ASSESSING THE EFFECTS OF CLIMATE CHANGE

ON AGRICULTURAL PRODUCTION AND PROFITABILITY

by

RUOHONG CAI

(Under the Direction of John C. Bergstrom)

ABSTRACT

The dissertation is concerned with comparing the effects of climate change on agricultural production and profitability, across alternative climate change scenarios. The research objectives include estimating the effects of climate change on crop yields and simulating the effects of climate change on farm profit.

In the first major step of this dissertation, a historical relationship between weather and crop yields was estimated using a principal components regression (PCR) model. Long-run climate change predictions generated from three climate change scenarios were incorporated into the estimated PCR model to predict crop yields through 2050. The PCR model was estimated for several northern and southern U.S. states at the county level. This result is consistent with the expectation that a probable impact of global climate change, should it occur as predicted, would be to shift some cropping patterns from the southern U.S. to the northern U.S..

In the second major step of this dissertation, predicted crop yields were used to generate farm profits in several northern and southern U.S. states using a dynamic simulation approach. Farm profits were generated by allowing acreage response with the consideration of crop rotation. By incorporating the Bellman equation in the crop rotation model, optimized acreage responses among multiple crops were determined based on their relative profitability. The results showed that acreage response alone is not able to eliminate the differences in production and profitability effects between warm and cold climate scenarios.

INDEX WORDS: Climate change, Agricultural production and profitability, Principal component regression, Bellman equation, Acreage response, Crop rotation, Simulation model

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CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

1.1 Background and Literature Review

Climate change is the long-run change in weather patterns. It is commonly agreed that climate change is one of the greatest threats to human society, especially to many economic sectors. Among them, agriculture is believed to be affected more directly and therefore one of the most vulnerable economic sectors under the threat of climate change. Most scientists believe that increased greenhouse gas concentration in the atmosphere contributes to global warming (IPCC, 2007). In recent years, many studies have focused on the impact of climate change in the agriculture and natural resources sectors since these sectors are directly impacted by climate change. Contemporary, state-of-the art general circulation models (GCM) including the Australian CSIRO 3.5, Canadian CGCM 3.1 and Japanese MIROC 3.2 models all predict that average temperature will keep rising and precipitation will have a mild change for most states in the continental United States for the rest of the century assuming greenhouse gas emissions follow the IPCC SRA1B scenario[1]. Many researchers believe that these projected changes in temperature and precipitation will directly impact crop yields in many regions and therefore farm profitability. Because agricultural production is a significant part of the U.S. economy

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[1] A future world of very rapid growth, low population growth, and rapid introduction of new and more efficient technology. Major underlying themes are economic and cultural convergence and capacity building, with a substantial reduction in regional differences in per capita income. In this world, people pursue personal wealth rather than environmental quality (IPCC 2007).

contributing $132 billion to national GDP in 2008 (BEA), we cannot afford to ignore the potential effects of global climate change on agricultural production and profitability.

A direct impact of climate change on agriculture is through its impact on crop yields. Yield weather models are therefore usually the first step in a climate change impact study. There have been many studies about the relationship between weather and crop yields in the last several decades. In recent years, many researchers have become interested in the economic effects of climate change. However, most climate change impact studies on agriculture were conducted without considering farmers' adaptation behavior (Singh and Stewart 1991; Brklacich and Smit 1992). Farmers' adaptation practices to climate change could reduce the negative effects, or take advantage of positive effects of global climate change. Therefore, farmers' adaptation practice is essential for the study of economic impacts of climate change to agriculture.

Crop growth models consider impact of climate change in a purely agronomic way, and therefore do not include adaptation considerations. The Ricardian approach attempts to directly measure the effect of climate on land values and incorporate farmers' adaptations in response to climate change (Mendelsohn and Dinar 1999). However, this approach unrealistically assumes a full range of immediate response from farmers. Weersink et al. (2009) studied how acreage responds to weather, yield and price. However, yield and price were assumed to be independent in their research.

Farmers could have many adaptation practices such as acreage response, shifts in planting dates, changed fertilizer application, development of new varieties, and installation of irrigation systems. In this research, we assume acreage response is the only adaptation option for farmers for possible climate change.

Overall, in this study, we estimated the historical relationship between weather and crop yields and then simulated the effects of future climate change on agricultural production and profitability by analyzing the interrelationships between different agricultural production factors using a dynamic approach.

1.2 Objective

Although climate change impacts have been intensively studied in recent decades, a comprehensive study of its impact on agricultural production and profitability is still rare. By conducting analysis in several northern and southern U.S. states, this dissertation tries to provide an alternative simulation approach to current literature.

The overall objective of this dissertation is to evaluate the effects of climate change on agricultural production and profitability. This objective is achieved by comparing the relative effects of alternative climate change scenarios on agricultural production and profitability. The specific research objectives include:

1. Static Model (weather-yield model): Estimate an econometric model for determining the effects of climate change on crop yields.
2. Dynamic Model (acreage response simulation model): Estimate a crop rotation model for simulating the effects of climate change on farm profitability.

1.3 Outline of Dissertation

In what follows, a weather-yield model is introduced and analyzed in Chapter 2. Specifically, a historical relationship between weather and crop yields is estimated using a principal components regression (PCR) model. Next, long-run climate change predictions generated from the three GCM models mentioned above under the SRA1B emissions scenario, are incorporated into the estimated PCR model to predict future crop yields through 2050.

In Chapter 3, an economic model of crop rotation is developed as a modified version of the Bellman equation. This crop rotation allows inputs of crop profit and is able to generate acreage response in a dynamic optimization framework.

In Chapter 4, predicted changes in crop yields are used with a simulation process to derive predicted changes in farm profits in several northern and southern U.S. counties. Compared to the empirical estimation approach employed in the first step (Chapter 2), the second step represents a dynamic simulation approach.

In Chapter 5, a summary of the dissertation research, and as well as implications, limitations and future research are discussed.

CHAPTER 2

STATIC MODEL

PRINCIPAL COMPONENT ANALYSIS OF CROP YIELD RESPONSE TO CLIMATE CHANGE[2]

[2] Cai, R., J. Bergstrom, J. Mullen, and M. Wetzstein. To be submitted to *Journal of Agricultural and Applied Economics.*

2.1 Abstract

A climate change index is developed based on principal component analysis to estimate the relationships between climate change and crop yield for corn, cotton, soybeans, and peanuts. The climate change index is then projected into the future based on three climate models and applied to forecast future crop yield response. The key contribution of our study is identifying different climate change indexes across U.S. states. Specifically, our results indicate that future warmer weather will have a negative impact for southern U.S. states, while it has insignificant impact for northern U.S. states.

