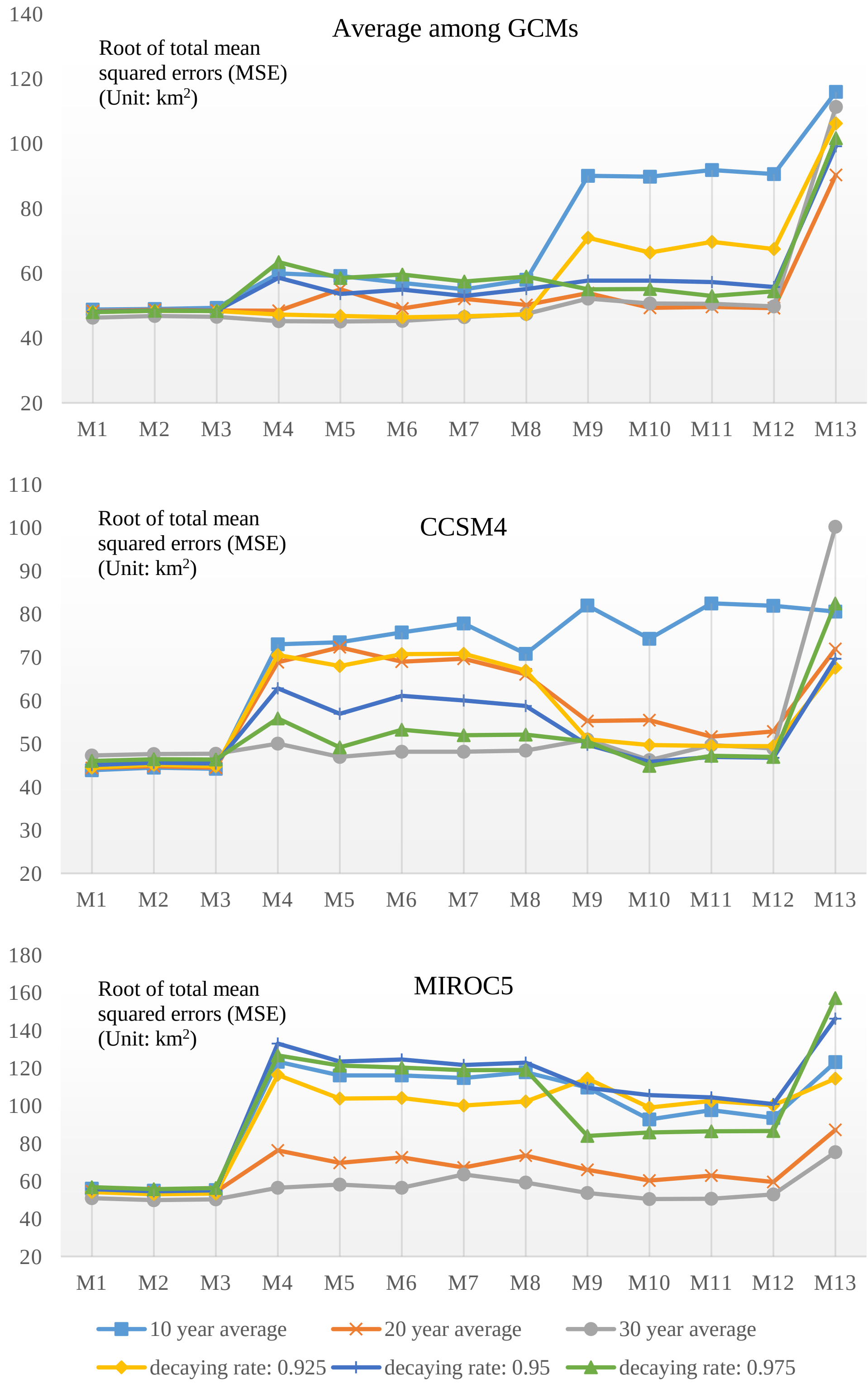
Note: The horizontal axis corresponds to models in Table 4. The vertical axis means values of score function in Equation (13). Each line represents one way of constructing farmers' expected weather conditions, and its variation shows how predictive accuracy varies depending on thirteen models.

Figure 4.8. Results of out-of-sample forecasting test for Lake States



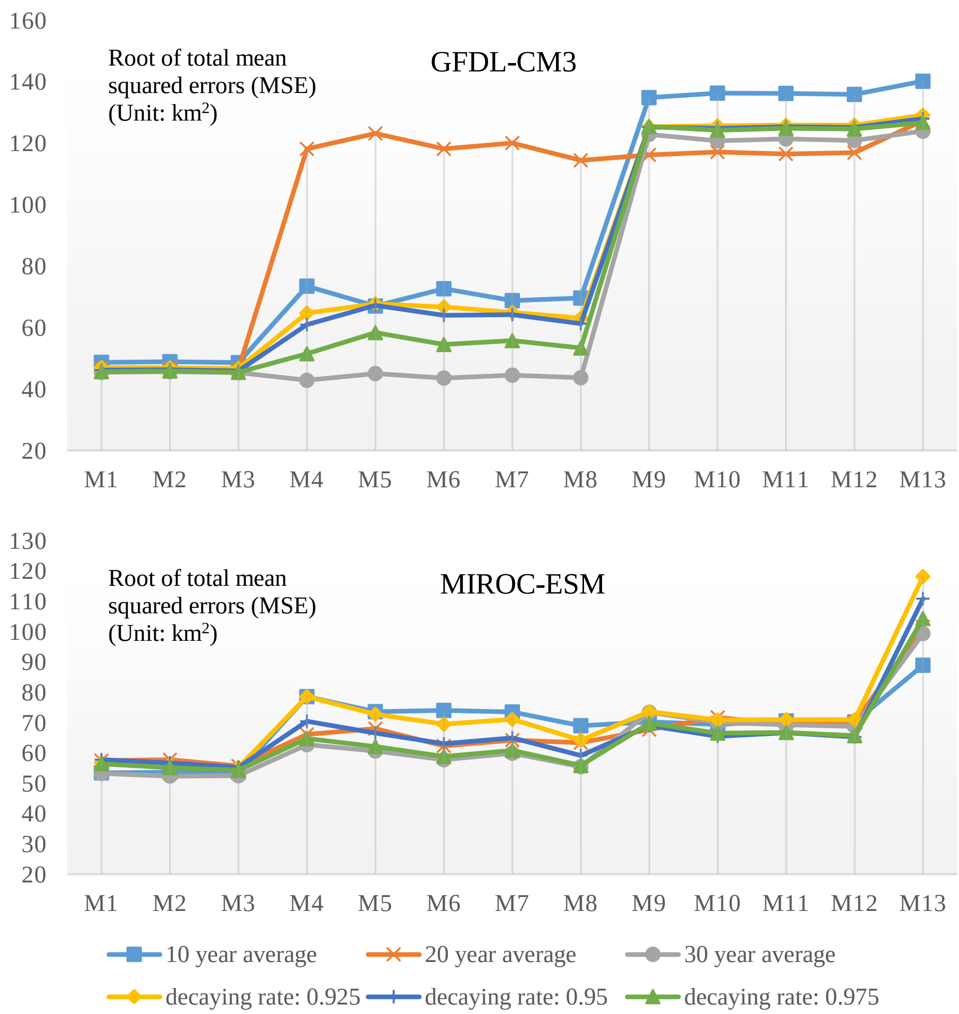
Note: The horizontal axis corresponds to models in Table 4. The vertical axis means values of score function in Equation (13). Each line represents one way of constructing farmers' expected weather conditions, and its variation shows how predictive accuracy varies depending on thirteen models.

Figure 4.8 (Continued)



Note: The horizontal axis corresponds to models in Table 4. The vertical axis means values of score function in Equation (13). Each line represents one way of constructing farmers' expected weather conditions, and its variation shows how predictive accuracy varies depending on thirteen models.

Figure 4.9. Results of out-of-sample forecasting test for Northern Plains



Note: The horizontal axis corresponds to models in Table 4. The vertical axis means values of score function in Equation (13). Each line represents one way of constructing farmers' expected weather conditions, and its variation shows how predictive accuracy varies depending on thirteen models.

Figure 4.9 (Continued)

Table 4.5. Predicted land use in 2030 based on M3

	AVE	CCSM4	GFDL-CM3	MIROC-ESM	MIROC5	2000s
			Corn Belt			
Corn	0.200 (0.001)	0.207 (0.002)	0.188 (0.006)	0.188 (0.006)	0.214 (0.005)	0.229
Soybeans	0.212 (0.003)	0.213 (0.004)	0.213 (0.006)	0.218 (0.002)	0.207 (0.007)	0.196
Wheat	0.037 (0.002)	0.034 (0.002)	0.064 (0.009)	0.035 (0.003)	0.030 (0.003)	0.021
Other crops	0.009 (0.002)	0.006 (0.000)	0.006 (0.002)	0.009 (0.001)	0.005 (0.002)	0.004
Grass lands	0.382 (0.003)	0.379 (0.004)	0.372 (0.012)	0.390 (0.004)	0.384 (0.007)	0.389
			Lake States			
Corn	0.177 (0.023)	0.137 (0.012)	0.178 (0.010)	0.225 (0.005)	0.161 (0.004)	0.114
Soybeans	0.086 (0.006)	0.091 (0.005)	0.086 (0.015)	0.085 (0.004)	0.095 (0.006)	0.081
Wheat	0.022 (0.001)	0.025 (0.004)	0.019 (0.001)	0.013 (0.000)	0.024 (0.001)	0.026
Other crops	0.007 (0.001)	0.008 (0.004)	0.004 (0.002)	0.007 (0.000)	0.007 (0.001)	0.009
Grass lands	0.350 (0.017)	0.381 (0.008)	0.356 (0.023)	0.312 (0.002)	0.355 (0.006)	0.412
			Northern Plains			
Corn	0.095 (0.002)	0.093 (0.003)	0.094 (0.003)	0.089 (0.008)	0.094 (0.003)	0.100
Soybeans	0.070 (0.003)	0.069 (0.002)	0.070 (0.002)	0.077 (0.004)	0.075 (0.006)	0.077
Wheat	0.138 (0.005)	0.139 (0.004)	0.149 (0.010)	0.133 (0.013)	0.137 (0.005)	0.126
Other crops	0.036 (0.001)	0.038 (0.001)	0.038 (0.001)	0.038 (0.001)	0.036 (0.002)	0.038
Grass lands	0.624 (0.002)	0.625 (0.002)	0.612 (0.006)	0.627 (0.004)	0.623 (0.005)	0.624

Note: Within a GCM, there are six predicted proportions of acreage for each crop to total land depending on six way to construct farmers' expected weather conditions. The estimates indicate the average of the six predicted proportions of acreage for each crop. Also ( ) means the standard deviation among these six predicted proportions of acreage for each crop.

Table 4.6. Predicted land use in 2030 based on M7

	AVE	CCSM4	GFDL-CM3	MIROC-ESM	MIROC5	2000s
			Corn Belt			
Corn	0.196 (0.028)	0.204 (0.010)	0.107 (0.031)	0.177 (0.024)	0.168 (0.023)	0.229
Soybeans	0.185 (0.015)	0.225 (0.022)	0.126 (0.040)	0.209 (0.017)	0.184 (0.023)	0.196
Wheat	0.024 (0.011)	0.069 (0.031)	0.022 (0.022)	0.045 (0.017)	0.023 (0.012)	0.021
Other crops	0.020 (0.013)	0.005 (0.006)	0.031 (0.010)	0.027 (0.022)	0.024 (0.013)	0.004
Grass lands	0.415 (0.032)	0.337 (0.031)	0.554 (0.085)	0.382 (0.044)	0.441 (0.043)	0.389
			Lake States			
Corn	0.133 (0.017)	0.170 (0.024)	0.114 (0.018)	0.153 (0.025)	0.136 (0.025)	0.114
Soybeans	0.115 (0.019)	0.085 (0.005)	0.081 (0.038)	0.124 (0.016)	0.106 (0.008)	0.081
Wheat	0.017 (0.009)	0.009 (0.002)	0.017 (0.006)	0.033 (0.013)	0.015 (0.005)	0.026
Other crops	0.006 (0.006)	0.007 (0.005)	0.009 (0.002)	0.006 (0.006)	0.017 (0.006)	0.009
Grass lands	0.372 (0.037)	0.371 (0.029)	0.420 (0.059)	0.326 (0.007)	0.368 (0.026)	0.412
			Northern Plains			
Corn	0.077 (0.045)	0.065 (0.012)	0.138 (0.057)	0.050 (0.024)	0.049 (0.011)	0.100
Soybeans	0.062 (0.007)	0.047 (0.016)	0.043 (0.026)	0.038 (0.021)	0.065 (0.008)	0.077
Wheat	0.171 (0.031)	0.143 (0.007)	0.140 (0.042)	0.235 (0.041)	0.182 (0.027)	0.126
Other crops	0.029 (0.012)	0.034 (0.011)	0.040 (0.037)	0.050 (0.017)	0.051 (0.016)	0.038
Grass lands	0.624 (0.028)	0.676 (0.024)	0.603 (0.022)	0.591 (0.025)	0.617 (0.035)	0.624

Note: Within a GCM, there are six predicted proportions of acreage for each crop to total land depending on six way to construct farmers' expected weather conditions. The estimates indicate the average of the six predicted proportions of acreage for each crop. Also ( ) means the standard deviation among these six predicted proportions of acreage for each crop.

Table 4.7. Corn acreage response elasticity: Expected weather conditions - Corn Belt

	10-year average	20-year average	30-year average	Decay rate:0.925	Decay rate:0.95	Decay rate:0.975
GDD	0.070	0.089	0.111	0.094	0.098	0.105
HDD	-0.009*	-0.008*	-0.013**	-0.009*	-0.009*	-0.009*
Precipitation	-0.277***	-0.315***	-0.278***	-0.305***	-0.306***	-0.298***
Intensive rainfall	0.717***	0.624**	0.726***	0.699***	0.694***	0.697***
NCCPI-all	0.092***	0.091***	0.088***	0.095***	0.096***	0.095***
Percent sand	0.352***	0.356***	0.349***	0.352***	0.352***	0.350***
Percent silt	0.477	0.475	0.476	0.474	0.473	0.471
Slope	-0.047	-0.033	-0.077	-0.036	-0.034	-0.041
RZAWS	0.037	0.041	0.038	0.037	0.037	0.037
Organic Carbon	0.148***	0.152***	0.147***	0.149***	0.149***	0.149***
Total land	0.047**	0.047**	0.046**	0.046**	0.046**	0.046**

Note: *** significant at 1% level. ** significant at 5% level. * significant at 10% level. Results are based on Equation (10) and (11). Model M3 and the averages of climate measures among GCMs are used for estimation. Inferences are based on 1,000 cluster bootstrap runs.

Table 4.8. Corn acreage response elasticity: GCMs - Corn Belt (Climate normal)

	CCSM4	GFDL-CM3	MIROC-ESM	MIROC5	Averages
GDD	0.094	0.031	0.154*	0.090	0.111
HDD	-0.013**	-0.009*	-0.013***	-0.014***	-0.013**
Precipitation	-0.279***	-0.122*	-0.332***	-0.142*	-0.278***
Intensive rainfall	0.402***	0.490**	0.073	0.384***	0.726***
NCCPI-all	0.073**	0.069**	0.060*	0.085**	0.088***
Percent sand	0.347***	0.334***	0.359***	0.354***	0.349***
Percent silt	0.468***	0.459***	0.468***	0.489***	0.476***
Slope	-0.083	-0.137	-0.063	-0.137	-0.077
RZAWS	0.059*	0.054	0.064**	0.039	0.038
Organic Carbon	0.156***	0.155***	0.164***	0.157***	0.147***
Total land	0.048**	0.047**	0.053***	0.045**	0.046**

Note: *** significant at 1% level. ** significant at 5% level. * significant at 10% level. Results are based on Equation (10) and (11). Model M3 and the average of weather conditions over previous 30 year are used for estimation. Inferences are based on 1,000 cluster bootstrap runs.

Table 4.9. Corn acreage response elasticity: Expected weather conditions – Lake States

	10-year average	20-year average	30-year average	Decay rate:0.925	Decay rate:0.95	Decay rate:0.975
GDD	0.093**	0.049	0.092*	0.053	0.064	0.070
HDD	0.019***	0.021***	0.019***	0.021***	0.019***	0.018***
Precipitation	0.170***	0.229***	0.183***	0.209***	0.211***	0.217***
Intensive rainfall	-0.254	-0.222	-0.271*	-0.267	-0.280*	-0.291*
NCCPI-all	0.060***	0.057***	0.057***	0.057***	0.058***	0.058***
Percent sand	-0.099***	-0.109***	-0.111***	-0.106***	-0.106***	-0.107***
Percent silt	0.009	-0.005	-0.007	-0.001	-0.001	-0.002
Slope	0.027	-0.014	-0.022	-0.007	-0.012	-0.016
RZAWS	-0.090***	-0.089***	-0.087***	-0.089***	-0.089***	-0.089***
Organic Carbon	0.038***	0.037***	0.036***	0.037***	0.038***	0.038***
Total land	0.036***	0.038***	0.034***	0.038***	0.037***	0.037***

Note: *** significant at 1% level. ** significant at 5% level. * significant at 10% level. Results are based on Equation (10) and (11). Model M3 and the averages of climate measures among GCMs are used for estimation. Inferences are based on 1,000 cluster bootstrap runs.