Key words: Climate change index, Crop yield response

2.2 Introduction

Current general circulation models (GCM) including the Australian CSIRO 3.5, Canadian CGCM 3.1, and Japanese MIROC 3.2 models all predict that average global temperature will keep rising and precipitation will have a mild change for most U.S. states over the rest of the century. This is assuming greenhouse gas emissions follow the IPCC SRA1B scenario of rapid economic growth, low population growth, and introduction of new and more efficient technology. Variations in climatic conditions such as a late spring, a rainy planting season, or a hot and dry growing season could all directly affect agricultural crop yields. Although agricultural technologies have been greatly improved in recent decades, research indicates that variations in temperature and precipitation induced by global climate change will a have significant impact on crop yield (Tao et al. 2006; Schelenker and Roberts 2006; Lobell, Cahill, and Field 2007; Almaraz et al. 2008).

We hypothesize that climate change crop-yield effects are not homogeneous across regions. Heterogeneous regional environmental conditions including soil properties and weather will likely yield varying climate change effects. While research generally indicates that a warmer climate can reduce U.S. crop yields, only limited studies directly compare the effects of climate change on crop yields across regions. One test of this hypothesis is to compare results from a number of regional studies. However, comparison is difficult when studies differ in scope, variable selection, and methodology. As an attempt to test this hypothesis, this study avoids these difficulties by developing a consistent climate change index for crop yield response across regions.

Two major methodologies are employed to study the relationship between weather and crop yield: a crop growth model and production function analysis. Crop growth modeling is a computer-based simulation approach based on a mathematical integration of biology, physics, and chemistry (Jones 1993; Hoogenboom 2000; Jones et al. 2003). With agronomic characteristics of a crop's growth and development, a computer-based model incorporates weather information−temperature, precipitation, solar radiation, and humidity−with other factors−fertilizer applications and soil properties to simulate crop yield. Crop yield distributions are then generated based on alternative weather scenarios. The Decision Support System for Agrotechnology Transfer (DSSAT) is a popular software package using this method (Hoogenboom 2000).

A disadvantage of crop-growth modeling is its data demands and complexity requiring extensive information on weather, soil, and management options. Such data is usually incomplete and sometimes unavailable (Walker 1989). A production function analysis is then an alternative method for predicting yield (Horie, Yajima, and Nakagawa 1992; Kandiannan et al. 2002; Tannura, Irwin, and Good 2008). Compared to the crop-growth modeling approach, data limitations in production function analysis are less restrictive. Furthermore, Tannura, Irwin, and Good (2008) found that production functions have high explanatory power. For testing the hypothesis of heterogeneous regional climate change crop yield effects, production functions also have the advantage of not requiring a consistent crop-growth model unique to each region.

Developing a production function requires determining the appropriate set of weather factors affecting crop growth and yield. Temperature and precipitation are the major weather variables impacting crop yields. High temperature affects soil moisture which negatively impacts crop yields if precipitation is not sufficient to maintain crop growth and supplemental irrigation is not sufficient (Mitchell et al. 1990). On the other hand, supplemental irrigation can offset inadequate precipitation. Temperatures can also affect growing season lengths inducing crop-yield variation. High temperature tends to shorten crop growing seasons, which exposes crops to less solar radiation required for photosynthesis. In the long run, climate change impacts on temperature and precipitation could alter cropping patterns in many regions (Lotsch et al. 2007). Therefore, monthly temperature and precipitation during the growing season are employed for constructing a weather index.

With a typical growing season of at least seven to eight months, this results in over 14 monthly weather variables for both temperature and precipitation, which leads to unstable estimation results. Previous studies reduced the number of weather variables by dividing the growing season into crop growth stages (Dixon et al. 1994; Kafumann and Snell 1997). However, it is difficult to specify the exact boundary between two crop growing stages. Also, crop growing stages vary from year to year, and by region.

Alternatively, statistical techniques such as T-statistics and R-square are used to select significant weather variables. A disadvantage of statistical variable selection methods is they exclusively lean on data while ignoring agronomic implications of different growing season months. This results in statistical methods alone leading to agronomic mistakes by dropping important months and retaining unimportant months. In addition, the weather variables are collinearly related so a variable selection approach will lead to unstable estimated coefficients.

Research indicates that the effects of weather conditions on crop yields are not linear relationships (Deschenes and Greenstone 2007; Schlenker and Roberts 2009). For example, the response of crop yields to a one degree Celsius increase in temperature depends on the baseline temperature. Therefore, quadratic weather variables are used to consider nonlinearity. The effects of climate variability on crop yields are also likely to decrease crops yields (Porter et al. 2005), such as increased extreme weather events. Therefore, we also include the difference between monthly mean maximum and minimum temperature to account for the effects of extreme temperature events on crop yields. However, the issue of too many weather variables becomes even more severe when quadratic terms for weather variables are introduced into regression models.

Agronomically speaking, crop growth is a cumulative dynamic process. Weather conditions in any growing month would affect final realized crop yields; suggesting retaining all months in the production function. This suggests the development of a climate change index which accounts for the variation in weather variables across months. Such an index will retain the influence of all months without losing degrees of freedom. Principal component analysis (PCA) can be used to construct such an index. Specifically, using PCA eliminates possible severe multicollinearity issues in multiple regression models (Dixon et al. 1994). Instead of using original weather variables as predictor variables, PCA constructs an index of climate change. PCA is a variable compression technique, which transforms a large number of interrelated variables to a new set of uncorrelated variables that are linear combinations of the original variables (Jolliffe 2002). The index is then a weight combination of all weather variables. Many studies have employed PCA in regression analysis (Pandzic and Tminic 1992; Yu, Chu, and Schroeder 1997; Hansen, Jorgensen, and Thomsen 2002; Martinez, Baigorria, and Jones 2009).

PCA generates the same number of weather indices as the original weather variables and orders them by the magnitude of variances. In order to reduce the number of indices, previous studies only consider the first several indices with large variances (Martinez et al., 2009). An eigenvalue greater than or equal to 1 indicating relatively large variances are usually considered to be significant for retaining an index. However, as addressed by Jolliffe 1982 and Jolliffe 2002, it is generally not appropriate to use only the indices with large variances. Hadi and Ling (1998) demonstrate it is possible for the index with the smallest variance to be the only index correlated to a response variable. Weather variables with larger variance are not necessary more important than weather variables with smaller variance for crop growth. Therefore, a statistical variable selection technique is used to select an appropriate subset of indices.

In previous studies, application of PCA in climatic data modeling has concentrated on investigating geographic patterns of temperature and precipitation. The constraints and interdependency of spatiotemporal climate data can be identified by the use of PCA (Preisendorfer 1988). Since different units and magnitudes could dominate the grouping of principal components, temperature and precipitation variables should be standardized before PCA is employed (Jolliffe 2002).

The study conducted by Kantanantha, Serban and Griffin (2010) is one of few to use PCA to study the relationships between crop yields and weather indicators. However, in their study, temperature and precipitation variables were processed under PCA separately, which leaves multicollinearity issues between precipitation and temperature unsolved. Also, they only use original terms for temperature and precipitation variables. In this study, we include quadratic terms for temperature and precipitation to account for the nonlinear relationships between crop yields and weather. Besides the mean value of weather indicators, the effects of weather variability on crop yields are also likely to decrease crop yields (Porter et al. 2005), such as increased extreme weather events. For this reason, we include the difference of mean daily maximum and minimum temperatures of the month to account for the effects of extreme temperature events on crop yields.

Technology change has an important role in long-run crop yield changes since it improves the crop yields over time. Previous studies generally include an additional predictor to represent technology change. Possible candidates for this predictor include GDP and a linear or nonlinear time trend (Buller 1972; Choi and Helmberger 1993; McCarl, Villavicencio and Wu 2008). Nonlinear time trends were used since yield improvement is not necessary linear which could happen when improved crop varieties are adopted.

In this study, the primary purpose of the production function is to investigate the relationship between crop yields and the climate change index. By adding GDP or a time trend to represent technology change, the significance of the model will be mostly explained by this technology trend removal instead of weather variables. Although it is statistical appropriate to add GDP or a time trend to the regression model, it is better to use de-trended yield to investigate the connections between weather variables and crop yields. Another issue related to using GDP or a time trend variable is spatial difference. Assuming a linear technology trend, some places could benefit from larger technology advances. By using a technology trend predictor, spatial differences in technology will determine the main trend when forecasting changes in crop yields.

2.3 Methodology

In this study, a weather-crop yield principal components regression (PCR) model is developed to study the response of crop yields to weather changes. Before presenting the PCR model, it is necessary to show how the Principal Components (PCs) are generated. The following is a generalized expression of the crop yield regression model. It is a statistical function that demonstrates the historical relationship between weather variables and crop yields. After holding all other inputs such as fertilizers and insect infestations constant, equation (2.1) estimates the connections between crop yields and weather conditions:

$$y = X\beta + \epsilon \tag{2.1}$$

where X is a matrix of p random variables of weather indicators with dimension $n \times p$, y is a vector of crop yields with n observations, β is a vector of p regression coefficients and ϵ is a vector of error terms. The weather vectors within X matrix include monthly mean temperature, a square term of monthly mean temperature, total monthly precipitation, a square term of total monthly precipitation, and the difference between monthly mean maximum and minimum temperatures.

As previously mentioned, the PCR model uses PCs of weather indicators as explanatory variables. The first step of the PCR model is generating PCs of the original variables. PCA derives the same number of PCs as the original variables. These PCs are ranked by the magnitude of their variances. The first PC of weather indicators with the largest variance could be represented as a linear combination of original variables:

(2.2) $$\underbrace{\boldsymbol{X\alpha_1}}_{(\boldsymbol{n}\times\boldsymbol{1})} = x_1\alpha_{11} + x_2\alpha_{12} + \cdots + x_p\alpha_{1p} = \sum_{j=1}^{p} \alpha_{1j}x_j,$$

where $\boldsymbol{\alpha_1}$ is an eigenvector of covariance matrix $\boldsymbol{\Sigma}$ of $\boldsymbol{X}$ corresponding to its 1st largest eigenvalue λ_1. The second and following PCs could be generated in a similar way. A list of PCs of weather indicators is:

(2.3) $$\underbrace{\boldsymbol{Z}}_{(\boldsymbol{n}\times\boldsymbol{p})} = \underbrace{\boldsymbol{X}}_{(\boldsymbol{n}\times\boldsymbol{p})} \underbrace{\boldsymbol{A}}_{(\boldsymbol{p}\times\boldsymbol{p})} = [\boldsymbol{X\alpha_1}, \boldsymbol{X\alpha_2}, \ldots, \boldsymbol{X\alpha_p}],$$

where any PC is uncorrelated with the rest of the PCs.

Since $\boldsymbol{A}$ is orthogonal, we can rewrite equation (2.1) as:

(2.4) $$\underbrace{\mathrm{y}}_{(\boldsymbol{n}\times\boldsymbol{1})} = \mathrm{X}\beta + \epsilon = \mathrm{X}\boldsymbol{AA}'\beta + \epsilon = \underbrace{\boldsymbol{Z}}_{(\boldsymbol{n}\times\boldsymbol{p})} \underbrace{\boldsymbol{\gamma}}_{(\boldsymbol{p}\times\boldsymbol{1})} + \epsilon$$

Equation (2.4) is a general expression of the PCR model. The PCs matrix $\boldsymbol{Z}$ replaces the original weather variables matrix $\boldsymbol{X}$. $\boldsymbol{Z}$ has exactly the same dimension $n \times p$ as $\boldsymbol{X}$. Since a key advantage of the PCR model compared to a standard regression model is reducing the number of explanatory variables, it is preferable to select a subset of principal components to use as explanatory variables in the PCR. As mentioned previously, most early related studies only selected the first several principal components claiming that these components explain most of the variance in the data. However, this component selection process is not appropriate since even if a particular principal component explains only a small variance in the weather variables, this does not necessarily mean it has weak power in explaining the variance in crop yields. Out of the several variable selection techniques discussed by Jolliffe (2002), we chose to use p-value criterion where the coefficients with a p-value less than 10% be kept in the model.

An applicable expression of PCR model is:

(2.5) $$\underbrace{\boldsymbol{y}}_{(\boldsymbol{n}\times\mathbf{1})} = \underbrace{\boldsymbol{Z_k}}_{(\boldsymbol{n}\times\boldsymbol{k})} \underbrace{\boldsymbol{\gamma_k}}_{(\boldsymbol{k}\times\mathbf{1})} + \boldsymbol{\epsilon_k},$$

where γ_k is a vector of $\boldsymbol{k}$ elements that are a subset of elements of γ, $\boldsymbol{Z_k}$ is an $(n \times k)$ matrix whose columns are the corresponding subset of columns of $\boldsymbol{Z}$, and ϵ_k is the appropriate error term. These *k* PCs that remained in the model of equation (2.5) are not necessarily the first *k* PCs.