Table 4.10. Corn acreage response elasticity: GCMs – Lake States (Climate normal)

	CCSM4	GFDL-CM3	MIROC-ESM	MIROC5	Averages
GDD	0.092*	0.135***	0.092*	0.098*	0.092*
HDD	0.019***	0.009**	0.012**	0.017**	0.019***
Precipitation	0.183***	0.183***	0.223***	0.145***	0.183***
Intensive rainfall	-0.287**	-0.373**	0.261	-0.290**	-0.271*
NCCPI-all	0.057***	0.057***	0.057***	0.070***	0.057***
Percent sand	-0.100***	-0.117***	-0.098***	-0.116***	-0.111***
Percent silt	0.007	-0.007	-0.006	-0.006	-0.007
Slope	-0.016	-0.023	-0.052	0.065	-0.022
RZAWS	-0.087***	-0.081***	-0.084***	-0.093***	-0.087***
Organic Carbon	0.036***	0.033***	0.032***	0.039***	0.036***
Total land	0.034***	0.038***	0.034***	0.031***	0.034***

Note: *** significant at 1% level. ** significant at 5% level. * significant at 10% level. Results are based on Equation (10) and (11). Model M3 and the average of weather conditions over previous 30 year are used for estimation. Inferences are based on 1,000 cluster bootstrap runs.

Table 4.11. Corn acreage response elasticity: Expected weather conditions – Northern Plains

	10-year average	20-year average	30-year average	Decay rate:0.925	Decay rate:0.95	Decay rate:0.975
GDD	0.217*	0.221**	0.255**	0.227**	0.205*	0.198*
HDD	-0.033***	-0.033***	-0.038***	-0.032***	-0.029***	-0.028***
Precipitation	-0.120**	-0.122*	-0.129*	-0.135**	-0.129**	-0.127*
Intensive rainfall	-0.715***	-0.828***	-0.850***	-0.885***	-0.932***	-0.950***
NCCPI-all	0.113***	0.105***	0.098**	0.110***	0.110***	0.108***
Percent sand	0.291***	0.308***	0.313***	0.309***	0.308***	0.308***
Percent silt	0.156	0.170	0.170	0.173	0.168	0.166
Slope	-0.362**	-0.374**	-0.384**	-0.364**	-0.374**	-0.378**
RZAWS	0.157***	0.163***	0.166***	0.158***	0.161***	0.163***
Organic Carbon	-0.021	-0.020	-0.018	-0.018	-0.021	-0.022
Total land	0.037	0.031	0.027	0.031	0.029	0.028

Note: *** significant at 1% level. ** significant at 5% level. * significant at 10% level. Results are based on Equation (10) and (11). Model M3 and the averages of climate measures among GCMs are used for estimation. Inferences are based on 1,000 cluster bootstrap runs.

Table 4.12. Corn acreage response elasticity: GCMs – Northern Plains (Climate normal)

	CCSM4	GFDL-CM3	MIROC-ESM	MIROC5	Averages
GDD	0.162	0.178	0.351***	0.279***	0.255**
HDD	-0.029***	-0.036***	-0.047***	-0.048***	-0.038***
Precipitation	-0.133**	-0.048	-0.162***	-0.087	-0.129*
Intensive rainfall	-0.752***	-0.389**	0.519**	-0.393**	-0.850***
NCCPI-all	0.104***	0.086**	0.143***	0.096**	0.098**
Percent sand	0.312***	0.267**	0.217**	0.282**	0.313***
Percent silt	0.188	0.126	0.022	0.108	0.170
Slope	-0.439**	-0.416**	-0.246	-0.373**	-0.384**
RZAWS	0.156***	0.192***	0.150***	0.177***	0.166***
Organic Carbon	-0.016	-0.037	-0.004	-0.027	-0.018
Total land	0.023	0.056	0.046	0.024	0.027

Note: *** significant at 1% level. ** significant at 5% level. * significant at 10% level. Results are based on Equation (10) and (11). Model M3 and the average of weather conditions over previous 30 year are used for estimation. Inferences are based on 1,000 cluster bootstrap runs.

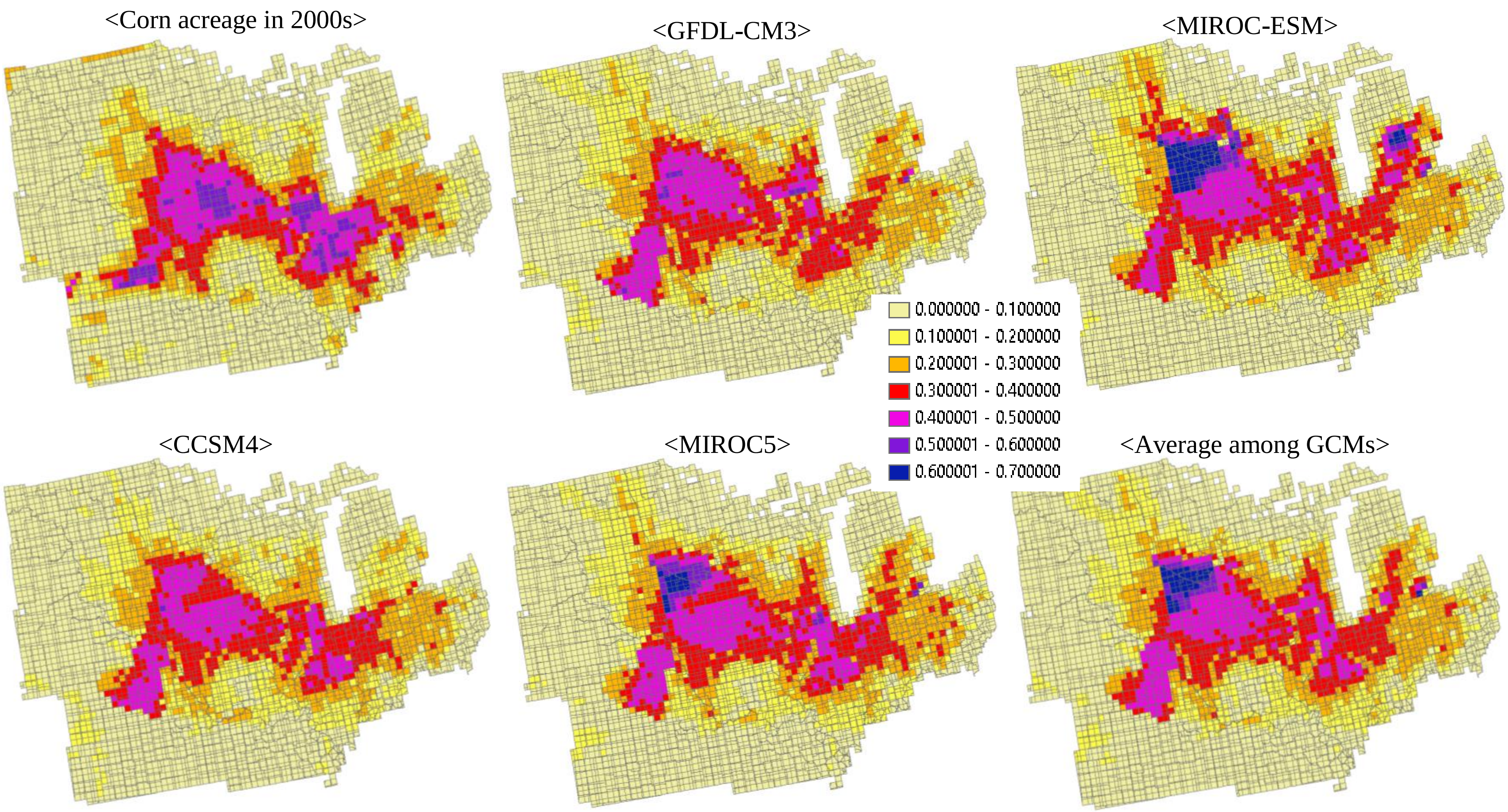


Figure 4.10. The forecasted land use for corn in 2030 based on M3

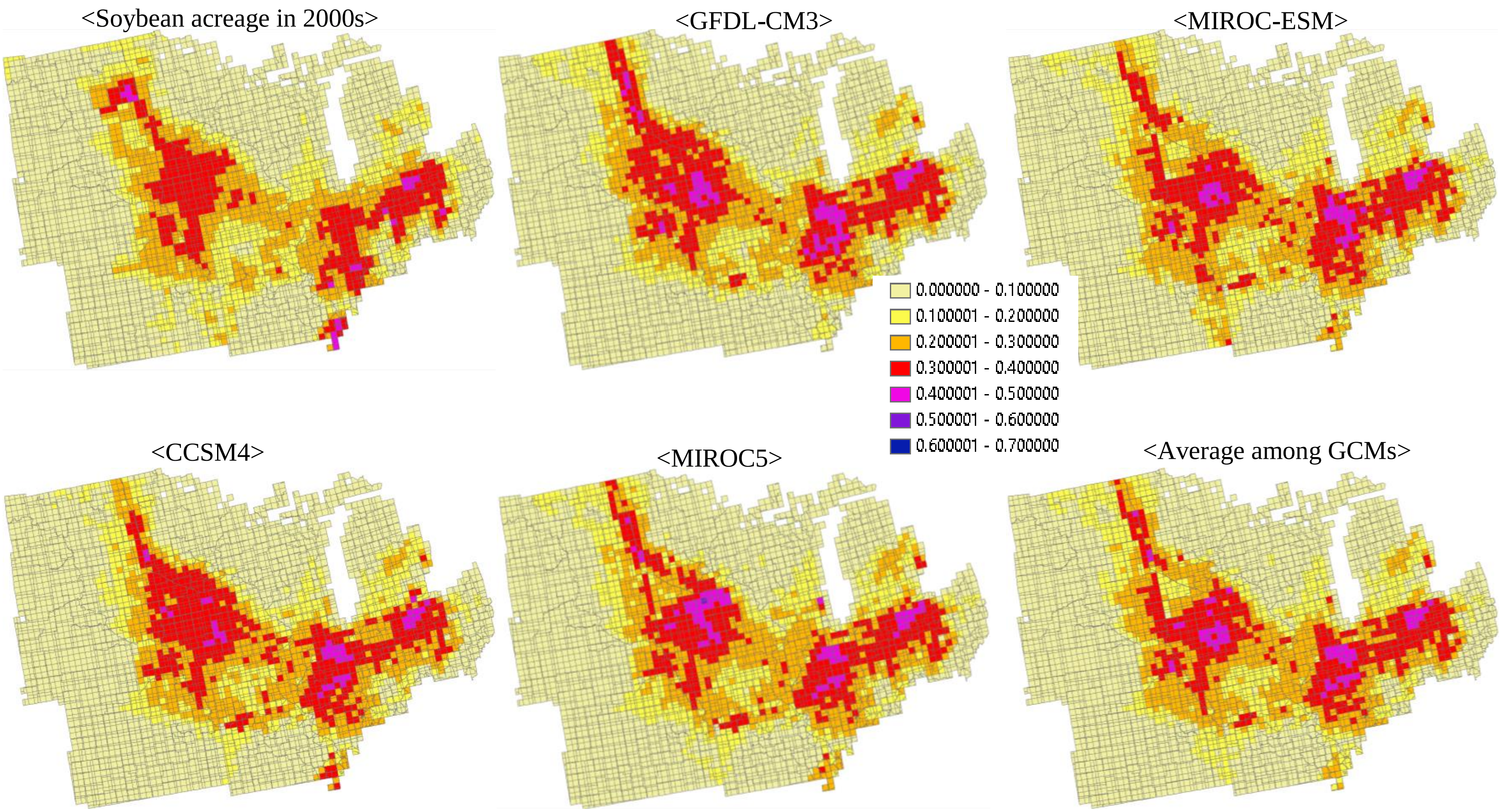


Figure 4.11. The forecasted land use for soybeans in 2030 based on M3

Appendix-A: Generating crop type land use using county level crop statistics

1. Summary

1) Spatial Coverage: AR, CO, IA, IL, IN, KS, KY, LA, MI, MN, MS, MO, NE, ND, OH, OK, SD, TN, TX, WI, WY

2) Temporal Coverage: 1940s~2000s

3) Data resolution:

Latitude Resolution: 0.25 degrees (25 km)

Longitude Resolution: 0.25 degrees (25 km)

Temporal Resolution: decadal

4) Land Use Classes

	Description
1	Evergreen Needleleaf Forest
2	Evergreen Broadleaf Forest
3	Deciduous Needleleaf Forest
4	Deciduous Broadleaf Forest
5	Mixed Forests
6	Closed Shrublands + Barren or Sparse Veg + Wooded Tundra + Mixed Tundra
7	Open Shrublands
8	Woody Savannas
9	Savannas
10	Grasslands
11	Permanent Wetlands
12	Water + Snow and Ice
13	Urban and Built-Up
14	Cropland/Natural Vegetation Mosaic
15	Other C3 Crops (Canola, Cotton (all), Beans, Dry Edible (all), Flaxseed, Lentils, Peanuts, Dry Edible Peas, Rice, Sugarbeets, Sunflower (all))
16	Other C4 Crops (Sorghum)
17	Corn
18	Spring Wheat (Spring Wheat, Durum Wheat, Oats, Rye, Barley)
19	Winter Wheat
20	Soybeans
21	Unused

2. Method

Input datasets

Base Land Use/Land Cover map, County boundaries containing land and water area, county-level statistics on planted and harvested acreage as well as irrigated acres for crops.

Data processing

USDA NASS county statistics for each states are processed into planted and harvested summary tables for all counties for analysis. To identify each item during processing, two additional fields are included: 5 digit FIPS code (Federal Information Processing System code) and identifier merging 5 digit FIPS code, planting year, and item identifier. Planting and harvest data is first filtered to non-null FIPS entries to remove crop reporting district data and only data in the period of analysis.

NASS data is not recorded with the same attributes everywhere; in some states they break crop acreage into ‘Irrigated’ and ‘Non-Irrigated’ categories and some crops (corn and sorghum) are broken into ‘Silage’ and ‘Grain’ categories. For consistent calculations, all data are assigned into Irrigated and Non-Irrigated categories and total crop acreage. If data are classified into ‘Grain’ or ‘Silage’ categories, the data is placed into the corresponding category. However, if no distinguisher is given, it is placed into the ‘Grain’ category as that is the majority of acres of each crop. Also, if ‘Irrigated’ or ‘Non-Irrigated’ categories are present, the data is placed into the appropriate category. But if no identifier is found, the acres are placed into the ‘Non-Irrigated’ category.

Planted acreage still transpires, even if the crop is not harvested. Planted acreage is the preferred method of estimating crop coverage in a county. We primarily want to work with planted acreage data but this is not available for all years and all crops. Thus harvested acreage is only used to estimate planted acreage when data is not available. The data at which planted acreage is available varies by crop and state, but generally starts being available in the 1950s to 1970s. An average Planted/Harvested acreage fraction is computed by year for the period of record. This is not broken out by crop because small acreage crops can easily skew the numbers.

Now that yearly crop planted acreages have been calculated for the counties, we can begin to apportion each crop’s acreage out to each county. We choose a target year each decade for which to make our estimate but calculate this yearly acreage as the average of the target, preceding, and following year to smooth out year to year crop acreage spikes. For this analysis the target year was X8, so from 1948 to 2008 we calculated three year averages (e.g. 1947, 1948, and 1949)