Compared to many other research areas, climate change study is special in that future observations (climate change projection data) are usually already available before conducting the research. This also requires a different approach in PCR forecasting. To predict future crop yields with estimated PCR model, a direct approach is to generate a new set of PCs by directly transforming future weather variables. However, a new set of PCs would have completely different eigenvectors from those transformed from historical weather variables. Therefore, this approach is not appropriate. An alternative approach (Approach 1) is to use eigenvectors associated with historical weather variables to construct PCs for future weather variables. However, using eigenvectors based on historical data to generate PCs for future data is inappropriate, since previous eigenvectors are uniquely selected for historical data.

To solve the above issue of utilizing a PCR model for forecasting purposes, we propose to transform weather variables into PCs using both historical climate data and future climate change data simultaneously (Approach 2). One set of future climate change data is specifically related to a particular estimated PCR model. Thus, although we only have one set of historical weather data, there will be three different PCR models for forecasting based on three climate change projection data sets. Approach 2 avoids applying historical eigenvectors to future data sets. Meanwhile, a concern about its prediction performance is raised since the estimated coefficient is a function of future observations, which is different from traditional econometric approaches. To test the prediction performance for Approach 1 and Approach 2, a Monte Carlo experiment is designed to compare their mean squared errors (Monte Carlo experiment procedure and results are showed in the Appendix A). After running the Monte Carlo experiment for 1,000 times, it is observed that the differences between the averages mean squared error for both approaches are insignificant. Therefore, Approach 2 is chosen for its advantage mentioned earlier. To the best of our knowledge, this approach has never been conducted in previous literature.

Based on the above discussion, we modify equation (2.5) to a PCR model that is applicable to forecasting purpose. Suppose we have three sets of climate change data $\boldsymbol{\Phi_1}, \boldsymbol{\Phi_2}$, and $\boldsymbol{\Phi_3}$ each with dimension of $(\boldsymbol{m} \times \boldsymbol{1})$. Each of them is combined with historical weather data $\boldsymbol{X}$ to generate three sets of weather data $\boldsymbol{\Psi}_1$, $\boldsymbol{\Psi}_2$ and $\boldsymbol{\Psi}_3$ as follows:

(2.6a) $$\underbrace{\boldsymbol{\Psi}_1}_{((\boldsymbol{n}+\boldsymbol{m})\times\boldsymbol{p})} = \left[\underbrace{\boldsymbol{X}'}_{(\boldsymbol{p}\times\boldsymbol{n})}, \underbrace{\boldsymbol{\Phi}_1'}_{(\boldsymbol{p}\times\boldsymbol{m})}\right]'$$

(2.6b) $$\boldsymbol{\Psi}_2 = \left[\boldsymbol{X}', \boldsymbol{\Phi}_2'\right]'$$

(2.6c) $$\boldsymbol{\Psi}_3 = \left[\boldsymbol{X}', \boldsymbol{\Phi}_3'\right]'$$

$\boldsymbol{\Psi}_1$, $\boldsymbol{\Psi}_2$ and $\boldsymbol{\Psi}_3$ were then transformed into PCs matrices $\boldsymbol{Z_1}, \boldsymbol{Z_2}$ and $\boldsymbol{Z_3}$:

(2.7a) $$\underbrace{\boldsymbol{Z_1}}_{((\boldsymbol{n}+\boldsymbol{m})\times\boldsymbol{p})} = \underbrace{\boldsymbol{\Psi}_1}_{((\boldsymbol{n}+\boldsymbol{m})\times\boldsymbol{p})} \underbrace{\boldsymbol{A_2}}_{(\boldsymbol{p}\times\boldsymbol{p})} = \left[\boldsymbol{\Psi}_1\boldsymbol{\alpha_{11}}, \boldsymbol{\Psi}_1\boldsymbol{\alpha_{12}}, \dots, \boldsymbol{\Psi}_1\boldsymbol{\alpha_{1p}}\right]$$

(2.7b) $$\boldsymbol{Z_2} = \boldsymbol{\Psi}_2\boldsymbol{A_2} = \left[\boldsymbol{\Psi}_2\boldsymbol{\alpha_{21}}, \boldsymbol{\Psi}_2\boldsymbol{\alpha_{22}}, \dots, \boldsymbol{\Psi}_2\boldsymbol{\alpha_{2p}}\right] = [\dot{\boldsymbol{Z}}_{\boldsymbol{2}}{}', \ddot{\boldsymbol{Z}}_{\boldsymbol{2}}{}']'$$

(2.7c) $$\boldsymbol{Z_3} = \boldsymbol{\Psi}_3\boldsymbol{A_3} = \left[\boldsymbol{\Psi}_3\boldsymbol{\alpha_{31}}, \boldsymbol{\Psi}_3\boldsymbol{\alpha_{32}}, \dots, \boldsymbol{\Psi}_3\boldsymbol{\alpha_{3p}}\right] = [\dot{\boldsymbol{Z}}_{\boldsymbol{3}}{}', \ddot{\boldsymbol{Z}}_{\boldsymbol{3}}{}']'$$

The PCR model will result in the following equations, where each equation has a unique PCs matrix $\dot{\boldsymbol{Z}}_{\boldsymbol{1}}, \dot{\boldsymbol{Z}}_{\boldsymbol{2}}$ and $\dot{\boldsymbol{Z}}_{\boldsymbol{3}}$, depending on the climate change data that will be used for yield forecasting:

(2.8a) $$\underbrace{\mathrm{y}}_{(\boldsymbol{n}\times\boldsymbol{1})} = \underbrace{\dot{\boldsymbol{Z}}_{\boldsymbol{1}}}_{(\boldsymbol{n}\times\boldsymbol{p})} \underbrace{\boldsymbol{\gamma_1}}_{(\boldsymbol{p}\times\boldsymbol{1})} + \epsilon$$

(2.8b) $$\mathrm{y} = \dot{\boldsymbol{Z}}_{\boldsymbol{2}}\boldsymbol{\gamma_2} + \epsilon$$

(2.8c) $$\mathrm{y} = \dot{\boldsymbol{Z}}_{\boldsymbol{3}}\boldsymbol{\gamma_3} + \epsilon$$

Although the PCs used in the PCR model are still based on historical weather data, they are different since future weather data are combined to generate PCs. After estimation, these three climate models were then used to predict crop yields based on the estimated PCR models (see equations 2.8a, 2.8b, and 2.8c).

The predicted yields from the PCR model using future climate change data were used to generate a Climate Change Impact Index (CCII). Forty one predicted yields for certain crops in selected counties were compared between three climate change models. The number of years for which MIROC 3.2 (warmest climate scenario) generates lower crop yields as compared to the CSIRO 3.5 (coldest climate scenario) was recorded. The CCII is generated by dividing the number of these particular years by total years.