Appendix-B: The forecasted land use for wheat, other crop, and grassland

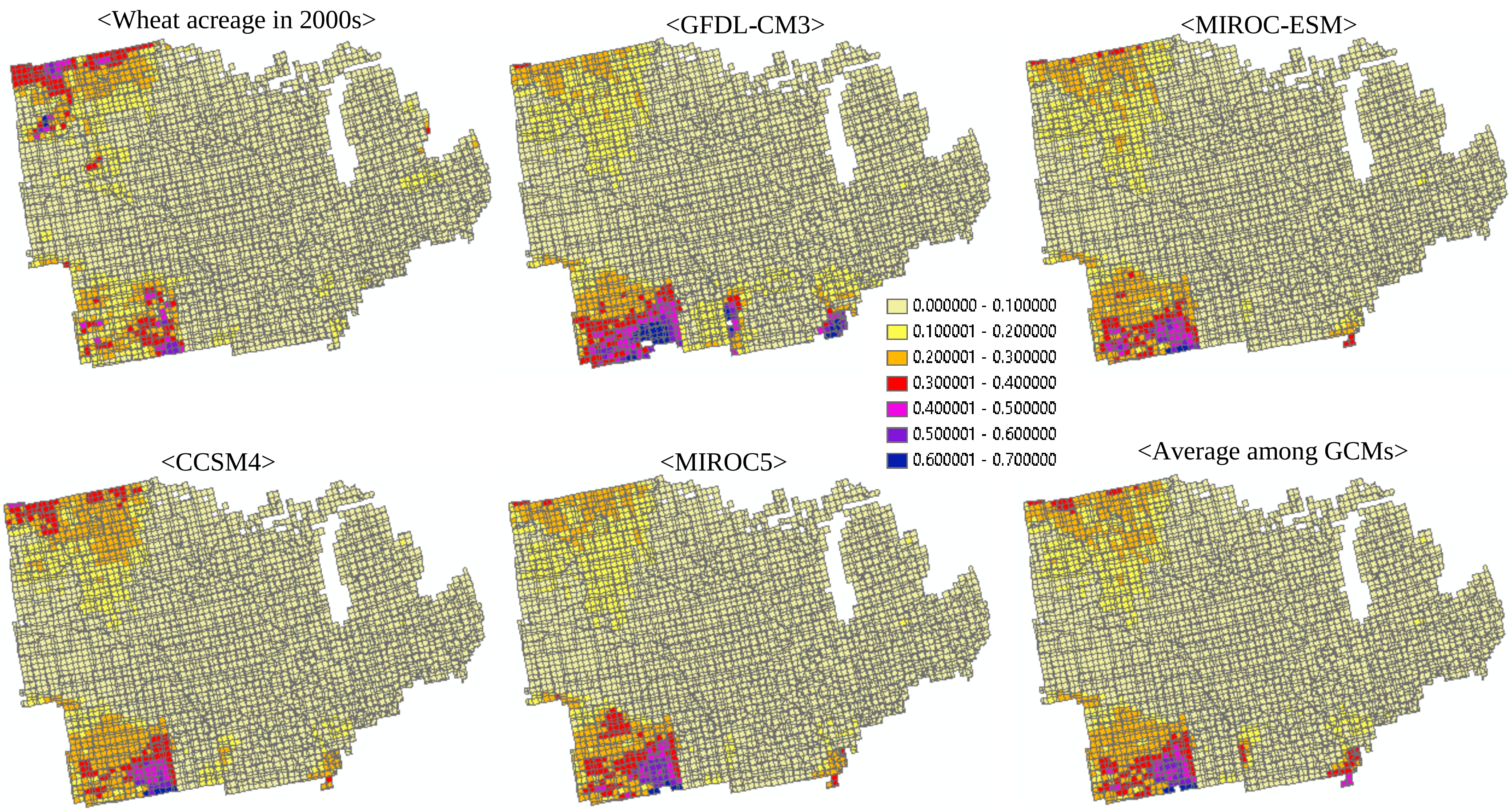


Figure A-1. The forecasted land use for wheat in 2030 based on M3

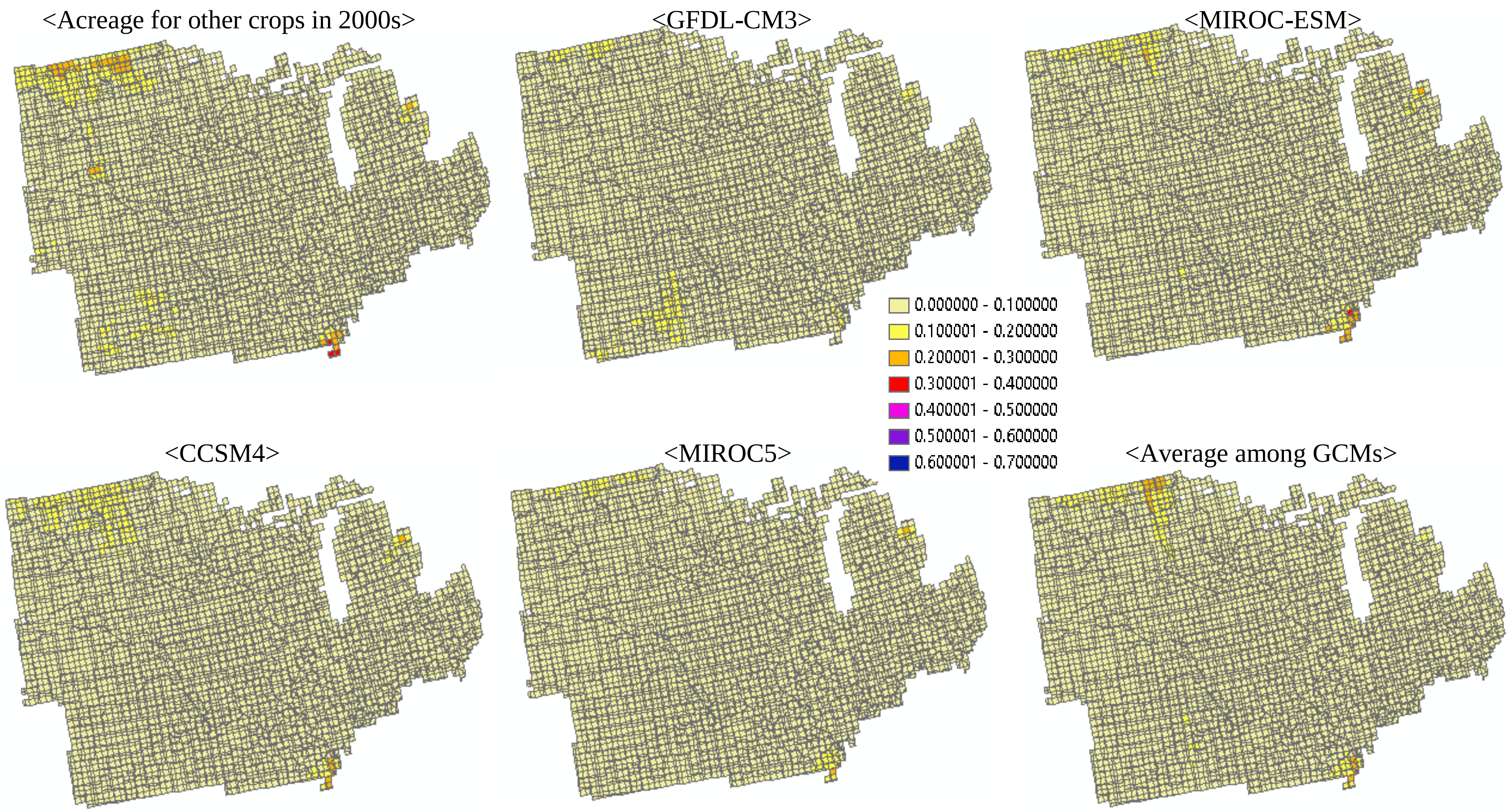


Figure A-2. The forecasted land use for other crops in 2030 based on M3

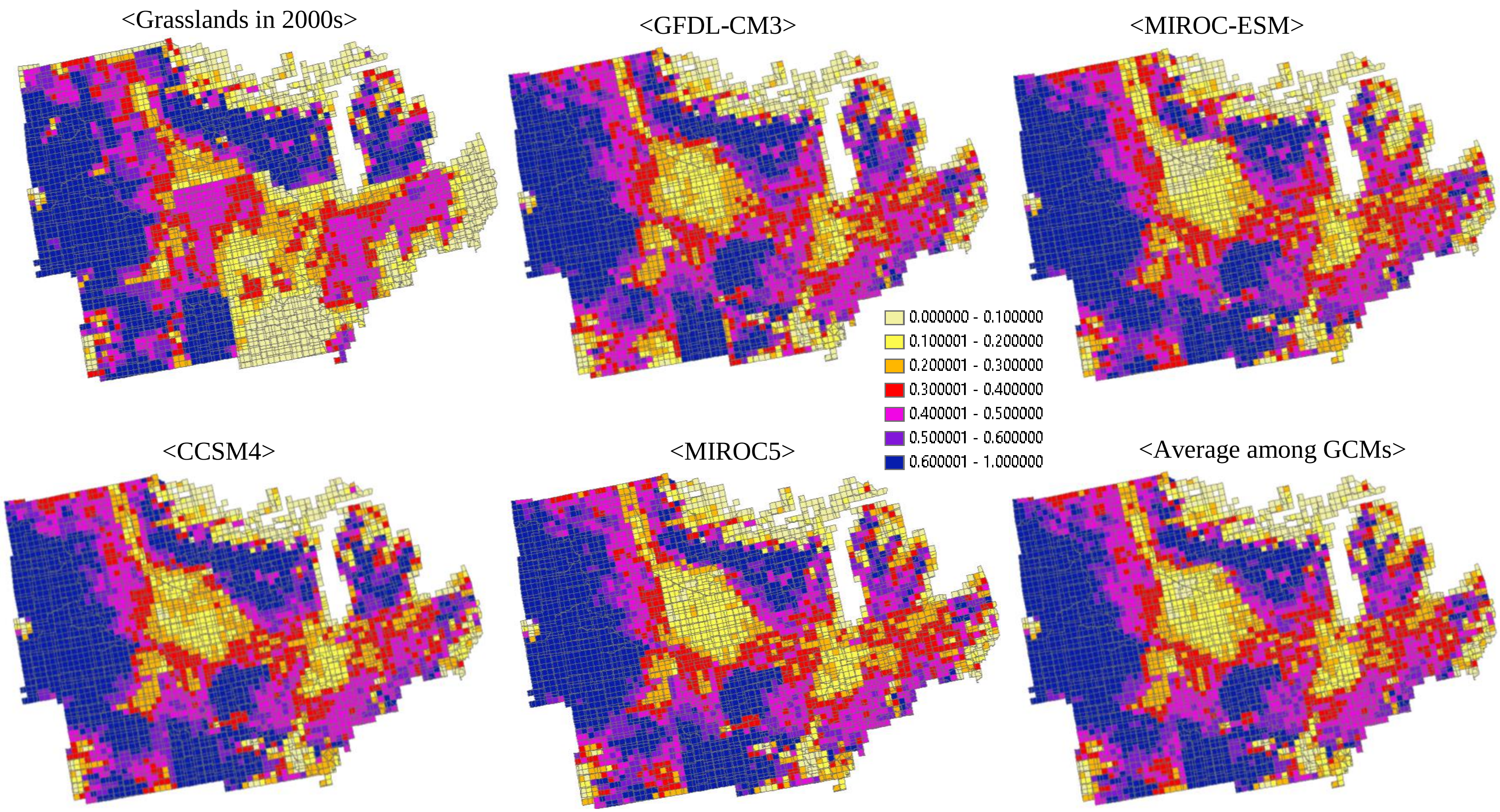


Figure A-3. The forecasted grasslands in 2030 based on M3

Appendix-C: Summary statistics for climate measures

<Table A-1> Summary statistics of climate variables based on MIROC-ESM: Corn Belt

		10 year averages		20 year averages		30 year averages		Decaying rate: 0.925		Decaying rate: 0.95		Decaying rate: 0.975	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Average Temperature	Mar	5.09	2.40	4.87	2.37	4.75	2.40	4.92	2.37	4.86	2.38	4.80	2.39
	Apr	11.86	1.95	11.71	1.90	11.53	1.90	11.75	1.90	11.68	1.90	11.60	1.90
	May	17.07	1.47	17.04	1.46	17.03	1.46	17.06	1.46	17.04	1.46	17.03	1.46
	Jun	22.18	1.19	22.01	1.17	21.94	1.18	22.04	1.18	22.00	1.18	21.97	1.18
	Jul	24.35	1.32	24.12	1.29	24.08	1.28	24.23	1.30	24.17	1.29	24.12	1.28
	Aug	23.51	1.46	23.24	1.40	23.12	1.42	23.30	1.44	23.24	1.43	23.18	1.42
	Sep	19.55	1.63	19.26	1.52	19.09	1.50	19.34	1.55	19.26	1.53	19.17	1.51
Precipitation	Mar	74.14	15.87	73.03	16.31	72.51	16.32	72.31	15.58	72.48	15.85	72.55	16.10
	Apr	91.67	15.90	92.02	11.75	91.67	10.51	92.17	10.91	92.08	10.64	91.91	10.48
	May	109.96	16.80	110.75	13.17	110.67	11.53	111.03	13.24	110.91	12.60	110.80	12.01
	Jun	102.20	14.74	103.45	10.69	105.28	10.16	103.47	10.19	103.96	9.88	104.57	9.86
	Jul	101.84	12.19	105.83	10.23	104.44	9.35	102.84	10.07	103.57	9.53	104.11	9.25
	Aug	85.64	13.56	90.27	10.14	91.86	9.37	90.03	10.35	90.54	9.86	91.16	9.52
	Sep	83.28	17.15	84.29	13.22	85.78	12.32	85.02	13.22	85.19	12.72	85.45	12.41
Precipitation		648.74	54.71	659.64	45.73	662.21	42.60	653.96	46.27	655.88	44.68	657.74	43.34
Heavy rainfall 1		2.18	0.82	2.28	0.72	2.29	0.68	2.23	0.70	2.25	0.69	2.26	0.68
Heavy rainfall 2		0.02	0.05	0.02	0.04	0.02	0.04	0.02	0.04	0.02	0.04	0.02	0.04
Heavy rainfall 3		0.32	0.02	0.32	0.02	0.32	0.02	0.32	0.02	0.32	0.02	0.32	0.02
GDD		2233.23	274.27	2198.11	266.14	2180.74	265.13	2207.95	268.59	2198.46	267.21	2189.21	266.02
HDD		1.35	2.32	0.96	1.49	0.94	1.35	1.16	1.82	1.07	1.63	1.00	1.47

Note: Heavy rainfall 1 is the number of daily rain events above 25.4 mm per year, Heavy rainfall 2 is the number of daily rain events above 76.2 mm per year, and Heavy rainfall 3 is the fraction of precipitation (mm) during the ten wettest days per year.

<Table A-2> Summary statistics of climate variables based on GFDL-CM3: Corn Belt

		10 year averages		20 year averages		30 year averages		Decaying rate: 0.925		Decaying rate: 0.95		Decaying rate: 0.975	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Average Temperature	Mar	4.99	2.37	5.08	2.29	5.13	2.31	5.04	2.31	5.05	2.30	5.06	2.29
	Apr	11.53	1.84	11.56	1.89	11.56	1.86	11.58	1.86	11.58	1.87	11.57	1.88
	May	17.41	1.48	17.11	1.46	17.28	1.46	17.27	1.48	17.21	1.47	17.16	1.46
	Jun	22.12	1.34	21.85	1.20	22.02	1.25	22.00	1.27	21.95	1.25	21.90	1.22
	Jul	24.18	1.32	23.98	1.25	24.09	1.26	24.10	1.27	24.06	1.26	24.02	1.25
	Aug	23.26	1.48	23.03	1.41	23.19	1.42	23.16	1.42	23.12	1.42	23.07	1.41
	Sep	19.28	1.57	18.95	1.43	19.06	1.47	19.08	1.49	19.04	1.46	18.99	1.44
Precipitation	Mar	73.22	22.29	72.87	19.49	72.63	20.20	73.02	20.84	72.83	20.28	72.78	19.82
	Apr	101.48	19.92	97.17	12.55	100.27	15.11	101.54	15.78	100.08	14.68	98.61	13.57
	May	116.68	13.27	117.47	12.12	114.76	11.50	116.76	11.39	116.87	11.43	117.12	11.68
	Jun	108.61	15.72	105.77	12.46	104.37	14.04	105.32	12.33	105.42	12.17	105.56	12.18
	Jul	99.83	13.59	100.96	9.72	98.91	9.82	101.62	10.13	101.38	9.82	101.16	9.67
	Aug	94.40	13.65	94.66	10.90	93.17	11.09	93.83	11.12	93.88	10.86	94.15	10.78
	Sep	82.62	13.36	77.34	12.47	81.08	12.76	79.44	11.92	78.90	11.97	78.18	12.16
Precipitation		676.82	47.80	666.24	43.78	665.19	45.96	668.04	45.09	665.76	44.19	663.85	43.60
Heavy rainfall 1		4.05	0.97	3.93	0.83	3.90	0.86	3.99	0.84	3.96	0.82	3.93	0.82
Heavy rainfall 2		0.07	0.10	0.07	0.06	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.06
Heavy rainfall 3		0.39	0.02	0.39	0.02	0.39	0.02	0.39	0.02	0.39	0.02	0.39	0.02
GDD		2220.23	269.29	2182.97	262.08	2204.55	263.65	2203.58	265.60	2196.82	264.16	2189.82	262.98
HDD		1.67	2.43	1.15	1.54	1.45	1.99	1.36	1.88	1.30	1.77	1.23	1.66

Note: Heavy rainfall 1 is the number of daily rain events above 25.4 mm per year, Heavy rainfall 2 is the number of daily rain events above 76.2 mm per year, and Heavy rainfall 3 is the fraction of precipitation (mm) during the ten wettest days per year.

<Table A-3> Summary statistics of climate variables based on MIROC5: Corn Belt

		10 year averages		20 year averages		30 year averages		Decaying rate: 0.925		Decaying rate: 0.95		Decaying rate: 0.975	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Average Temperature	Mar	4.98	2.48	4.85	2.44	4.81	2.47	4.97	2.46	5.35	2.54	5.82	2.59
	Apr	11.76	2.05	11.47	1.94	11.54	1.97	11.65	2.01	11.83	2.26	11.83	2.34
	May	17.38	1.58	17.13	1.48	17.17	1.50	17.35	1.53	17.69	1.67	17.81	1.69
	Jun	22.27	1.29	22.08	1.24	22.18	1.25	22.21	1.26	22.29	1.29	22.31	1.28
	Jul	24.15	1.42	23.94	1.31	23.99	1.34	24.03	1.34	24.04	1.38	23.99	1.36
	Aug	23.30	1.48	23.14	1.39	23.16	1.41	23.19	1.42	23.23	1.45	23.20	1.47
	Sep	19.32	1.63	18.97	1.45	19.09	1.52	19.15	1.52	19.30	1.60	19.38	1.65
Precipitation	Mar	75.44	20.97	75.60	18.30	75.12	18.73	74.18	18.60	74.64	18.43	75.11	18.32
	Apr	91.98	16.22	95.63	10.45	96.37	12.84	95.99	11.98	95.87	11.22	95.75	10.67
	May	114.02	21.65	116.53	10.91	118.29	12.77	116.11	13.99	116.36	12.61	116.51	11.54
	Jun	104.13	16.09	106.41	9.91	104.66	10.93	106.35	11.00	106.14	10.20	106.16	9.80
	Jul	101.89	18.14	103.55	10.41	104.16	13.29	104.64	12.47	104.18	11.43	103.82	10.71
	Aug	95.98	18.90	95.39	8.46	96.78	11.00	98.26	11.05	97.41	9.78	96.44	8.87
	Sep	87.74	19.36	81.31	12.93	82.14	15.04	83.40	15.79	82.55	14.50	81.83	13.50
Precipitation		671.18	73.92	674.42	39.34	677.52	49.51	677.14	47.71	675.23	44.01	673.62	41.01
Heavy rainfall 1		5.20	1.33	5.17	0.97	5.25	1.09	5.27	1.06	5.23	1.02	5.19	0.99
Heavy rainfall 2		0.17	0.16	0.17	0.12	0.18	0.13	0.18	0.13	0.18	0.12	0.17	0.12
Heavy rainfall 3		0.45	0.04	0.44	0.03	0.44	0.03	0.45	0.03	0.45	0.03	0.45	0.03
GDD		2226.33	285.31	2183.67	269.76	2194.80	274.48	2208.71	277.35	2235.18	290.82	2243.85	295.44
HDD		2.40	3.48	1.62	2.11	1.81	2.47	1.81	2.51	1.52	2.35	1.14	1.99

Note: Heavy rainfall 1 is the number of daily rain events above 25.4 mm per year, Heavy rainfall 2 is the number of daily rain events above 76.2 mm per year, and Heavy rainfall 3 is the fraction of precipitation (mm) during the ten wettest days per year.

<Table A-4> Summary statistics of climate variables based on CCSM4: Corn Belt

		10 year averages		20 year averages		30 year averages		Decaying rate: 0.925		Decaying rate: 0.95		Decaying rate: 0.975	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Average Temperature	Mar	5.24	2.40	5.02	2.38	5.14	2.37	5.14	2.39	5.10	2.39	5.07	2.38
	Apr	11.70	2.01	11.67	1.92	11.80	1.93	11.80	1.95	11.76	1.94	11.71	1.93
	May	17.65	1.54	17.24	1.51	17.46	1.54	17.41	1.52	17.36	1.52	17.30	1.51
	Jun	22.32	1.30	21.92	1.22	22.06	1.25	22.10	1.27	22.04	1.25	21.98	1.24
	Jul	24.43	1.33	24.03	1.29	24.21	1.31	24.22	1.30	24.16	1.30	24.10	1.30
	Aug	23.53	1.40	23.15	1.40	23.34	1.39	23.37	1.40	23.30	1.40	23.23	1.40
	Sep	19.72	1.42	19.31	1.42	19.55	1.41	19.51	1.43	19.45	1.43	19.38	1.42
Precipitation	Mar	72.61	17.34	72.31	15.20	71.86	14.87	72.46	14.92	72.41	14.86	72.35	14.94
	Apr	92.51	13.26	95.40	10.39	94.80	10.96	96.35	11.34	95.92	10.81	95.61	10.48
	May	114.91	18.07	115.96	12.84	116.58	15.19	115.72	13.18	115.83	12.75	115.92	12.60
	Jun	101.28	14.02	106.79	10.18	105.03	11.26	104.77	10.27	105.43	9.85	106.12	9.82
	Jul	104.23	15.10	107.64	9.89	107.00	12.12	107.66	11.19	107.68	10.43	107.68	9.96
	Aug	93.22	12.78	91.86	8.30	91.05	8.56	92.60	9.24	92.43	8.64	92.18	8.30
	Sep	77.62	17.88	78.89	11.69	76.38	13.07	77.81	12.73	78.09	11.87	78.45	11.50
Precipitation		656.38	49.25	668.86	42.38	662.69	45.57	664.81	41.40	665.29	40.94	665.84	41.17
Heavy rainfall 1		4.96	1.15	5.08	0.97	5.00	1.01	5.04	0.97	5.04	0.96	5.05	0.95
Heavy rainfall 2		0.19	0.16	0.19	0.12	0.19	0.13	0.19	0.13	0.19	0.12	0.19	0.12
Heavy rainfall 3		0.45	0.03	0.44	0.03	0.45	0.03	0.45	0.03	0.45	0.03	0.45	0.03
GDD		2274.21	271.75	2211.54	267.60	2244.48	269.92	2244.72	270.99	2234.10	269.78	2222.86	268.64
HDD		2.81	3.73	1.70	2.18	2.15	2.86	2.10	2.82	1.98	2.62	1.84	2.40

Note: Heavy rainfall 1 is the number of daily rain events above 25.4 mm per year, Heavy rainfall 2 is the number of daily rain events above 76.2 mm per year, and Heavy rainfall 3 is the fraction of precipitation (mm) during the ten wettest days per year.

<Table A-5> Summary statistics of climate variables based on averages among GCMs: Corn Belt

		10 year averages		20 year averages		30 year averages		Decaying rate: 0.925		Decaying rate: 0.95		Decaying rate: 0.975	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Average Temperature	Mar	5.08	2.39	4.93	2.37	4.99	2.37	5.02	2.38	5.09	2.38	5.19	2.37
	Apr	11.71	1.92	11.56	1.91	11.65	1.91	11.69	1.91	11.71	1.92	11.68	1.92
	May	17.38	1.49	17.13	1.47	17.24	1.48	17.27	1.49	17.33	1.51	17.32	1.51
	Jun	22.22	1.25	21.94	1.21	22.07	1.23	22.09	1.24	22.07	1.23	22.04	1.22
	Jul	24.27	1.33	24.01	1.28	24.10	1.30	24.14	1.30	24.11	1.30	24.06	1.28
	Aug	23.40	1.44	23.11	1.40	23.23	1.40	23.26	1.42	23.22	1.42	23.17	1.41
	Sep	19.47	1.54	19.08	1.45	19.24	1.47	19.27	1.49	19.26	1.49	19.23	1.49
Precipitation	Mar	73.85	17.49	73.32	17.07	73.16	16.99	72.99	16.94	73.09	16.97	73.20	17.01
	Apr	94.41	10.82	94.97	10.07	95.86	9.92	96.51	10.47	95.99	10.29	95.47	10.15
	May	113.89	11.30	115.16	10.50	115.10	10.65	114.90	10.63	114.99	10.57	115.09	10.52
	Jun	104.05	10.97	106.06	9.53	104.37	9.38	104.98	9.15	105.24	9.16	105.60	9.28
	Jul	101.95	10.27	104.15	8.64	103.98	9.69	104.19	9.27	104.20	8.91	104.19	8.69
	Aug	92.31	10.43	93.45	7.52	92.82	7.65	93.68	8.31	93.56	7.91	93.48	7.63
	Sep	82.81	11.34	80.83	10.71	80.97	11.03	81.42	10.77	81.18	10.71	80.98	10.69
Precipitation		663.28	43.31	667.93	39.10	666.26	40.12	665.99	39.81	665.54	39.38	665.26	39.05
Heavy rainfall 1		4.10	0.83	4.12	0.78	4.11	0.80	4.13	0.79	4.12	0.78	4.11	0.78
Heavy rainfall 2		0.11	0.08	0.11	0.07	0.11	0.07	0.12	0.07	0.11	0.07	0.11	0.07
Heavy rainfall 3		0.40	0.02	0.40	0.02	0.40	0.02	0.40	0.02	0.40	0.02	0.40	0.02
GDD		2238.50	273.82	2189.73	265.76	2210.49	268.24	2216.24	270.20	2216.14	271.52	2211.44	270.99
HDD		2.05	2.86	1.35	1.76	1.59	2.17	1.61	2.22	1.47	2.05	1.30	1.83

Note: Heavy rainfall 1 is the number of daily rain events above 25.4 mm per year, Heavy rainfall 2 is the number of daily rain events above 76.2 mm per year, and Heavy rainfall 3 is the fraction of precipitation (mm) during the ten wettest days per year.

<Table A-6> Summary statistics of climate variables in 2030 based on MIROC-ESM: Corn Belt

		10 year averages		20 year averages		30 year averages		Decaying rate: 0.925		Decaying rate: 0.95		Decaying rate: 0.975	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Average Temperature	Mar	6.23	2.25	6.14	2.23	6.59	2.14	6.28	2.21	6.25	2.21	6.20	2.22
	Apr	13.26	1.85	12.95	1.92	13.30	1.88	13.22	1.87	13.13	1.89	13.04	1.90
	May	18.74	1.40	18.06	1.45	18.30	1.45	18.38	1.43	18.28	1.44	18.18	1.45
	Jun	23.20	1.07	22.91	1.17	23.00	1.13	23.07	1.14	23.01	1.15	22.96	1.16
	Jul	25.42	0.94	25.27	1.08	25.37	0.98	25.35	1.00	25.33	1.02	25.31	1.05
	Aug	24.40	1.16	24.41	1.30	24.35	1.23	24.36	1.22	24.38	1.24	24.40	1.27
	Sep	21.08	1.30	20.76	1.48	20.77	1.42	20.88	1.39	20.84	1.42	20.80	1.45
Precipitation	Mar	80.54	17.78	77.25	14.70	81.73	15.90	81.05	16.33	79.92	15.73	78.62	15.18
	Apr	102.97	12.09	99.24	10.66	101.42	10.39	101.68	10.70	100.81	10.66	99.97	10.64
	May	126.40	12.43	116.79	10.53	124.52	11.70	121.36	10.57	120.18	10.39	118.63	10.35
	Jun	112.42	19.27	107.37	11.71	114.84	15.39	112.90	15.28	111.20	14.13	109.35	12.91
	Jul	126.72	16.18	111.39	11.23	118.44	13.34	120.00	13.48	117.08	12.66	114.14	11.89
	Aug	103.78	12.76	90.77	8.57	98.62	9.73	98.72	10.14	96.10	9.48	93.42	8.95
	Sep	85.27	13.56	78.76	9.65	83.26	11.18	85.00	11.26	82.84	10.67	80.73	10.11
Precipitation		738.10	49.75	681.58	42.59	722.83	46.30	720.71	45.81	708.14	44.58	694.85	43.47
Heavy rainfall 1		2.89	0.79	2.37	0.65	2.68	0.74	2.72	0.72	2.61	0.70	2.49	0.67
Heavy rainfall 2		0.04	0.06	0.02	0.03	0.03	0.04	0.03	0.05	0.03	0.04	0.02	0.03
Heavy rainfall 3		0.32	0.02	0.32	0.02	0.31	0.02	0.32	0.02	0.32	0.02	0.32	0.02
GDD		2458.96	242.80	2410.06	261.69	2432.34	255.37	2435.16	252.68	2427.56	255.65	2419.06	258.72
HDD		1.24	1.53	2.48	2.92	1.55	1.83	1.84	2.10	2.05	2.36	2.27	2.64

Note: Heavy rainfall 1 is the number of daily rain events above 25.4 mm per year, Heavy rainfall 2 is the number of daily rain events above 76.2 mm per year, and Heavy rainfall 3 is the fraction of precipitation (mm) during the ten wettest days per year.

<Table A-7> Summary statistics of climate variables in 2030 based on GFDL-CM3

		10 year averages		20 year averages		30 year averages		Decaying rate: 0.925		Decaying rate: 0.95		Decaying rate: 0.975	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Average Temperature	Mar	5.74	2.32	5.00	2.39	5.25	2.31	5.45	2.30	5.30	2.33	5.15	2.36
	Apr	14.08	1.82	12.36	1.89	12.88	1.93	13.14	1.88	12.89	1.88	12.63	1.89
	May	18.70	1.45	18.22	1.38	18.35	1.41	18.52	1.41	18.43	1.40	18.33	1.39
	Jun	23.09	1.08	22.78	1.22	22.91	1.23	22.96	1.19	22.90	1.20	22.84	1.21
	Jul	26.31	1.36	25.51	1.30	25.89	1.35	25.92	1.32	25.80	1.32	25.66	1.31
	Aug	25.53	1.53	24.67	1.48	25.11	1.53	25.23	1.52	25.05	1.51	24.86	1.50
	Sep	21.36	1.28	20.82	1.37	21.28	1.40	21.17	1.36	21.08	1.36	20.96	1.36
Precipitation	Mar	78.71	22.80	75.05	19.88	74.13	21.14	75.49	20.52	75.48	20.35	75.33	20.13
	Apr	94.14	8.93	106.25	13.27	104.11	11.12	102.68	11.03	103.99	11.63	105.22	12.39
	May	132.61	16.09	129.27	15.19	137.19	17.65	129.28	15.25	130.02	15.31	130.03	15.30
	Jun	98.28	14.11	111.79	11.26	114.42	12.22	108.30	11.94	109.62	11.55	110.81	11.31
	Jul	129.36	12.76	120.95	8.54	126.47	9.02	124.81	9.38	123.57	8.95	122.26	8.66
	Aug	119.92	15.38	105.27	12.25	107.17	15.06	108.79	13.20	107.64	12.93	106.43	12.60
	Sep	76.29	12.23	82.34	12.85	83.67	14.56	79.11	12.51	80.04	12.64	81.14	12.75
Precipitation		729.31	44.48	730.92	50.00	747.17	52.28	728.46	46.94	730.35	48.02	731.23	49.07
Heavy rainfall 1		4.26	0.78	4.45	0.88	4.56	0.88	4.29	0.83	4.36	0.84	4.41	0.86
Heavy rainfall 2		0.09	0.11	0.09	0.07	0.10	0.09	0.09	0.08	0.09	0.08	0.09	0.07
Heavy rainfall 3		0.37	0.02	0.38	0.02	0.37	0.02	0.37	0.02	0.38	0.02	0.38	0.02
GDD		2542.78	266.78	2412.19	265.04	2470.27	271.58	2486.05	268.28	2463.08	267.42	2438.08	266.32
HDD		8.17	9.13	4.89	5.42	6.35	6.89	6.73	7.31	6.14	6.71	5.52	6.06

Note: Heavy rainfall 1 is the number of daily rain events above 25.4 mm per year, Heavy rainfall 2 is the number of daily rain events above 76.2 mm per year, and Heavy rainfall 3 is the fraction of precipitation (mm) during the ten wettest days per year.

<Table A-8> Summary statistics of climate variables in 2030 based on MIROC5: Corn Belt

		10 year averages		20 year averages		30 year averages		Decaying rate: 0.925		Decaying rate: 0.95		Decaying rate: 0.975	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Average Temperature	Mar	7.81	1.98	6.79	2.08	7.28	2.01	7.21	2.03	7.11	2.05	6.97	2.06
	Apr	14.68	1.67	13.79	1.72	14.20	1.67	14.28	1.68	14.12	1.69	13.96	1.71
	May	19.36	1.48	18.66	1.38	18.79	1.40	18.96	1.43	18.87	1.41	18.76	1.40
	Jun	23.57	1.19	22.92	1.13	23.19	1.10	23.28	1.14	23.16	1.14	23.04	1.13
	Jul	25.44	1.33	25.22	1.24	25.42	1.19	25.38	1.28	25.33	1.26	25.28	1.25
	Aug	24.66	1.42	24.31	1.38	24.59	1.32	24.48	1.37	24.43	1.37	24.37	1.37
	Sep	20.49	1.44	20.41	1.44	20.50	1.40	20.47	1.43	20.45	1.43	20.43	1.44
Precipitation	Mar	85.56	26.36	76.96	22.55	80.48	23.37	80.74	23.44	79.70	23.10	78.42	22.80
	Apr	105.44	10.22	96.34	8.07	105.44	9.40	101.02	9.10	99.91	8.69	98.34	8.35
	May	114.97	10.38	103.13	8.71	111.65	10.52	110.53	8.47	108.17	8.37	105.66	8.43
	Jun	96.84	16.82	101.98	13.63	106.06	14.69	100.34	14.66	101.43	14.24	102.00	13.90
	Jul	102.42	21.48	101.32	11.62	105.39	14.67	102.34	16.09	102.48	14.46	102.15	12.94
	Aug	75.47	13.36	79.20	10.98	77.36	11.44	79.36	11.49	79.42	11.23	79.36	11.06
	Sep	90.43	19.78	96.21	15.13	93.35	15.18	95.64	16.40	95.70	15.78	95.90	15.35
Precipitation		671.14	48.88	655.13	48.33	679.73	51.10	669.96	47.69	666.81	47.81	661.83	48.04
Heavy rainfall 1		5.38	0.99	5.14	0.93	5.46	0.96	5.34	0.94	5.30	0.93	5.23	0.93
Heavy rainfall 2		0.26	0.19	0.22	0.14	0.26	0.16	0.25	0.16	0.24	0.15	0.23	0.14
Heavy rainfall 3		0.47	0.03	0.46	0.03	0.46	0.03	0.46	0.03	0.46	0.03	0.46	0.03
GDD		2539.38	273.00	2447.08	262.10	2490.70	258.09	2494.25	265.49	2479.31	264.16	2463.38	262.99
HDD		4.87	5.75	4.09	4.37	3.95	4.30	4.41	4.97	4.25	4.71	4.14	4.51

Note: Heavy rainfall 1 is the number of daily rain events above 25.4 mm per year, Heavy rainfall 2 is the number of daily rain events above 76.2 mm per year, and Heavy rainfall 3 is the fraction of precipitation (mm) during the ten wettest days per year.