(2.9) $$\boldsymbol{CCII_s} = \frac{\sum_{i=1}^{c}\boldsymbol{\varphi}}{\boldsymbol{c}} * \frac{\boldsymbol{1}}{\boldsymbol{41}}$$

where s denotes specific states, c denotes number of counties in specific states, φ denotes the number of years for which MIROC 3.2 (warmest) generates lower crop yields as compared to CSIRO 3.5 (coldest). Each county has different crop acreage; CCII for a county with higher crop acreage should have more weight than a county with lower crop acreage in equation (2.9). Therefore, weighted state-level CCII was generated. The CCII was generated by using the above formula for several northern and southern U.S. states. A high value of CCII indicates that global warming is a serious influence on crop yields, while a low value of CCII indicates that global warming is less of a concern.

2.4 Data

Climate represents long-run weather patterns. Therefore, to study the historic effects of climate on agriculture, the longest possible period is preferred. Due to data availability, 1960 is the earliest year with both of the required crop yield and weather data available. Thus, our study observes the period 1960-2009.

Because they are the top producing states for corn, soybeans, cotton and peanuts, we selected the northern U.S. states of Minnesota, Nebraska, Indiana, Illinois, Iowa, and the southern U.S. states of Georgia and Texas for our empirical application. County-level crop yields and weather data in these states were analyzed using the PCR model. Although CCII were generated for all available counties in these states, the last five years (2006-2009) were omitted from the model in order to test for model robustness for two specific counties: Mitchell County located in the southwestern Georgia, and Hancock County, Illinois located in the traditional U.S. Corn Belt region.

The historical weather data which includes monthly average temperature, monthly average temperature difference and monthly total precipitation were retrieved from the National Climate Data Center (NCDC)[3]. We selected monthly temperature and precipitation as weather variables because of the availability of these variables in the climate data for our time period of analysis. Data was retrieved only for months during which crops are grown. The following table summarizes planting months used in the PCR model associated with specific crops and states.

Monthly average temperatures used in this study were the difference between monthly mean maximum temperature and monthly mean minimum temperature. It is also preferable to include some predictors to account for variations in precipitation. Although daily precipitation data is available to calculate precipitation variation within a month, it is not available in the NCDC data. Thus, for the purpose of forecasting yield response under climate change, we did not account for precipitation variation.

To project future climate change with alternative greenhouse gas scenarios, many climate change models have been developed by atmospheric scientists. Different climate change models provide different climate change projections based on different approaches and underlying scenarios. In this study, three climate change projections were developed by the USDA Forest Service as part of the 2010 Renewable Resources Planning (RPA) Act assessment of natural resource demand and supply in the U.S. The projections were derived from global climate models: CGCM 3.1, CSIRO 3.5 and MIROC 3.2 and the SRA1B socioeconomic scenario from the Special Report on Emission Scenarios (SRES) of IPCC (Nakicenovic et al. 2000; IPCC 2007; Coulson et al. 2010). Climate change projections from these three climate models provide monthly projection of temperature and precipitation up to the year 2100. In general, as the time

[3] Historical weather data were retrieved from:
http://gis.ncdc.noaa.gov/map/monthly/ (last accessed on May, 2011)

horizon increases, crop yield response forecasting will become more unreliable. Therefore, we only use the climate change data up to the year 2050. The following weather indicator projections were used for crop yield forecasting: total annual precipitation, monthly mean maximum temperature and monthly mean minimum temperature.

A large amount of data including historical weather and crop yield data and climate change projection data are needed for crop yield response estimation. However, most of original data are not in the correct form; therefore, a statistical software package was used to reconstruct the original data in a manner compatible with estimating the relationships between climate change and crop yields.

Annual corn yield data was obtained from USDA-National Agricultural Statistical Service (NASS)[4] for the past 50 years for Mitchell County, Georgia and Hancock County, Illinois. Corn was chosen as the study crop since it is one of the most weather sensitive crops. Corn yield data were de-trended to a 2009 technology level.

2.5 Results

We used the estimated coefficients from our estimated PCR model to predict future crop yields, incorporating predicted changes in temperature and rainfall based on the US Forest Service climate change predictions. The corn yield response to climate change projected by three climate change models: CSIRO 3.5 (coldest scenario), CGCM 3.1 (middle scenario), MIROC 3.2 (warmest scenario) under the SRA1B socioeconomic scenario were forecasted and compared for both counties.

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[4] Crop yield data were retrieved from:
http://quickstats.nass.usda.gov/ (last accessed on May, 2011)

For Mitchell County, Georgia (see figure 2.1), 31 out of 41 forecast years showed lower predicted corn yields under MIROC32 (warmest scenario) compared to predicted corn yields under CSIRO35 (coldest scenario). Consistent with previous studies, this result indicates that warming temperatures under future climate change scenarios will tend to reduce corn yields. For Hancock County, Illinois (see figure 2.2), 18 out of 41 forecast years showed lower corn yields under MIROC32 (warmest scenario) compared to predicted corn yields under CSIRO35 (coldest scenario). This result for Hancock County is different from Mitchell County which indicates the existence of different effects of climate change on different regions. Farms in the northern U.S. may actually benefit from warming temperatures compared to farms in the southern U.S. where temperatures are already comparatively higher.

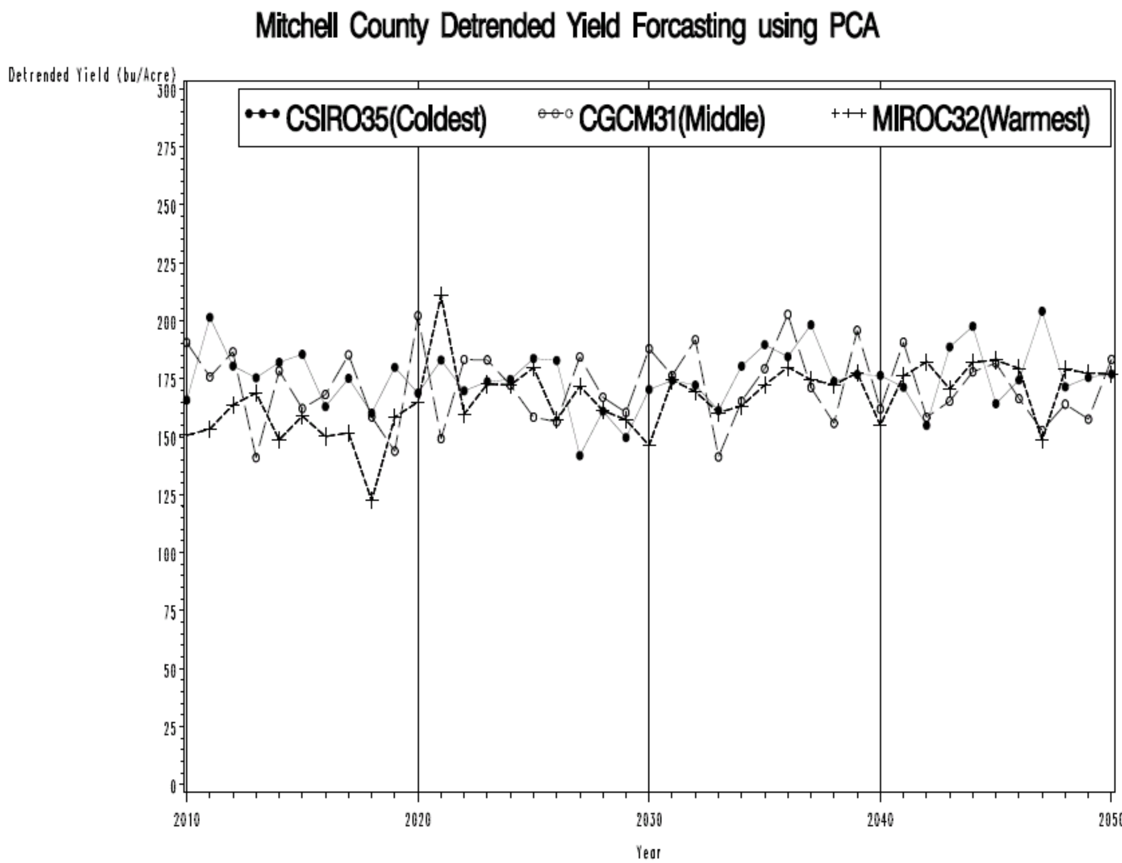

Figure 2.1. Forecasted corn yields in Mitchell County, Georgia from 2010 to 2050

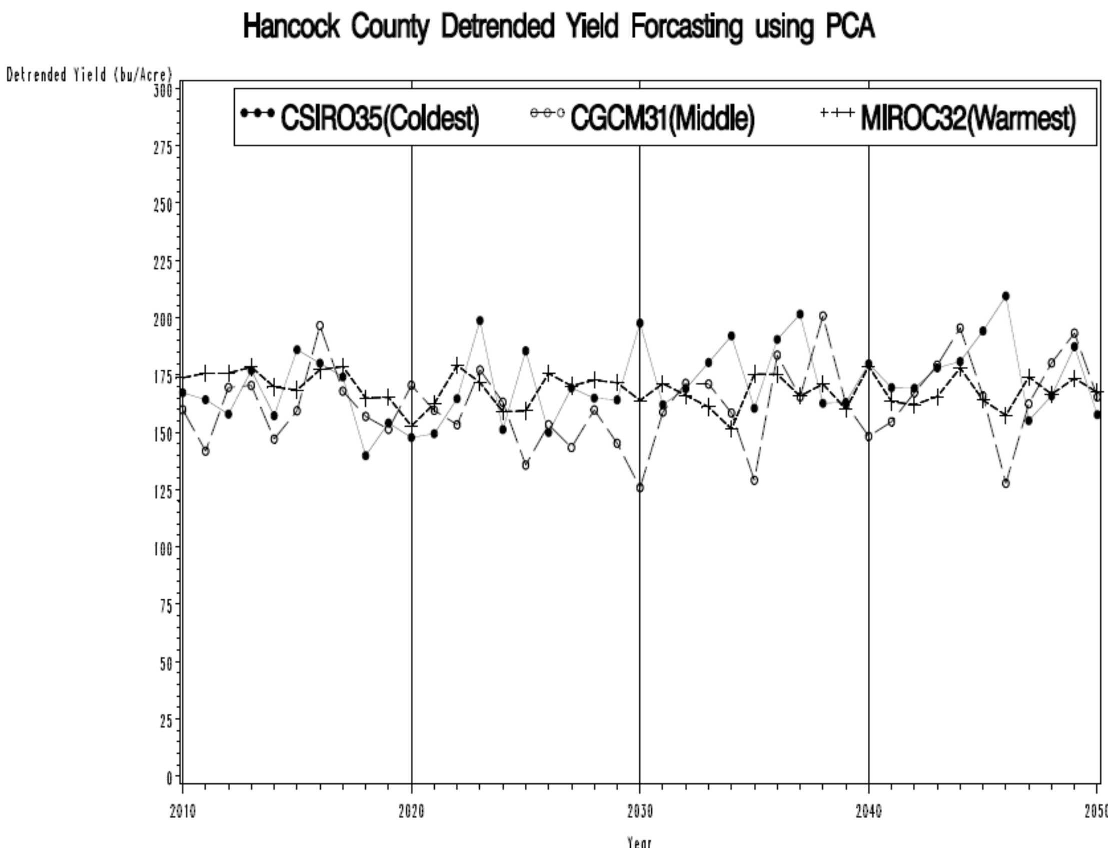

Figure 2.2. Forecasted corn yields in Hancock County, Illinois from 2010 to 2050

To provide stronger evidence for the above hypothesis, county level studies were conducted for all available counties in the eight specified states. Generated CCIIs are presented in Table 2.1. It is observed that northern states have a lower CCII value compared to southern states in terms of corn and soybeans. The results indicate that corn and soybeans' yields generally have a mild decrease due to predicted global climate change in the northern U.S. states studied, and a relatively more pronounced negative effect in the southern U.S. states studies where warm temperatures and periodic drought already pose significant constraints to crop production. This result is consistent with the expectation that a probable impact of global climate change, should it occur as predicted, would be to shift some cropping patterns from the southern U.S. to the northern U.S..

Table 2.1. Climate Change Impact Index (by states, by crops)

	Corn	Soybeans	Cotton	Peanuts
MN	0.528	0.421		
IA	0.561	0.445		
NE	0.488	0.516		
IL	0.526	0.505		
IN	0.532	0.520		
TX	0.598	0.626	0.542	0.534
AL	0.706	0.590		
GA	0.687	0.630	0.633	0.489

Table 2.2-2.7 list the average yields by crops and by states. These tables provide extra information by comparing historical yields with future yields. The tables indicate that corn and soybeans have decreasing trends for the state of Georgia, while for the northern states, no significant trend could be observed for both corn and soybeans.