<Table A-9> Summary statistics of climate variables in 2030 based on CCSM4: Corn Belt

		10 year averages		20 year averages		30 year averages		Decaying rate: 0.925		Decaying rate: 0.95		Decaying rate: 0.975	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Average Temperature	Mar	6.59	2.36	5.74	2.43	6.01	2.39	6.11	2.37	5.99	2.39	5.86	2.41
	Apr	12.92	2.02	12.48	1.94	12.91	1.97	12.85	1.98	12.74	1.97	12.62	1.96
	May	18.03	1.51	18.24	1.46	18.30	1.50	18.15	1.49	18.18	1.48	18.22	1.47
	Jun	23.43	1.32	23.15	1.25	23.20	1.31	23.19	1.29	23.18	1.28	23.17	1.27
	Jul	25.50	1.27	25.16	1.24	25.12	1.29	25.33	1.26	25.26	1.25	25.20	1.25
	Aug	25.52	1.48	24.54	1.39	24.88	1.36	25.00	1.42	24.85	1.41	24.69	1.40
	Sep	20.54	1.50	20.46	1.53	20.69	1.54	20.52	1.53	20.51	1.54	20.50	1.54
Precipitation	Mar	78.22	20.20	83.21	17.86	83.84	20.03	81.39	18.87	82.04	18.61	82.67	18.27
	Apr	99.11	13.25	92.94	12.11	97.70	14.92	95.59	12.62	95.08	12.56	94.18	12.38
	May	116.25	17.41	109.79	12.37	107.00	14.28	108.86	13.87	109.13	13.24	109.42	12.72
	Jun	119.83	20.20	115.41	14.06	117.97	16.27	117.14	15.99	116.80	15.35	116.22	14.69
	Jul	95.52	17.80	105.81	13.83	111.99	16.69	104.59	15.19	105.61	14.67	106.03	14.21
	Aug	63.92	12.49	85.48	8.80	73.07	8.68	76.45	8.97	79.26	8.70	82.32	8.64
	Sep	75.38	14.06	86.29	10.13	80.69	10.49	80.22	10.69	82.10	10.31	84.16	10.12
Precipitation		648.24	41.06	678.93	37.38	672.27	38.53	664.23	37.10	670.01	36.94	674.99	37.06
Heavy rainfall 1		5.03	0.88	5.42	0.78	5.24	0.78	5.21	0.76	5.29	0.76	5.36	0.77
Heavy rainfall 2		0.18	0.15	0.20	0.11	0.18	0.11	0.19	0.12	0.19	0.11	0.19	0.11
Heavy rainfall 3		0.46	0.03	0.45	0.02	0.45	0.02	0.45	0.02	0.45	0.02	0.45	0.02
GDD		2471.24	280.34	2410.63	271.97	2440.39	277.58	2439.87	276.73	2430.55	275.44	2420.70	273.84
HDD		6.57	7.59	4.69	5.12	4.82	5.39	5.48	6.13	5.15	5.74	4.88	5.40

Note: Heavy rainfall 1 is the number of daily rain events above 25.4 mm per year, Heavy rainfall 2 is the number of daily rain events above 76.2 mm per year, and Heavy rainfall 3 is the fraction of precipitation (mm) during the ten wettest days per year.

<Table A-10> Summary statistics of climate variables in 2030 based on averages among GCMs: Corn Belt

		10 year averages		20 year averages		30 year averages		Decaying rate: 0.925		Decaying rate: 0.95		Decaying rate: 0.975	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Average Temperature	Mar	6.59	2.22	5.92	2.28	6.28	2.21	6.26	2.22	6.16	2.24	6.05	2.26
	Apr	13.74	1.83	12.90	1.87	13.32	1.86	13.37	1.85	13.22	1.85	13.06	1.86
	May	18.71	1.45	18.30	1.41	18.43	1.43	18.50	1.44	18.44	1.43	18.37	1.42
	Jun	23.32	1.16	22.94	1.19	23.08	1.19	23.13	1.18	23.06	1.18	23.00	1.19
	Jul	25.67	1.21	25.29	1.21	25.45	1.19	25.49	1.21	25.43	1.21	25.36	1.21
	Aug	25.02	1.38	24.48	1.38	24.73	1.35	24.77	1.37	24.68	1.37	24.58	1.38
	Sep	20.87	1.37	20.61	1.45	20.81	1.43	20.76	1.42	20.72	1.43	20.67	1.44
Precipitation	Mar	80.76	21.27	78.12	18.45	80.04	19.69	79.67	19.43	79.29	19.12	78.76	18.79
	Apr	100.41	8.58	98.69	9.56	102.17	9.41	100.24	9.03	99.95	9.19	99.43	9.37
	May	122.56	10.60	114.74	9.86	120.09	10.35	117.51	9.51	116.87	9.59	115.93	9.71
	Jun	106.84	13.16	109.14	10.19	113.32	11.20	109.67	11.46	109.76	10.98	109.59	10.55
	Jul	113.51	13.37	109.87	9.50	115.57	10.66	112.94	11.15	112.18	10.54	111.14	9.99
	Aug	90.77	9.31	90.18	8.52	89.06	8.74	90.83	8.79	90.60	8.70	90.38	8.61
	Sep	81.84	10.64	85.90	10.10	85.24	10.49	84.99	10.04	85.17	10.04	85.48	10.06
Precipitation		696.70	39.01	686.64	41.47	705.50	42.38	695.84	40.24	693.83	40.66	690.72	41.08
Heavy rainfall 1		4.39	0.65	4.35	0.72	4.49	0.71	4.39	0.69	4.39	0.70	4.37	0.71
Heavy rainfall 2		0.14	0.08	0.13	0.07	0.14	0.07	0.14	0.07	0.14	0.07	0.14	0.07
Heavy rainfall 3		0.40	0.02	0.40	0.02	0.40	0.02	0.40	0.02	0.40	0.02	0.40	0.02
GDD		2503.09	265.30	2419.99	264.83	2458.43	265.12	2463.83	265.38	2450.12	265.27	2435.30	265.08
HDD		5.21	5.92	4.04	4.43	4.17	4.55	4.61	5.09	4.40	4.85	4.20	4.63

Note: Heavy rainfall 1 is the number of daily rain events above 25.4 mm per year, Heavy rainfall 2 is the number of daily rain events above 76.2 mm per year, and Heavy rainfall 3 is the fraction of precipitation (mm) during the ten wettest days per year.

<Table A-11> **Summary statistics of climate variables based on MIROC-ESM: Lake States**

		10 year averages		20 year averages		30 year averages		Decaying rate: 0.925		Decaying rate: 0.95		Decaying rate: 0.975	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Average Temperature	Mar	1.25	0.52	1.28	0.46	1.27	0.43	1.24	0.43	1.25	0.43	1.25	0.42
	Apr	0.01	0.02	0.01	0.02	0.01	0.01	0.01	0.02	0.01	0.02	0.01	0.01
	May	0.32	0.02	0.32	0.02	0.32	0.02	0.32	0.02	0.32	0.02	0.32	0.02
	Jun	-1.05	1.91	-1.38	1.94	-1.61	1.95	-1.30	1.93	-1.41	1.94	-1.52	1.95
	Jul	7.00	1.54	6.75	1.55	6.52	1.58	6.79	1.56	6.70	1.57	6.61	1.57
	Aug	13.09	1.37	13.05	1.37	13.02	1.38	13.07	1.38	13.05	1.38	13.03	1.38
	Sep	18.53	1.43	18.38	1.43	18.29	1.44	18.39	1.43	18.36	1.43	18.32	1.44
Precipitation	Mar	47.67	11.38	46.05	11.03	45.04	11.05	46.74	10.83	46.22	10.92	45.64	11.00
	Apr	62.92	14.18	61.77	12.16	62.20	11.35	63.08	12.18	62.74	11.80	62.45	11.52
	May	80.46	12.98	82.51	9.62	82.43	9.56	81.25	9.72	81.59	9.50	81.99	9.43
	Jun	98.93	13.56	98.83	12.58	98.36	12.67	97.26	11.77	97.61	11.97	97.98	12.28
	Jul	89.58	14.47	93.69	14.23	94.14	12.84	90.72	13.06	91.91	12.83	93.07	12.74
	Aug	88.76	14.51	90.73	11.89	91.13	10.04	90.56	11.80	90.77	11.08	90.97	10.48
	Sep	80.15	10.08	80.79	9.68	80.76	9.42	81.66	9.91	81.33	9.68	81.03	9.52
Precipitation		548.46	53.42	554.38	53.11	554.07	52.41	548.32	52.48	549.21	52.19	550.13	52.06
Heavy rainfall 1		1.25	0.52	1.28	0.46	1.27	0.43	1.24	0.43	1.25	0.43	1.25	0.42
Heavy rainfall 2		0.01	0.02	0.01	0.02	0.01	0.01	0.01	0.02	0.01	0.02	0.01	0.01
Heavy rainfall 3		0.32	0.02	0.32	0.02	0.32	0.02	0.32	0.02	0.32	0.02	0.32	0.02
GDD		1551.24	219.47	1524.04	214.35	1508.20	211.90	1530.03	215.63	1522.65	214.39	1515.23	213.11
HDD		0.03	0.06	0.02	0.04	0.02	0.03	0.02	0.05	0.02	0.04	0.02	0.04

Note: Heavy rainfall 1 is the number of daily rain events above 25.4 mm per year, Heavy rainfall 2 is the number of daily rain events above 76.2 mm per year, and Heavy rainfall 3 is the fraction of precipitation (mm) during the ten wettest days per year.

<Table A-12> Summary statistics of climate variables based on GFDL-CM3: Lake States

		10 year averages		20 year averages		30 year averages		Decaying rate: 0.925		Decaying rate: 0.95		Decaying rate: 0.975	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Average Temperature	Mar	-1.04	1.90	-0.85	1.85	-0.92	1.80	-0.98	1.81	-0.96	1.80	-0.94	1.80
	Apr	6.90	1.40	6.86	1.40	6.76	1.44	6.88	1.40	6.84	1.41	6.80	1.42
	May	13.44	1.41	13.32	1.39	13.15	1.38	13.28	1.43	13.23	1.41	13.19	1.39
	Jun	18.44	1.42	18.38	1.40	18.26	1.39	18.38	1.41	18.34	1.40	18.30	1.39
	Jul	20.87	1.30	20.77	1.27	20.65	1.27	20.74	1.30	20.71	1.28	20.68	1.27
	Aug	19.67	1.31	19.63	1.25	19.49	1.23	19.62	1.25	19.58	1.24	19.53	1.24
	Sep	15.30	1.53	15.06	1.40	14.97	1.36	15.07	1.42	15.03	1.39	15.00	1.38
Precipitation	Mar	41.45	11.99	40.80	10.57	41.24	10.75	41.24	10.75	41.15	10.62	41.15	10.62
	Apr	62.27	16.35	63.08	13.30	63.35	11.93	63.17	13.51	63.21	12.81	63.27	12.27
	May	92.09	13.39	88.78	13.02	87.36	11.58	91.13	11.19	89.87	11.20	88.60	11.32
	Jun	100.08	21.04	98.86	16.87	95.78	13.77	96.40	16.02	96.27	15.08	96.05	14.31
	Jul	92.84	14.73	91.85	12.91	93.33	12.31	94.57	13.63	94.11	13.05	93.70	12.61
	Aug	92.76	14.84	91.29	12.49	92.30	12.17	92.40	12.71	92.23	12.44	92.20	12.26
	Sep	77.91	12.33	76.78	11.95	76.10	11.50	77.24	11.49	76.91	11.48	76.52	11.48
Precipitation		559.40	56.66	551.44	56.22	549.46	54.42	553.97	54.21	551.51	54.01	549.16	53.92
Heavy rainfall 1		2.38	0.77	2.31	0.68	2.29	0.67	2.36	0.68	2.34	0.67	2.31	0.66
Heavy rainfall 2		0.01	0.04	0.01	0.03	0.01	0.02	0.01	0.03	0.01	0.02	0.01	0.02
Heavy rainfall 3		0.38	0.02	0.38	0.02	0.38	0.02	0.38	0.02	0.38	0.02	0.38	0.02
GDD		1560.05	209.34	1545.32	205.15	1526.36	203.51	1543.34	207.70	1537.71	205.89	1531.95	204.50
HDD		0.05	0.11	0.06	0.10	0.06	0.09	0.06	0.10	0.06	0.09	0.06	0.09

Note: Heavy rainfall 1 is the number of daily rain events above 25.4 mm per year, Heavy rainfall 2 is the number of daily rain events above 76.2 mm per year, and Heavy rainfall 3 is the fraction of precipitation (mm) during the ten wettest days per year.

<Table A-13> Summary statistics of climate variables based on MIROC5: Lake States

		10 year averages		20 year averages		30 year averages		Decaying rate: 0.925		Decaying rate: 0.95		Decaying rate: 0.975	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Average Temperature	Mar	-1.44	1.96	-1.60	1.89	-1.54	1.88	-1.46	1.94	-1.07	2.20	-0.58	2.34
	Apr	6.79	1.67	6.51	1.56	6.45	1.53	6.69	1.63	7.02	2.00	7.12	2.15
	May	13.42	1.59	13.12	1.47	13.06	1.42	13.29	1.53	13.57	1.70	13.64	1.75
	Jun	18.52	1.49	18.48	1.44	18.37	1.42	18.48	1.45	18.57	1.52	18.65	1.58
	Jul	20.75	1.41	20.54	1.38	20.45	1.31	20.64	1.37	20.86	1.43	20.99	1.43
	Aug	19.57	1.32	19.52	1.29	19.54	1.28	19.54	1.31	19.60	1.36	19.66	1.40
	Sep	15.21	1.50	14.99	1.46	14.88	1.39	15.07	1.44	15.22	1.44	15.27	1.43
Precipitation	Mar	42.55	14.43	42.72	12.54	43.00	11.86	42.03	11.45	42.35	11.50	42.68	11.63
	Apr	64.55	11.68	68.60	13.65	69.38	11.62	67.33	11.71	67.95	11.58	68.64	11.54
	May	85.06	16.58	88.06	14.06	87.33	12.20	89.10	13.60	88.48	12.98	87.89	12.49
	Jun	90.75	15.25	92.89	12.14	94.39	12.16	91.62	12.80	92.64	12.35	93.58	12.15
	Jul	94.76	15.54	97.27	14.35	97.57	12.27	95.67	13.03	96.34	12.72	96.97	12.44
	Aug	93.84	12.28	93.59	10.21	91.16	9.84	93.07	10.27	92.44	9.83	91.79	9.68
	Sep	86.98	16.36	83.67	13.61	82.17	11.71	83.63	13.74	83.19	12.95	82.69	12.27
Precipitation		558.49	62.88	566.80	57.41	565.01	53.00	560.69	54.99	561.55	53.93	562.34	53.12
Heavy rainfall 1		3.38	0.87	3.42	0.74	3.39	0.69	3.36	0.73	3.37	0.71	3.37	0.69
Heavy rainfall 2		0.07	0.09	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
Heavy rainfall 3		0.44	0.03	0.44	0.03	0.44	0.03	0.44	0.03	0.44	0.03	0.44	0.03
GDD		1544.34	226.57	1515.82	216.73	1506.21	209.57	1529.06	220.03	1555.92	233.42	1568.55	238.49
HDD		0.13	0.17	0.10	0.14	0.09	0.12	0.10	0.13	0.07	0.11	0.05	0.09

Note: Heavy rainfall 1 is the number of daily rain events above 25.4 mm per year, Heavy rainfall 2 is the number of daily rain events above 76.2 mm per year, and Heavy rainfall 3 is the fraction of precipitation (mm) during the ten wettest days per year.

<Table A-14> Summary statistics of climate variables based on CCSM4: Lake States

		10 year averages		20 year averages		30 year averages		Decaying rate: 0.925		Decaying rate: 0.95		Decaying rate: 0.975	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Average Temperature	Mar	-0.91	1.86	-1.08	1.82	-1.22	1.84	-1.11	1.83	-1.13	1.83	-1.17	1.83
	Apr	6.71	1.58	6.80	1.49	6.65	1.51	6.79	1.50	6.75	1.50	6.70	1.50
	May	13.57	1.45	13.42	1.43	13.25	1.41	13.42	1.42	13.36	1.41	13.30	1.41
	Jun	18.71	1.47	18.44	1.45	18.30	1.44	18.50	1.45	18.43	1.44	18.36	1.44
	Jul	20.96	1.42	20.72	1.34	20.58	1.31	20.78	1.34	20.71	1.33	20.65	1.32
	Aug	19.97	1.27	19.82	1.28	19.62	1.29	19.83	1.26	19.76	1.27	19.69	1.28
	Sep	15.67	1.35	15.54	1.37	15.29	1.41	15.49	1.37	15.42	1.38	15.36	1.40
Precipitation	Mar	39.48	12.65	42.19	12.35	42.78	11.62	42.11	11.64	42.33	11.54	42.55	11.53
	Apr	67.86	14.06	69.90	12.22	68.61	12.20	69.43	12.27	69.13	12.09	68.85	12.06
	May	86.14	13.45	85.84	11.56	85.75	10.36	84.59	10.63	85.00	10.41	85.39	10.31
	Jun	91.21	14.54	93.61	13.30	95.41	12.68	92.76	12.64	93.69	12.49	94.59	12.51
	Jul	94.62	15.23	99.04	14.71	100.83	14.01	99.83	14.31	100.16	14.09	100.51	13.99
	Aug	92.42	18.40	89.70	11.95	90.47	10.75	92.81	13.49	92.08	12.33	91.29	11.38
	Sep	80.66	12.50	81.79	11.98	84.63	12.56	82.23	12.10	82.93	11.93	83.74	12.10
Precipitation		552.39	56.91	562.08	56.71	568.48	56.14	561.59	56.46	563.16	55.96	564.76	55.75
Heavy rainfall 1		3.78	0.83	3.86	0.78	3.92	0.79	3.85	0.78	3.87	0.77	3.89	0.78
Heavy rainfall 2		0.10	0.10	0.10	0.08	0.10	0.07	0.10	0.08	0.10	0.07	0.10	0.07
Heavy rainfall 3		0.47	0.04	0.46	0.03	0.46	0.03	0.46	0.03	0.46	0.03	0.46	0.03
GDD		1597.11	214.83	1571.11	212.46	1543.10	210.56	1573.23	211.72	1563.36	211.36	1553.14	210.96
HDD		0.15	0.23	0.13	0.19	0.09	0.14	0.12	0.18	0.11	0.17	0.10	0.15

Note: Heavy rainfall 1 is the number of daily rain events above 25.4 mm per year, Heavy rainfall 2 is the number of daily rain events above 76.2 mm per year, and Heavy rainfall 3 is the fraction of precipitation (mm) during the ten wettest days per year.

<Table A-15> Summary statistics of climate variables based on Average among GCMs: Lake States

		10 year averages		20 year averages		30 year averages		Decaying rate: 0.925		Decaying rate: 0.95		Decaying rate: 0.975	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Average Temperature	Mar	-1.11	1.84	-1.23	1.84	-1.32	1.85	-1.21	1.85	-1.14	1.88	-1.05	1.89
	Apr	6.85	1.49	6.73	1.49	6.59	1.50	6.79	1.50	6.83	1.55	6.80	1.56
	May	13.38	1.43	13.23	1.41	13.12	1.39	13.27	1.43	13.30	1.45	13.29	1.46
	Jun	18.55	1.44	18.42	1.43	18.31	1.42	18.44	1.43	18.42	1.44	18.41	1.45
	Jul	20.86	1.36	20.68	1.32	20.59	1.29	20.73	1.33	20.75	1.32	20.75	1.31
	Aug	19.78	1.30	19.66	1.28	19.55	1.27	19.67	1.29	19.65	1.30	19.62	1.30
	Sep	15.36	1.44	15.17	1.41	15.02	1.39	15.18	1.41	15.18	1.40	15.16	1.40
Precipitation	Mar	42.79	11.00	42.94	10.97	43.02	11.03	43.03	10.69	43.01	10.79	43.01	10.91
	Apr	64.40	10.89	65.84	11.45	65.89	11.34	65.76	11.47	65.76	11.37	65.80	11.32
	May	85.94	11.69	86.30	10.54	85.72	10.20	86.52	10.38	86.24	10.29	85.97	10.22
	Jun	95.24	13.23	96.05	11.79	95.99	11.66	94.51	11.62	95.05	11.60	95.55	11.61
	Jul	92.95	12.61	95.46	12.95	96.47	12.09	95.20	12.48	95.63	12.31	96.06	12.17
	Aug	91.94	11.79	91.33	10.19	91.27	9.82	92.21	10.57	91.88	10.27	91.56	10.01
	Sep	81.42	10.49	80.76	10.39	80.92	10.36	81.19	10.30	81.09	10.30	81.00	10.32
Precipitation		554.68	52.65	558.67	52.81	559.26	52.54	556.14	52.43	556.35	52.30	556.60	52.23
Heavy rainfall 1		2.70	0.58	2.72	0.56	2.72	0.56	2.70	0.56	2.71	0.56	2.71	0.56
Heavy rainfall 2		0.05	0.04	0.05	0.03	0.05	0.03	0.05	0.03	0.05	0.03	0.05	0.03
Heavy rainfall 3		0.40	0.02	0.40	0.02	0.40	0.02	0.40	0.02	0.40	0.02	0.40	0.02
GDD		1563.19	216.70	1539.07	211.80	1520.97	208.53	1543.92	213.46	1544.91	215.31	1542.22	215.41
HDD		0.09	0.13	0.08	0.11	0.07	0.09	0.08	0.11	0.07	0.10	0.06	0.08

Note: Heavy rainfall 1 is the number of daily rain events above 25.4 mm per year, Heavy rainfall 2 is the number of daily rain events above 76.2 mm per year, and Heavy rainfall 3 is the fraction of precipitation (mm) during the ten wettest days per year.

<Table A-16> Summary statistics of climate variables in 2030 based on MIROC-ESM: Lake States

		10 year averages		20 year averages		30 year averages		Decaying rate: 0.925		Decaying rate: 0.95		Decaying rate: 0.975	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Average Temperature	Mar	0.54	1.76	1.21	1.76	0.43	1.80	0.72	1.76	0.65	1.78	0.55	1.79
	Apr	9.00	1.13	8.91	1.18	8.35	1.27	8.82	1.19	8.67	1.22	8.51	1.24
	May	15.09	1.23	14.44	1.30	14.09	1.33	14.53	1.29	14.40	1.30	14.25	1.32
	Jun	20.09	1.24	19.70	1.29	19.44	1.32	19.70	1.29	19.63	1.30	19.54	1.31
	Jul	23.09	1.07	22.76	1.15	22.32	1.24	22.68	1.15	22.58	1.18	22.46	1.21
	Aug	21.53	1.24	21.12	1.31	20.92	1.35	21.20	1.29	21.11	1.31	21.01	1.33
	Sep	17.17	1.44	16.64	1.44	16.39	1.50	16.76	1.45	16.64	1.47	16.51	1.49
Precipitation	Mar	47.36	13.25	51.15	13.00	48.94	11.87	49.56	12.92	49.53	12.61	49.31	12.26
	Apr	67.93	15.02	67.86	15.09	68.39	14.37	67.67	14.44	67.89	14.42	68.13	14.39
	May	93.31	13.24	89.73	12.96	85.39	10.30	91.23	11.46	89.29	11.16	87.32	10.77
	Jun	102.35	21.69	106.60	19.03	102.48	16.46	104.33	17.82	104.01	17.52	103.38	17.06
	Jul	91.84	12.72	94.10	10.79	88.59	9.67	93.29	10.66	91.73	10.30	90.14	9.95
	Aug	90.34	10.71	82.56	8.42	81.48	7.61	85.15	9.13	83.75	8.49	82.51	7.97
	Sep	87.39	16.80	83.47	14.18	80.30	12.12	84.94	14.53	83.32	13.68	81.74	12.85
Precipitation		580.53	55.97	575.46	54.24	555.58	49.76	576.16	54.28	569.52	52.82	562.54	51.28
Heavy rainfall 1		1.64	0.50	1.51	0.49	1.32	0.40	1.55	0.46	1.47	0.44	1.39	0.42
Heavy rainfall 2		0.01	0.03	0.01	0.02	0.01	0.01	0.01	0.03	0.01	0.02	0.01	0.02
Heavy rainfall 3		0.33	0.02	0.32	0.02	0.32	0.02	0.32	0.02	0.32	0.02	0.32	0.02
GDD		1854.66	198.60	1789.38	207.76	1735.86	214.62	1792.38	207.16	1774.96	209.49	1755.73	212.03
HDD		0.34	0.31	0.26	0.25	0.19	0.19	0.26	0.24	0.24	0.22	0.22	0.21

Note: Heavy rainfall 1 is the number of daily rain events above 25.4 mm per year, Heavy rainfall 2 is the number of daily rain events above 76.2 mm per year, and Heavy rainfall 3 is the fraction of precipitation (mm) during the ten wettest days per year.

<Table A-17> Summary statistics of climate variables in 2030 based on GFDL-CM3: Lake States

		10 year averages		20 year averages		30 year averages		Decaying rate: 0.925		Decaying rate: 0.95		Decaying rate: 0.975	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Average Temperature	Mar	-0.02	1.70	-0.90	1.81	-1.26	1.78	-0.49	1.74	-0.74	1.75	-1.00	1.77
	Apr	9.61	1.52	8.06	1.52	7.55	1.50	8.47	1.48	8.18	1.48	7.87	1.49
	May	14.92	1.32	14.53	1.35	14.38	1.37	14.71	1.34	14.61	1.35	14.49	1.36
	Jun	19.98	1.15	19.30	1.21	19.14	1.29	19.48	1.21	19.36	1.24	19.25	1.26
	Jul	23.00	1.10	22.60	1.09	22.21	1.16	22.65	1.10	22.51	1.12	22.37	1.14
	Aug	21.76	1.19	21.20	1.23	20.82	1.25	21.36	1.22	21.18	1.22	21.00	1.23
	Sep	17.54	1.32	17.10	1.40	16.70	1.40	17.09	1.39	16.98	1.39	16.84	1.40
Precipitation	Mar	40.07	9.80	41.92	9.37	42.89	10.47	42.32	9.68	42.57	9.91	42.75	10.18
	Apr	72.99	14.87	67.36	15.36	67.04	14.64	70.13	14.37	69.04	14.50	67.99	14.60
	May	105.62	15.86	97.77	12.80	96.17	11.25	101.43	13.29	99.73	12.56	97.95	11.87
	Jun	93.42	14.82	108.51	12.50	102.18	13.35	101.68	13.76	102.31	13.44	102.48	13.30
	Jul	121.27	16.13	115.64	17.10	110.97	15.53	114.63	15.45	113.52	15.53	112.27	15.56
	Aug	103.52	17.18	110.05	16.45	108.17	14.81	106.25	15.70	107.01	15.51	107.69	15.21
	Sep	69.66	11.83	83.09	13.62	81.56	11.69	79.00	13.10	79.83	12.65	80.73	12.17
Precipitation		606.56	59.28	624.34	64.38	608.98	58.08	615.44	59.57	614.00	59.39	611.87	58.88
Heavy rainfall 1		2.93	0.74	3.29	0.81	3.02	0.73	3.06	0.73	3.06	0.73	3.05	0.73
Heavy rainfall 2		0.04	0.07	0.06	0.06	0.04	0.04	0.04	0.05	0.04	0.05	0.04	0.05
Heavy rainfall 3		0.39	0.02	0.39	0.02	0.39	0.02	0.38	0.02	0.39	0.02	0.39	0.02
GDD		1877.80	201.77	1782.40	201.97	1730.65	206.03	1804.91	203.03	1781.58	203.84	1756.40	204.86
HDD		0.40	0.52	0.26	0.35	0.21	0.27	0.28	0.36	0.26	0.34	0.23	0.30

Note: Heavy rainfall 1 is the number of daily rain events above 25.4 mm per year, Heavy rainfall 2 is the number of daily rain events above 76.2 mm per year, and Heavy rainfall 3 is the fraction of precipitation (mm) during the ten wettest days per year.

<Table A-18> Summary statistics of climate variables in 2030 based on MIROC5: Lake States

		10 year averages		20 year averages		30 year averages		Decaying rate: 0.925		Decaying rate: 0.95		Decaying rate: 0.975	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Average Temperature	Mar	2.16	1.85	1.70	1.78	1.06	1.80	1.59	1.79	1.46	1.79	1.28	1.79
	Apr	10.41	1.59	10.08	1.55	9.39	1.54	10.03	1.56	9.83	1.55	9.62	1.54
	May	15.47	1.44	15.08	1.39	14.93	1.41	15.19	1.41	15.11	1.41	15.02	1.41
	Jun	19.65	1.48	19.51	1.52	19.26	1.49	19.51	1.49	19.43	1.49	19.34	1.49
	Jul	22.26	1.26	22.40	1.28	22.01	1.32	22.16	1.29	22.13	1.30	22.08	1.31
	Aug	21.04	1.40	21.18	1.39	20.74	1.40	20.93	1.39	20.88	1.39	20.82	1.39
	Sep	16.25	1.47	16.36	1.44	16.11	1.47	16.21	1.46	16.19	1.46	16.15	1.46
Precipitation	Mar	43.29	15.84	44.59	11.40	40.84	10.90	43.12	12.58	42.60	12.00	41.83	11.42
	Apr	92.26	15.17	80.64	14.19	75.82	12.23	83.25	13.31	80.78	13.07	78.28	12.72
	May	86.18	12.48	83.92	11.61	79.99	10.36	83.89	11.14	82.79	10.86	81.45	10.60
	Jun	105.11	18.08	98.98	12.37	91.37	12.40	99.94	15.33	96.99	14.10	94.08	13.11
	Jul	88.38	12.54	83.96	11.44	86.92	11.46	86.66	12.66	86.71	12.09	86.80	11.69
	Aug	79.26	15.09	79.41	12.58	81.27	11.62	80.36	12.67	80.66	12.30	80.97	11.94
	Sep	92.98	15.78	84.30	11.43	89.57	12.23	90.64	13.04	89.91	12.54	89.54	12.25
Precipitation		587.44	50.95	555.81	46.08	545.79	45.96	567.85	48.60	560.43	47.50	552.95	46.60
Heavy rainfall 1		3.56	0.77	3.44	0.69	3.32	0.63	3.48	0.69	3.43	0.67	3.37	0.65
Heavy rainfall 2		0.13	0.12	0.11	0.09	0.09	0.07	0.11	0.10	0.10	0.09	0.10	0.08
Heavy rainfall 3		0.44	0.03	0.45	0.02	0.45	0.02	0.44	0.02	0.45	0.02	0.45	0.02
GDD		1820.83	240.60	1813.36	236.51	1757.34	235.51	1795.42	237.35	1784.44	236.86	1771.63	236.23
HDD		0.48	0.60	0.45	0.46	0.36	0.38	0.37	0.41	0.37	0.40	0.37	0.39

Note: Heavy rainfall 1 is the number of daily rain events above 25.4 mm per year, Heavy rainfall 2 is the number of daily rain events above 76.2 mm per year, and Heavy rainfall 3 is the fraction of precipitation (mm) during the ten wettest days per year.

<Table A-19> Summary statistics of climate variables in 2030 based on CCSM4: Lake States

		10 year averages		20 year averages		30 year averages		Decaying rate: 0.925		Decaying rate: 0.95		Decaying rate: 0.975	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Average Temperature	Mar	0.72	1.96	0.16	1.89	-0.19	1.83	0.21	1.91	0.09	1.88	-0.05	1.86
	Apr	7.97	1.49	8.13	1.40	7.74	1.39	8.00	1.43	7.93	1.41	7.85	1.40
	May	14.16	1.39	14.46	1.36	14.36	1.39	14.29	1.38	14.32	1.39	14.34	1.39
	Jun	19.36	1.44	19.28	1.45	19.32	1.44	19.29	1.44	19.30	1.44	19.31	1.44
	Jul	22.20	1.24	21.89	1.33	21.94	1.31	22.10	1.29	22.03	1.29	21.98	1.30
	Aug	21.50	1.41	21.35	1.31	20.92	1.29	21.29	1.33	21.18	1.32	21.05	1.30
	Sep	16.02	1.45	16.04	1.50	15.94	1.44	15.96	1.46	15.95	1.45	15.95	1.45
Precipitation	Mar	44.65	9.80	46.33	11.31	45.66	11.43	46.40	10.66	46.05	10.89	45.80	11.16
	Apr	77.02	10.74	67.31	10.10	65.16	9.07	69.65	9.40	68.25	9.31	66.73	9.20
	May	83.92	12.11	82.37	10.38	82.15	8.97	82.92	9.47	82.85	9.34	82.57	9.16
	Jun	112.76	22.64	106.09	18.68	101.35	16.98	105.23	18.15	104.33	17.63	102.99	17.24
	Jul	100.16	14.71	93.38	13.31	90.91	12.33	95.03	13.63	93.70	13.12	92.29	12.68
	Aug	97.36	20.06	92.68	13.47	95.36	11.41	94.53	14.09	94.94	12.88	95.21	11.89
	Sep	67.67	13.61	82.76	13.63	84.94	13.09	77.53	13.38	80.26	13.26	82.78	13.17
Precipitation		583.55	55.82	570.92	55.36	565.52	55.64	571.29	52.75	570.39	53.65	568.37	54.64
Heavy rainfall 1		4.08	0.75	3.94	0.63	3.95	0.60	3.99	0.63	3.99	0.61	3.97	0.60
Heavy rainfall 2		0.15	0.15	0.13	0.12	0.12	0.09	0.13	0.11	0.13	0.10	0.13	0.10
Heavy rainfall 3		0.47	0.03	0.47	0.04	0.47	0.03	0.47	0.03	0.47	0.03	0.47	0.03
GDD		1744.31	220.58	1738.06	219.12	1716.11	215.65	1733.44	217.86	1727.87	217.18	1722.11	216.42
HDD		0.27	0.38	0.22	0.31	0.25	0.32	0.28	0.38	0.27	0.35	0.26	0.33

Note: Heavy rainfall 1 is the number of daily rain events above 25.4 mm per year, Heavy rainfall 2 is the number of daily rain events above 76.2 mm per year, and Heavy rainfall 3 is the fraction of precipitation (mm) during the ten wettest days per year.