Table 2.2. Average Yields for Corn, Soybeans, Peanuts, and Cotton in Georgia

State	Crop	Years	Scenarios	Average Yield	Percentage Change
GA	Corn	1960-2009	Historical	126.86	0.00%
		2010-2019	CSIRO 3.5	127.79	0.73%
			CGCM 3.1	118.67	-6.46%
			MIROC 3.2	114.66	-9.62%
		2020-2029	CSIRO 3.5	121.21	-4.45%
			CGCM 3.1	120.93	-4.67%
			MIROC 3.2	110.16	-13.16%
		2030-2039	CSIRO 3.5	118.49	-6.60%
			CGCM 3.1	118.26	-6.78%
			MIROC 3.2	106.05	-16.40%
	Soybeans	1960-2009	Historical	28.44	0.00%
		2010-2019	CSIRO 3.5	27.91	-1.86%
			CGCM 3.1	26.26	-7.67%
			MIROC 3.2	26.05	-8.40%
		2020-2029	CSIRO 3.5	26.99	-5.10%
			CGCM 3.1	25.94	-8.79%
			MIROC 3.2	24.19	-14.94%
		2030-2039	CSIRO 3.5	26.41	-7.14%
			CGCM 3.1	26.10	-8.23%
			MIROC 3.2	23.04	-18.99%
	Peanuts	1960-2009	Historical	3235.14	0.00%
		2010-2019	CSIRO 3.5	3041.90	-5.97%
			CGCM 3.1	2897.79	-10.43%
			MIROC 3.2	2994.39	-7.44%
		2020-2029	CSIRO 3.5	3135.02	-3.09%
			CGCM 3.1	2984.43	-7.75%
			MIROC 3.2	3037.70	-6.10%
		2030-2039	CSIRO 3.5	3061.46	-5.37%
			CGCM 3.1	3051.12	-5.69%
			MIROC 3.2	2949.49	-8.83%
	Cotton	1960-2009	Historical	1.70	0.00%
		2010-2019	CSIRO 3.5	1.79	5.29%
			CGCM 3.1	1.63	-4.12%
			MIROC 3.2	1.64	-3.53%
		2010-2019	CSIRO 3.5	1.73	1.76%
			CGCM 3.1	1.59	-6.47%
			MIROC 3.2	1.53	-10.00%
		2010-2019	CSIRO 3.5	1.79	5.29%
			CGCM 3.1	1.62	-4.71%
			MIROC 3.2	1.53	-10.00%

Table 2.3. Average Yields for Corn and Soybeans in Iowa

State	Crop	Years	Scenarios	Average Yield	Percentage Change
IA	Corn	1960-2009	Historical	170.12	0.00%
		2010-2019	CSIRO 3.5	169.73	-0.23%
			CGCM 3.1	165.66	-2.62%
			MIROC 3.2	168.95	-0.69%
		2020-2029	CSIRO 3.5	166.09	-2.37%
			CGCM 3.1	165.17	-2.91%
			MIROC 3.2	166.77	-1.97%
		2030-2039	CSIRO 3.5	170.52	0.24%
			CGCM 3.1	169.64	-0.28%
			MIROC 3.2	165.84	-2.52%
	Soybeans	1960-2009	Historical	50.28	0.00%
		2010-2019	CSIRO 3.5	50.24	-0.08%
			CGCM 3.1	49.52	-1.51%
			MIROC 3.2	50.66	0.76%
		2020-2029	CSIRO 3.5	49.29	-1.97%
			CGCM 3.1	49.64	-1.27%
			MIROC 3.2	50.88	1.19%
		2030-2039	CSIRO 3.5	50.83	1.09%
			CGCM 3.1	50.79	1.01%
			MIROC 3.2	51.61	2.65%

Table 2.4. Average Yields for Corn and Soybeans in Illinois

State	Crop	Years	Scenarios	Average Yield	Percentage Change
IL	Corn	1960-2009	Historical	167.78	0.00%
		2010-2019	CSIRO 3.5	162.31	-3.26%
			CGCM 3.1	162.42	-3.19%
			MIROC 3.2	167.49	-0.17%
		2020-2029	CSIRO 3.5	160.46	-4.36%
			CGCM 3.1	166.08	-1.01%
			MIROC 3.2	163.12	-2.78%
		2030-2039	CSIRO 3.5	164.37	-2.03%
			CGCM 3.1	164.59	-1.90%
			MIROC 3.2	158.24	-5.69%
	Soybeans	1960-2009	Historical	47.35	0.00%
		2010-2019	CSIRO 3.5	46.79	-1.18%
			CGCM 3.1	46.09	-2.66%
			MIROC 3.2	46.21	-2.41%
		2020-2029	CSIRO 3.5	45.08	-4.79%
			CGCM 3.1	46.68	-1.41%
			MIROC 3.2	44.64	-5.72%
		2030-2039	CSIRO 3.5	46.47	-1.86%
			CGCM 3.1	46.40	-2.01%
			MIROC 3.2	43.88	-7.33%

Table 2.5. Average Yields for Corn and Soybeans in Indiana

State	Crop	Years	Scenarios	Average Yield	Percentage Change
IN	Corn	1960-2009	Historical	158.54	0.00%
		2010-2019	CSIRO 3.5	154.61	-2.48%
			CGCM 3.1	149.36	-5.79%
			MIROC 3.2	156.26	-1.44%
		2020-2029	CSIRO 3.5	148.50	-6.33%
			CGCM 3.1	152.45	-3.84%
			MIROC 3.2	148.44	-6.37%
		2030-2039	CSIRO 3.5	155.95	-1.63%
			CGCM 3.1	153.41	-3.24%
			MIROC 3.2	145.64	-8.14%
	Soybeans	1960-2009	Historical	48.68	0.00%
		2010-2019	CSIRO 3.5	49.30	1.27%
			CGCM 3.1	48.69	0.02%
			MIROC 3.2	49.30	1.27%
		2020-2029	CSIRO 3.5	48.23	-0.92%
			CGCM 3.1	48.87	0.39%
			MIROC 3.2	48.44	-0.49%
		2030-2039	CSIRO 3.5	49.56	1.81%
			CGCM 3.1	49.11	0.88%
			MIROC 3.2	47.76	-1.89%

Table 2.6. Average Yields for Corn and Soybeans in Nebraska

State	Crop	Years	Scenarios	Average Yield	Percentage Change
NE	Corn	1960-2009	Historical	172.13	0.00%
		2010-2019	CSIRO 3.5	172.71	0.34%
			CGCM 3.1	167.31	-2.80%
			MIROC 3.2	171.80	-0.19%
		2020-2029	CSIRO 3.5	163.19	-5.19%
			CGCM 3.1	169.72	-1.40%
			MIROC 3.2	168.70	-1.99%
		2030-2039	CSIRO 3.5	168.79	-1.94%
			CGCM 3.1	170.76	-0.80%
			MIROC 3.2	166.66	-3.18%
	Soybeans	1960-2009	Historical	48.41	0.00%
		2010-2019	CSIRO 3.5	47.81	-1.24%
			CGCM 3.1	47.30	-2.29%
			MIROC 3.2	47.92	-1.01%
		2020-2029	CSIRO 3.5	45.34	-6.34%
			CGCM 3.1	48.05	-0.74%
			MIROC 3.2	47.10	-2.71%
		2030-2039	CSIRO 3.5	49.45	2.15%
			CGCM 3.1	49.12	1.47%
			MIROC 3.2	47.38	-2.13%