<Table A-20> Summary statistics of climate variables in 2030 based on averages among GCMs: Lake States

		10 year averages		20 year averages		30 year averages		Decaying rate: 0.925		Decaying rate: 0.95		Decaying rate: 0.975	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Average Temperature	Mar	0.85	1.80	0.54	1.80	0.01	1.80	0.51	1.79	0.36	1.79	0.20	1.79
	Apr	9.25	1.39	8.79	1.39	8.26	1.41	8.83	1.39	8.65	1.40	8.46	1.40
	May	14.91	1.33	14.63	1.34	14.44	1.37	14.68	1.35	14.61	1.35	14.53	1.36
	Jun	19.77	1.31	19.45	1.36	19.29	1.38	19.50	1.35	19.43	1.36	19.36	1.37
	Jul	22.64	1.16	22.41	1.20	22.12	1.25	22.40	1.20	22.31	1.21	22.22	1.23
	Aug	21.46	1.29	21.21	1.30	20.85	1.32	21.19	1.30	21.09	1.30	20.97	1.31
	Sep	16.74	1.41	16.53	1.44	16.28	1.45	16.51	1.44	16.44	1.44	16.36	1.45
Precipitation	Mar	43.84	11.50	46.00	10.83	44.58	10.78	45.35	10.97	45.19	10.92	44.92	10.85
	Apr	77.55	12.80	70.79	12.95	69.10	11.88	72.67	12.14	71.49	12.13	70.28	12.04
	May	92.26	10.88	88.45	10.63	85.93	9.30	89.87	9.76	88.66	9.69	87.32	9.53
	Jun	103.41	18.13	105.04	14.36	99.34	13.47	102.80	15.43	101.91	14.71	100.74	14.04
	Jul	100.41	10.91	96.77	10.59	94.35	10.36	97.40	10.51	96.42	10.44	95.38	10.39
	Aug	92.62	13.07	91.18	10.95	91.57	10.30	91.57	11.21	91.59	10.93	91.59	10.62
	Sep	79.43	12.19	83.41	11.43	84.09	10.94	83.03	11.86	83.33	11.52	83.70	11.21
Precipitation		589.52	52.52	581.63	52.57	568.97	49.99	582.69	51.44	578.58	51.06	573.94	50.57
Heavy rainfall 1		3.05	0.54	3.05	0.54	2.90	0.51	3.02	0.52	2.99	0.52	2.95	0.51
Heavy rainfall 2		0.08	0.06	0.07	0.05	0.07	0.04	0.07	0.05	0.07	0.04	0.07	0.04
Heavy rainfall 3		0.40	0.02	0.41	0.02	0.41	0.02	0.41	0.02	0.41	0.02	0.41	0.02
GDD		1824.40	214.49	1780.80	215.59	1734.99	217.45	1781.54	215.60	1767.21	216.18	1751.47	216.81
HDD		0.37	0.40	0.30	0.31	0.25	0.27	0.30	0.32	0.28	0.30	0.27	0.28

Note: Heavy rainfall 1 is the number of daily rain events above 25.4 mm per year, Heavy rainfall 2 is the number of daily rain events above 76.2 mm per year, and Heavy rainfall 3 is the fraction of precipitation (mm) during the ten wettest days per year.

<Table A-21> Summary statistics of climate variables based on MIROC-ESM: Northern Plains

		10 year averages		20 year averages		30 year averages		Decaying rate: 0.925		Decaying rate: 0.95		Decaying rate: 0.975	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Average Temperature	Mar	2.31	3.87	2.02	3.88	1.86	3.89	2.05	3.87	1.98	3.87	1.92	3.88
	Apr	9.52	2.86	9.33	2.91	9.11	2.94	9.35	2.90	9.28	2.92	9.19	2.93
	May	15.08	2.33	15.05	2.36	15.02	2.37	15.09	2.34	15.06	2.35	15.04	2.36
	Jun	20.67	2.38	20.51	2.37	20.43	2.37	20.55	2.35	20.51	2.36	20.47	2.37
	Jul	23.81	2.31	23.58	2.26	23.53	2.26	23.69	2.27	23.63	2.26	23.58	2.26
	Aug	22.90	2.26	22.66	2.24	22.54	2.24	22.70	2.24	22.65	2.24	22.59	2.24
	Sep	17.59	2.72	17.37	2.66	17.22	2.63	17.39	2.68	17.34	2.66	17.28	2.65
Precipitation	Mar	32.61	13.44	31.87	12.45	31.26	12.55	31.49	11.98	31.46	12.15	31.38	12.34
	Apr	53.00	19.41	51.75	16.82	51.01	14.89	52.02	16.60	51.75	16.05	51.41	15.47
	May	83.27	24.68	83.83	22.71	82.00	21.47	83.06	22.76	82.79	22.29	82.43	21.86
	Jun	86.71	18.20	88.77	16.50	89.98	16.49	87.87	16.87	88.54	16.62	89.27	16.49
	Jul	73.17	15.79	75.41	14.94	75.27	14.14	73.62	14.74	74.27	14.49	74.83	14.29
	Aug	61.77	18.59	63.19	18.05	64.43	18.05	63.49	18.58	63.79	18.30	64.11	18.12
	Sep	56.48	24.65	56.40	22.61	56.31	22.42	55.81	22.38	56.02	22.34	56.18	22.35
Precipitation		447.00	116.97	451.21	113.90	450.26	111.62	445.55	113.73	446.78	112.85	447.73	111.99
Heavy rainfall 1		1.19	0.98	1.21	0.92	1.19	0.88	1.18	0.91	1.18	0.90	1.18	0.89
Heavy rainfall 2		0.02	0.05	0.02	0.04	0.02	0.04	0.02	0.04	0.02	0.04	0.02	0.04
Heavy rainfall 3		0.36	0.02	0.36	0.02	0.36	0.02	0.36	0.02	0.36	0.02	0.36	0.02
GDD		1999.56	424.14	1969.40	420.88	1952.40	419.56	1977.63	420.09	1969.04	419.82	1960.46	419.64
HDD		3.50	5.16	2.90	4.10	2.80	3.86	3.15	4.40	3.02	4.19	2.90	4.00

Note: Heavy rainfall 1 is the number of daily rain events above 25.4 mm per year, Heavy rainfall 2 is the number of daily rain events above 76.2 mm per year, and Heavy rainfall 3 is the fraction of precipitation (mm) during the ten wettest days per year.

<Table A-22> Summary statistics of climate variables based on GFDL-CM3: Northern Plains

		10 year averages		20 year averages		30 year averages		Decaying rate: 0.925		Decaying rate: 0.95		Decaying rate: 0.975	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Average Temperature	Mar	2.39	3.69	2.47	3.61	2.39	3.62	2.39	3.64	2.39	3.63	2.39	3.62
	Apr	9.08	2.67	9.06	2.68	9.00	2.76	9.07	2.69	9.05	2.71	9.03	2.74
	May	15.35	2.44	15.30	2.38	15.13	2.36	15.24	2.41	15.20	2.39	15.16	2.37
	Jun	20.58	2.50	20.47	2.39	20.33	2.31	20.47	2.40	20.42	2.37	20.38	2.34
	Jul	23.44	2.33	23.38	2.25	23.29	2.20	23.37	2.27	23.35	2.24	23.32	2.22
	Aug	22.51	2.32	22.42	2.22	22.30	2.18	22.41	2.22	22.38	2.20	22.34	2.18
	Sep	17.29	2.67	17.10	2.56	17.10	2.49	17.17	2.56	17.15	2.53	17.12	2.51
Precipitation	Mar	31.93	15.01	31.58	15.18	31.25	14.80	31.29	14.62	31.23	14.66	31.22	14.72
	Apr	57.09	20.19	56.01	19.95	55.37	18.85	56.74	20.41	56.26	19.86	55.80	19.34
	May	84.35	20.42	83.02	18.07	83.34	18.76	83.86	18.25	83.58	18.32	83.40	18.49
	Jun	96.42	19.55	92.96	16.95	92.06	17.48	93.97	17.27	93.33	17.17	92.68	17.24
	Jul	76.64	19.20	77.33	16.31	78.95	15.18	77.83	15.29	78.12	15.15	78.50	15.10
	Aug	67.05	20.49	68.60	19.78	67.84	19.40	67.51	19.84	67.61	19.61	67.72	19.46
	Sep	2.39	3.69	2.47	3.61	2.39	3.62	2.39	3.64	2.39	3.63	2.39	3.62
Precipitation		53.73	23.09	52.70	22.75	51.48	21.02	52.43	21.39	52.13	21.28	51.81	21.15
Heavy rainfall 1		467.20	116.83	462.20	116.43	460.27	116.68	462.04	114.77	460.66	115.02	459.49	115.39
Heavy rainfall 2		1.99	1.29	1.98	1.23	2.00	1.23	1.99	1.23	1.99	1.23	1.99	1.22
Heavy rainfall 3		0.03	0.08	0.03	0.06	0.03	0.06	0.03	0.06	0.03	0.06	0.03	0.06
GDD		0.42	0.02	0.42	0.02	0.43	0.02	0.42	0.02	0.43	0.02	0.43	0.02
HDD		1969.79	422.07	1955.60	410.47	1940.26	404.51	1955.46	412.56	1950.64	409.55	1945.48	406.80

Note: Heavy rainfall 1 is the number of daily rain events above 25.4 mm per year, Heavy rainfall 2 is the number of daily rain events above 76.2 mm per year, and Heavy rainfall 3 is the fraction of precipitation (mm) during the ten wettest days per year.

<Table A-23> Summary statistics of climate variables based on MIROC5: Northern Plains

		10 year averages		20 year averages		30 year averages		Decaying rate: 0.925		Decaying rate: 0.95		Decaying rate: 0.975	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Average Temperature	Mar	4.98	2.48	4.85	2.44	4.81	2.47	4.97	2.46	5.35	2.54	5.82	2.59
	Apr	11.76	2.05	11.47	1.94	11.54	1.97	11.65	2.01	11.83	2.26	11.83	2.34
	May	17.38	1.58	17.13	1.48	17.17	1.50	17.35	1.53	17.69	1.67	17.81	1.69
	Jun	22.27	1.29	22.08	1.24	22.18	1.25	22.21	1.26	22.29	1.29	22.31	1.28
	Jul	24.15	1.42	23.94	1.31	23.99	1.34	24.03	1.34	24.04	1.38	23.99	1.36
	Aug	23.30	1.48	23.14	1.39	23.16	1.41	23.19	1.42	23.23	1.45	23.20	1.47
	Sep	19.32	1.63	18.97	1.45	19.09	1.52	19.15	1.52	19.30	1.60	19.38	1.65
Precipitation	Mar	75.44	20.97	75.60	18.30	75.12	18.73	74.18	18.60	74.64	18.43	75.11	18.32
	Apr	91.98	16.22	95.63	10.45	96.37	12.84	95.99	11.98	95.87	11.22	95.75	10.67
	May	114.02	21.65	116.53	10.91	118.29	12.77	116.11	13.99	116.36	12.61	116.51	11.54
	Jun	104.13	16.09	106.41	9.91	104.66	10.93	106.35	11.00	106.14	10.20	106.16	9.80
	Jul	101.89	18.14	103.55	10.41	104.16	13.29	104.64	12.47	104.18	11.43	103.82	10.71
	Aug	95.98	18.90	95.39	8.46	96.78	11.00	98.26	11.05	97.41	9.78	96.44	8.87
	Sep	87.74	19.36	81.31	12.93	82.14	15.04	83.40	15.79	82.55	14.50	81.83	13.50
Precipitation		671.18	73.92	674.42	39.34	677.52	49.51	677.14	47.71	675.23	44.01	673.62	41.01
Heavy rainfall 1		5.20	1.33	5.17	0.97	5.25	1.09	5.27	1.06	5.23	1.02	5.19	0.99
Heavy rainfall 2		0.17	0.16	0.17	0.12	0.18	0.13	0.18	0.13	0.18	0.12	0.17	0.12
Heavy rainfall 3		0.45	0.04	0.44	0.03	0.44	0.03	0.45	0.03	0.45	0.03	0.45	0.03
GDD		2226.33	285.31	2183.67	269.76	2194.80	274.48	2208.71	277.35	2235.18	290.82	2243.85	295.44
HDD		2.40	3.48	1.62	2.11	1.81	2.47	1.81	2.51	1.52	2.35	1.14	1.99

Note: Heavy rainfall 1 is the number of daily rain events above 25.4 mm per year, Heavy rainfall 2 is the number of daily rain events above 76.2 mm per year, and Heavy rainfall 3 is the fraction of precipitation (mm) during the ten wettest days per year.

<Table A-24> Summary statistics of climate variables based on CCSM4: Northern Plains

		10 year averages		20 year averages		30 year averages		Decaying rate: 0.925		Decaying rate: 0.95		Decaying rate: 0.975	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Average Temperature	Mar	2.44	3.77	2.34	3.79	2.23	3.80	2.31	3.83	2.29	3.82	2.26	3.81
	Apr	9.30	2.85	9.28	2.85	9.13	2.85	9.27	2.86	9.23	2.86	9.18	2.85
	May	15.61	2.39	15.43	2.39	15.23	2.37	15.38	2.37	15.34	2.37	15.28	2.37
	Jun	20.82	2.35	20.58	2.37	20.42	2.36	20.61	2.35	20.55	2.35	20.48	2.35
	Jul	23.81	2.25	23.54	2.23	23.37	2.19	23.58	2.22	23.51	2.21	23.44	2.20
	Aug	22.97	2.19	22.80	2.14	22.58	2.14	22.78	2.17	22.72	2.16	22.65	2.15
	Sep	18.02	2.51	17.79	2.52	17.48	2.56	17.75	2.53	17.67	2.54	17.58	2.55
Precipitation	Mar	33.47	15.26	32.66	15.15	32.33	15.12	32.71	15.07	32.58	15.06	32.44	15.08
	Apr	52.75	18.39	54.56	16.26	53.93	15.25	54.20	15.82	53.97	15.21	53.88	15.00
	May	84.49	19.11	85.28	21.02	85.06	21.14	84.16	20.29	84.49	20.48	84.79	20.77
	Jun	93.24	18.53	93.64	15.85	93.96	15.47	93.25	15.41	93.46	15.10	93.70	15.13
	Jul	72.11	21.23	77.68	20.67	79.69	18.67	77.10	18.98	78.06	18.80	78.94	18.68
	Aug	61.65	21.23	60.44	18.55	63.42	19.30	63.06	19.69	63.08	19.37	63.20	19.23
	Sep	53.57	20.77	53.74	20.68	53.60	20.88	53.40	20.66	53.47	20.61	53.54	20.69
Precipitation		451.27	107.29	457.99	114.40	461.98	115.80	456.54	110.85	457.71	112.00	459.03	113.44
Heavy rainfall 1		2.99	1.30	3.07	1.38	3.10	1.39	3.02	1.34	3.04	1.35	3.06	1.36
Heavy rainfall 2		0.11	0.15	0.11	0.12	0.11	0.12	0.11	0.13	0.10	0.12	0.10	0.12
Heavy rainfall 3		0.52	0.04	0.52	0.04	0.51	0.04	0.51	0.04	0.51	0.04	0.51	0.04
GDD		2035.35	415.13	2003.17	414.04	1969.73	411.57	2002.37	413.51	1992.07	413.02	1981.00	412.37
HDD		6.11	7.63	5.04	6.34	4.11	5.10	4.97	6.19	4.71	5.85	4.42	5.48

Note: Heavy rainfall 1 is the number of daily rain events above 25.4 mm per year, Heavy rainfall 2 is the number of daily rain events above 76.2 mm per year, and Heavy rainfall 3 is the fraction of precipitation (mm) during the ten wettest days per year.

<Table A-25> Summary statistics of climate variables based on averages among GCMs: Northern Plains

		10 year averages		20 year averages		30 year averages		Decaying rate: 0.925		Decaying rate: 0.95		Decaying rate: 0.975	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Average Temperature	Mar	2.30	3.76	2.17	3.78	2.10	3.79	2.20	3.79	2.30	3.79	2.42	3.79
	Apr	9.31	2.81	9.16	2.84	9.03	2.86	9.21	2.83	9.24	2.84	9.19	2.84
	May	15.34	2.40	15.21	2.40	15.09	2.40	15.24	2.40	15.29	2.40	15.29	2.41
	Jun	20.68	2.43	20.54	2.41	20.42	2.38	20.55	2.40	20.52	2.41	20.47	2.40
	Jul	23.65	2.30	23.45	2.27	23.35	2.24	23.50	2.26	23.47	2.22	23.43	2.18
	Aug	22.75	2.27	22.60	2.22	22.48	2.20	22.60	2.23	22.57	2.22	22.54	2.20
	Sep	17.57	2.63	17.38	2.59	17.24	2.57	17.39	2.59	17.36	2.59	17.32	2.59
Precipitation	Mar	32.32	13.67	31.75	13.59	31.37	13.71	31.69	13.42	31.57	13.51	31.46	13.61
	Apr	54.93	16.86	54.56	16.57	53.82	16.01	54.44	16.59	54.22	16.36	54.01	16.16
	May	83.77	19.29	83.89	19.37	83.28	19.35	83.47	19.14	83.42	19.21	83.36	19.28
	Jun	90.03	14.99	90.12	14.08	90.80	15.11	90.32	14.78	90.43	14.80	90.60	14.92
	Jul	74.91	17.69	77.20	16.86	78.12	15.63	76.87	16.43	77.32	16.11	77.75	15.83
	Aug	64.21	18.29	64.82	17.78	65.47	17.74	65.61	18.30	65.54	18.05	65.49	17.86
	Sep	54.83	21.67	53.87	21.33	53.59	20.91	53.92	20.96	53.80	20.94	53.69	20.92
Precipitation		455.00	110.53	456.21	111.10	456.44	111.59	454.88	110.85	454.83	110.87	454.84	110.94
Heavy rainfall 1		2.25	1.17	2.26	1.17	2.27	1.18	2.26	1.18	2.26	1.18	2.26	1.17
Heavy rainfall 2		0.06	0.08	0.06	0.08	0.06	0.08	0.06	0.08	0.06	0.08	0.06	0.08
Heavy rainfall 3		0.45	0.02	0.45	0.02	0.45	0.02	0.45	0.02	0.45	0.02	0.45	0.02
GDD		1996.92	423.28	1969.85	419.07	1951.06	415.05	1974.35	418.87	1973.29	418.55	1968.86	417.16
HDD		4.69	6.03	4.01	5.12	3.54	4.43	4.00	5.09	3.79	4.88	3.56	4.61

Note: Heavy rainfall 1 is the number of daily rain events above 25.4 mm per year, Heavy rainfall 2 is the number of daily rain events above 76.2 mm per year, and Heavy rainfall 3 is the fraction of precipitation (mm) during the ten wettest days per year.

<Table A-26> Summary statistics of climate variables in 2030 based on MIROC-ESM: Northern Plains

		10 year averages		20 year averages		30 year averages		Decaying rate: 0.925		Decaying rate: 0.95		Decaying rate: 0.975	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Average Temperature	Mar	4.33	3.52	4.43	3.41	3.90	3.55	4.16	3.48	4.09	3.49	4.00	3.52
	Apr	10.98	2.52	10.87	2.61	10.51	2.65	10.87	2.58	10.76	2.60	10.63	2.63
	May	16.60	2.24	16.28	2.31	15.99	2.31	16.27	2.31	16.20	2.31	16.10	2.31
	Jun	21.59	2.12	21.48	2.33	21.45	2.35	21.47	2.29	21.47	2.31	21.46	2.33
	Jul	24.86	1.71	24.81	1.95	24.79	2.08	24.82	1.93	24.82	1.98	24.81	2.03
	Aug	24.66	1.91	24.26	2.07	24.08	2.18	24.37	2.01	24.27	2.06	24.17	2.12
	Sep	19.15	2.56	18.86	2.65	18.72	2.80	18.91	2.66	18.85	2.70	18.78	2.75
Precipitation	Mar	37.11	10.87	38.56	12.92	36.17	12.52	37.51	11.96	37.10	12.15	36.64	12.34
	Apr	59.01	15.55	65.47	18.25	61.52	17.95	63.13	17.29	62.68	17.45	62.13	17.67
	May	91.64	23.22	87.24	21.74	82.18	18.41	87.01	19.84	85.50	19.51	83.85	19.02
	Jun	110.47	22.94	103.62	21.57	95.62	17.69	103.66	20.24	101.16	19.44	98.44	18.60
	Jul	86.68	20.54	79.47	18.17	74.06	17.24	79.37	18.67	77.71	18.16	75.89	17.67
	Aug	55.90	20.60	58.20	22.22	57.45	19.52	57.39	21.34	57.50	20.83	57.52	20.21
	Sep	54.89	23.97	52.08	21.14	50.85	20.21	53.30	22.26	52.31	21.49	51.47	20.78
Precipitation		495.69	127.20	484.65	121.12	457.84	112.97	481.38	121.17	473.94	118.50	465.94	115.70
Heavy rainfall 1		1.61	1.10	1.41	0.94	1.21	0.86	1.42	0.98	1.36	0.94	1.29	0.90
Heavy rainfall 2		0.02	0.05	0.02	0.04	0.01	0.03	0.02	0.04	0.02	0.04	0.01	0.03
Heavy rainfall 3		0.36	0.02	0.36	0.02	0.36	0.02	0.36	0.02	0.36	0.02	0.36	0.02
GDD		2233.33	389.34	2197.93	412.68	2169.98	421.87	2201.18	407.66	2191.82	412.31	2181.21	417.16
HDD		6.44	5.93	6.74	7.07	7.00	7.48	6.81	6.81	6.90	7.06	6.97	7.29

Note: Heavy rainfall 1 is the number of daily rain events above 25.4 mm per year, Heavy rainfall 2 is the number of daily rain events above 76.2 mm per year, and Heavy rainfall 3 is the fraction of precipitation (mm) during the ten wettest days per year.

<Table A-27> Summary statistics of climate variables in 2030 based on GFDL-CM3:Northern Plains

		10 year averages		20 year averages		30 year averages		Decaying rate: 0.925		Decaying rate: 0.95		Decaying rate: 0.975	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Average Temperature	Mar	3.93	3.25	3.32	3.55	2.91	3.69	3.45	3.48	3.28	3.55	3.10	3.62
	Apr	11.99	2.46	10.83	2.57	10.23	2.60	10.98	2.56	10.75	2.56	10.50	2.58
	May	16.09	2.60	16.07	2.40	16.00	2.40	16.13	2.49	16.08	2.46	16.04	2.43
	Jun	21.97	2.34	21.46	2.52	21.34	2.54	21.59	2.47	21.51	2.49	21.42	2.52
	Jul	25.72	2.45	25.27	2.37	24.83	2.37	25.26	2.38	25.13	2.38	24.99	2.38
	Aug	24.52	2.49	24.11	2.49	23.78	2.47	24.22	2.51	24.08	2.49	23.93	2.48
	Sep	19.69	2.47	19.11	2.63	18.71	2.63	19.12	2.59	19.00	2.60	18.86	2.62
Precipitation	Mar	36.13	16.33	34.69	13.99	33.65	13.23	34.75	13.60	34.46	13.54	34.09	13.42
	Apr	56.31	15.19	59.30	18.27	60.63	19.18	60.46	18.16	60.59	18.50	60.66	18.87
	May	105.59	21.58	101.91	23.74	93.83	21.08	101.20	20.87	99.20	21.08	96.71	21.14
	Jun	94.09	15.62	103.30	18.59	100.45	18.23	99.40	16.12	99.87	16.72	100.23	17.44
	Jul	84.24	14.26	86.90	14.16	83.89	14.15	84.95	14.10	84.68	13.99	84.32	14.01
	Aug	78.85	22.98	78.45	19.21	74.49	18.00	77.12	19.08	76.49	18.76	75.60	18.38
	Sep	48.87	19.70	57.03	21.86	56.51	20.63	52.91	20.51	54.14	20.52	55.37	20.56
Precipitation		504.07	108.11	521.58	118.94	503.46	115.19	510.78	111.46	509.43	112.94	506.99	114.20
Heavy rainfall 1		2.26	1.09	2.36	1.29	2.23	1.23	2.27	1.18	2.27	1.20	2.25	1.21
Heavy rainfall 2		0.03	0.07	0.04	0.06	0.04	0.06	0.04	0.06	0.04	0.06	0.04	0.06
Heavy rainfall 3		0.41	0.02	0.41	0.02	0.41	0.02	0.41	0.02	0.41	0.02	0.41	0.02
GDD		2284.52	437.05	2203.25	436.98	2152.21	435.45	2215.88	439.10	2196.10	437.92	2174.46	436.71
HDD		13.24	16.33	10.30	13.21	8.56	10.87	10.72	13.63	10.04	12.77	9.31	11.83

Note: Heavy rainfall 1 is the number of daily rain events above 25.4 mm per year, Heavy rainfall 2 is the number of daily rain events above 76.2 mm per year, and Heavy rainfall 3 is the fraction of precipitation (mm) during the ten wettest days per year.

<Table A-28> Summary statistics of climate variables in 2030 based on MIROC5: Northern Plains

		10 year averages		20 year averages		30 year averages		Decaying rate: 0.925		Decaying rate: 0.95		Decaying rate: 0.975	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Average Temperature	Mar	4.92	3.35	4.42	3.39	4.05	3.42	4.41	3.36	4.32	3.38	4.20	3.40
	Apr	12.12	2.70	11.73	2.56	11.30	2.65	11.76	2.64	11.61	2.63	11.46	2.64
	May	17.25	2.40	16.84	2.33	16.79	2.30	17.00	2.34	16.93	2.33	16.86	2.31
	Jun	21.84	2.56	21.53	2.45	21.30	2.44	21.58	2.51	21.48	2.49	21.39	2.46
	Jul	25.32	2.11	24.92	2.09	24.71	2.12	24.98	2.15	24.89	2.14	24.80	2.13
	Aug	24.35	2.15	24.28	2.08	23.92	2.16	24.17	2.14	24.09	2.15	24.01	2.15
	Sep	18.86	2.69	18.78	2.53	18.46	2.65	18.63	2.66	18.59	2.65	18.53	2.64
Precipitation	Mar	32.42	19.65	33.85	19.72	32.93	17.84	33.13	19.01	33.22	18.70	33.16	18.31
	Apr	55.14	19.31	53.34	16.23	54.70	13.65	55.11	16.44	54.76	15.41	54.63	14.46
	May	80.97	12.09	73.84	11.28	73.32	12.22	75.85	12.46	75.03	12.11	74.16	12.01
	Jun	90.34	19.01	86.65	15.58	84.05	14.95	87.37	15.50	86.28	15.29	85.17	15.11
	Jul	70.08	17.70	74.57	17.44	73.52	17.10	72.47	16.04	72.88	16.43	73.25	16.80
	Aug	60.68	26.80	58.39	24.38	57.56	20.89	59.06	22.94	58.63	22.51	58.13	21.82
	Sep	63.28	30.24	63.23	26.96	66.18	25.99	65.09	27.48	65.39	26.92	65.77	26.40
Precipitation		452.91	123.37	443.88	118.45	442.25	113.55	448.07	116.78	446.21	116.04	444.26	114.93
Heavy rainfall 1		2.97	1.70	2.82	1.60	2.78	1.49	2.88	1.58	2.85	1.55	2.81	1.52
Heavy rainfall 2		0.13	0.20	0.11	0.15	0.10	0.13	0.11	0.15	0.11	0.15	0.10	0.14
Heavy rainfall 3		0.51	0.03	0.50	0.03	0.50	0.03	0.51	0.03	0.50	0.03	0.50	0.03
GDD		2288.89	436.00	2241.89	417.82	2195.99	422.01	2241.50	428.16	2227.40	425.79	2211.99	423.69
HDD		12.50	11.14	10.05	9.39	9.25	9.01	10.70	10.24	10.19	9.78	9.70	9.36

Note: Heavy rainfall 1 is the number of daily rain events above 25.4 mm per year, Heavy rainfall 2 is the number of daily rain events above 76.2 mm per year, and Heavy rainfall 3 is the fraction of precipitation (mm) during the ten wettest days per year.

<Table A-29> Summary statistics of climate variables in 2030 based on CCSM4: Corn Belt

		10 year averages		20 year averages		30 year averages		Decaying rate: 0.925		Decaying rate: 0.95		Decaying rate: 0.975	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Average Temperature	Mar	3.41	3.61	2.80	3.55	2.60	3.59	2.89	3.55	2.81	3.56	2.71	3.57
	Apr	9.84	3.08	10.23	2.78	9.99	2.72	10.08	2.86	10.06	2.82	10.03	2.77
	May	16.59	2.27	16.71	2.23	16.50	2.22	16.55	2.23	16.54	2.23	16.53	2.22
	Jun	21.64	2.56	21.64	2.52	21.50	2.45	21.54	2.47	21.54	2.47	21.53	2.46
	Jul	24.98	1.96	24.84	1.90	24.85	1.96	24.95	1.93	24.91	1.93	24.87	1.94
	Aug	25.04	2.58	24.50	2.22	24.07	2.28	24.56	2.34	24.40	2.31	24.23	2.29
	Sep	18.79	2.64	18.61	2.78	18.51	2.72	18.65	2.70	18.60	2.71	18.56	2.72
Precipitation	Mar	41.02	15.69	43.47	19.23	42.12	18.56	43.35	17.71	42.92	18.01	42.50	18.30
	Apr	67.05	16.48	62.04	17.25	62.87	17.63	64.12	16.59	63.72	16.91	63.29	17.27
	May	74.65	22.65	72.78	16.02	76.90	13.61	75.33	16.38	75.54	15.41	76.06	14.46
	Jun	108.43	19.51	98.38	18.81	98.05	17.85	102.38	18.29	100.84	18.03	99.38	17.90
	Jul	67.99	10.67	71.22	14.89	66.99	12.42	65.67	11.98	66.43	12.20	66.88	12.36
	Aug	49.07	12.18	54.42	12.57	58.75	15.46	54.78	12.57	56.23	13.41	57.59	14.39
	Sep	41.29	17.02	53.49	17.81	55.82	18.87	49.05	17.45	51.46	17.86	53.77	18.34
Precipitation		449.49	89.18	455.80	103.88	461.49	103.44	454.68	97.85	457.14	100.04	459.45	101.95
Heavy rainfall 1		2.96	1.08	3.01	1.19	3.09	1.24	3.04	1.16	3.05	1.19	3.07	1.21
Heavy rainfall 2		0.09	0.13	0.10	0.12	0.11	0.11	0.10	0.12	0.10	0.11	0.10	0.11
Heavy rainfall 3		0.52	0.04	0.51	0.05	0.51	0.04	0.52	0.04	0.52	0.04	0.52	0.04
GDD		2219.50	435.77	2197.93	419.06	2165.40	415.97	2192.61	420.58	2184.49	419.19	2175.32	417.57
HDD		12.69	13.73	10.28	10.74	9.83	10.20	11.04	11.50	10.59	11.03	10.18	10.59

Note: Heavy rainfall 1 is the number of daily rain events above 25.4 mm per year, Heavy rainfall 2 is the number of daily rain events above 76.2 mm per year, and Heavy rainfall 3 is the fraction of precipitation (mm) during the ten wettest days per year.

<Table A-30> **Summary statistics of climate variables in 2030 based on averages among GCMs: Corn Belt**

		10 year averages		20 year averages		30 year averages		Decaying rate: 0.925		Decaying rate: 0.95		Decaying rate: 0.975	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Average Temperature	Mar	4.15	3.42	3.74	3.47	3.36	3.56	3.73	3.46	3.63	3.49	3.50	3.52
	Apr	11.23	2.68	10.91	2.63	10.51	2.65	10.92	2.65	10.80	2.65	10.66	2.65
	May	16.63	2.37	16.48	2.32	16.32	2.31	16.49	2.34	16.44	2.33	16.38	2.32
	Jun	21.76	2.39	21.53	2.45	21.40	2.44	21.54	2.43	21.50	2.44	21.45	2.44
	Jul	25.22	2.05	24.96	2.07	24.79	2.13	25.00	2.09	24.94	2.10	24.87	2.11
	Aug	24.64	2.28	24.29	2.21	23.96	2.27	24.33	2.24	24.21	2.25	24.09	2.26
	Sep	19.12	2.59	18.84	2.64	18.60	2.70	18.83	2.65	18.76	2.66	18.68	2.68
Precipitation	Mar	36.67	15.03	37.64	16.04	36.22	15.22	37.18	15.14	36.92	15.23	36.60	15.26
	Apr	59.38	15.18	60.04	16.52	59.93	16.57	60.70	16.15	60.44	16.27	60.18	16.42
	May	88.21	18.39	83.94	17.24	81.56	15.63	84.85	16.61	83.82	16.32	82.69	15.99
	Jun	100.83	17.14	97.99	16.93	94.54	16.16	98.20	16.54	97.04	16.42	95.80	16.29
	Jul	77.24	12.94	78.04	14.04	74.62	14.03	75.61	13.53	75.42	13.72	75.09	13.90
	Aug	61.12	17.78	62.36	18.26	62.06	17.81	62.09	17.79	62.21	17.91	62.21	17.91
	Sep	52.08	21.97	56.46	21.50	57.34	21.10	55.09	21.55	55.83	21.36	56.60	21.21
Precipitation		475.54	109.23	476.48	113.33	466.26	110.16	473.73	110.05	471.68	110.34	469.16	110.38
Heavy rainfall 1		2.45	1.16	2.40	1.20	2.33	1.16	2.40	1.18	2.38	1.17	2.36	1.17
Heavy rainfall 2		0.07	0.09	0.06	0.08	0.06	0.07	0.07	0.08	0.07	0.08	0.06	0.08
Heavy rainfall 3		0.45	0.02	0.45	0.02	0.45	0.02	0.45	0.02	0.45	0.02	0.45	0.02
GDD		2256.56	424.27	2210.25	421.29	2170.90	423.61	2212.79	423.65	2199.95	423.58	2185.74	423.57
HDD		11.22	11.62	9.34	9.97	8.66	9.33	9.82	10.44	9.43	10.07	9.04	9.69

Note: Heavy rainfall 1 is the number of daily rain events above 25.4 mm per year, Heavy rainfall 2 is the number of daily rain events above 76.2 mm per year, and Heavy rainfall 3 is the fraction of precipitation (mm) during the ten wettest days per year.

CHAPTER 5

GENERAL CONCLUSION

This dissertation analyzes changes in agricultural resource management of Midwestern farmers in response to three key factors of agricultural production: climate conditions, government policies, and available technologies. Climate conditions determine the productivity of land use, and farmers alter their crop mix to optimize their land use. The advent of biotechnology has improved crop yield and the marginal productivity of chemical inputs. During the last decade, information and precision technology have complemented biotechnology in improving corn yields and crop management practices. Last, government policies can alter farmers' management decisions in response to changes in regional environmental conditions and available technologies.

Our findings can be summarized as follows: First, climate conditions alter farmers' decisions regarding land use and insurance purchases. Second, the coupled subsidy structure of federal crop insurance programs may make farmers more susceptible to climate change and increase the potential risk of yield loss from climate change. Third, GM corn and information technologies (pest scouting and yield monitor) have significant effects on corn yield and nitrogen use. Fourth, the effects of GM corn and information technologies depend on variable combinations among them and given soil productivity. Fifth, climate change has decreased corn and soybean acreage in the Corn Belt but increased it in the Lake States, especially in areas close to the border between Iowa and Minnesota. Sixth, the choice of GCMs and ways of determining expected weather conditions can result in large variation in forecast future land use and the causal relationship between climate conditions and farmers' land use change.

This dissertation can be extended in several meaningful directions. First, analyzing the dynamic relationship between agricultural production and regional environmental conditions would be useful in understanding the environmental implications of climate change and technology adoption. For example, as discussed in Chapter 4, land use change greatly affects regional climate conditions, and changes in climate conditions alter agricultural productivity of land use. Second, accounting for the effect of asymmetric information on resource management may make our results more general. Our conceptual model in Chapter 2 does not assume information asymmetry, and a simple analytic model in Chapter 3 assumes risk-neutrality. However, farmers' moral hazard and limited information regarding technology should affect farm management decisions. Finally, technology adoption is one way to mitigate adverse climate effects, and climate change effects depend on available technologies. By analyzing the relationship between climate conditions and technology adoption, we can measure the climate change effects and effects of technology adoption on farm management decisions more comprehensively.