Table 2.7. Average Yields for Corn and Soybeans in Minnesota

State	Crop	Years	Scenarios	Average Yield	Percentage Change
MN	Corn	1960-2009	Historical	166.36	0.00%
		2010-2019	CSIRO 3.5	169.02	1.60%
			CGCM 3.1	168.62	1.36%
			MIROC 3.2	170.63	2.57%
		2020-2029	CSIRO 3.5	168.62	1.36%
			CGCM 3.1	167.02	0.40%
			MIROC 3.2	171.58	3.14%
		2030-2039	CSIRO 3.5	171.49	3.08%
			CGCM 3.1	173.19	4.11%
			MIROC 3.2	170.24	2.33%
	Soybeans	1960-2009	Historical	45.45	0.00%
		2010-2019	CSIRO 3.5	46.26	1.78%
			CGCM 3.1	47.42	4.33%
			MIROC 3.2	48.91	7.61%
		2020-2029	CSIRO 3.5	47.35	4.18%
			CGCM 3.1	47.65	4.84%
			MIROC 3.2	49.21	8.27%
		2030-2039	CSIRO 3.5	46.71	2.77%
			CGCM 3.1	49.10	8.03%
			MIROC 3.2	49.06	7.94%

2.6 Conclusions

In this research, we conducted an econometric analysis of weather factors influencing crop yields using county level data from major producing states for corn, soybeans, cotton and peanuts. Specifically, a principal component regression (PCR) model was developed with weather indices for monthly temperature and precipitation and their quadratic terms. We used an estimated PCR model to forecast the future crop yields in response to weather change projections based on three climate change models: CSIRO 3.5 (coldest), CGCM 3.1 (middle), and MIROC 3.2 (warmest).

The southern U.S. counties generally displayed lower predicted corn yields associated with warming temperature climate change projections, while the coldest climate change projections tended to result in higher predicted corn yields. This indicates that global warming could have a negative impact on southern counties. In the northern U.S. counties studied, the warmest climate change projections resulted in slightly higher predicted corn yields compared to predicted corn yields under the coldest climate change projections. This demonstrates that global warming trends may benefit corn production in the northern U.S., while negatively impacting corn production in the southern U.S. Furthermore, we compare historical yields with future yields. The results indicate that corn and soybeans yields would keep decreasing for the southern states, while no significant trend could be observed for either corn or soybeans yields for the northern states.

Overall, this research contributes to the literature in a number of ways. First, it is one of the first applications of PCA to estimate the relationships between weather and crop yields. We improve upon previous PCR models by adding quadratic terms for weather variables and temperature variations. Although these terms have been considered in traditional regression models, they have never been applied in principal components regression models. We also argue that previous related studies made mistakes by generating separate PCs for temperature and precipitation. To the best of our knowledge, this research is the first to note that it is impossible to apply different future data sets (for example, climate change data under different scenarios) to the same estimated PCR model. This is because future data is a determinant in estimating the PCR model (e.g., future data affects the PCR model by influencing how PCs are standardized and transformed).We also contribute to the literature by demonstrating different effects of climate change in northern and southern U.S. regions, while most previous climate change impact studies focused only in one region.

Crop yield response modeling is complex due to the growth process of crops; therefore, it is hard to implement a comprehensive model that considers all the influential factors. The results reported in this study are subject to several limitations. First, we assumed that there is no CO_2 fertilization effect for crop growth. Although numerous previous studies have demonstrated improvements in crop yields with CO_2 fertilization, most of these studies are based on crop simulation models. Some actual field research indicates a much smaller increase in crop yields under a higher CO_2 concentration environment (Long et al. 2006). In order to focus our study on weather and crop yield connections, we decided to exclude increased CO_2 effects not just to simplify the model, but also because of the inability to specify these effects.

Agronomically, the timing of precipitation is relatively more important than the amount of precipitation. Due to the availability of climate change data, we did not include the distribution of precipitation in the model. Therefore, extreme precipitation events such as drought or flood were not considered in this study. In future climate change studies where adequate climate change data is available, we recommend considering such extreme precipitation events.

2.7 References

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Appendix A

Monte Carlo Experiment

1. Obtain data set (x_i, y_i), i= *1, …, 50.*
2. Bootstrap $\widetilde{x_i}$ from data set in step 1, i= *1, …, 130.*
3. Generate $\widetilde{y_i}$ = $\widetilde{x_i}\hat{\beta}$ + $\widetilde{e_i}$, where $\hat{\beta}$ is estimated from (x_i, y_i), $\widetilde{e_i}$ is random normal error
4. Separate ($\widetilde{x_i}, \widetilde{y_i}$) into three groups:

   ($x1_i, y1_i$), i= 1,…, 50,

   ($x2_i, y2_i$), i= 1,…, 40,

   ($x3_i, y3_i$), i= 1,…, 40,
5. Generate Principal Components for $x1_i$ ($PC1_i$) based on PCA method
6. Estimate $\widehat{\beta 1}$ using (PC1_i, $y1_i$)
7. Generate Principal Components for $x2_i$ ($PC2_{\mathrm{i}}$) based on mean, standard deviation, and eigenvectors from PC1
8. Forecast $\widehat{y2_i}$ = $PC2_i\widehat{\beta 1}$
9. Generate Principal Components for $x3_i$ ($PC3_i$) based on mean, standard deviation, and eigenvectors from PC1
10. Forecast $\widehat{y3_i}$ = $PC3_i\widehat{\beta 1}$
11. Generate Principal Components for $x1_i$ and $x2_i$($PC12_i$) based on PCA method
12. Estimate $\widehat{\beta 12}$ using (PC12_i, $y1_i$)
13. Forecast $\widehat{y12_i}$ = $PC12_i\widehat{\beta 12}$
14. Generate Principal Components for $x1_i$ and $x3_i$($PC13_i$) based on PCA method
15. Estimate $\widehat{\beta 13}$ using (PC13_i, $y1_i$)
16. Forecast $\widehat{y13_i}$ = $PC13_i\widehat{\beta 13}$

17. Compare Mean Squared Error (MSE) in step (8), (10), (12), and (16)

Monte Carlo simulation results (average MSE based on 1,000 times of experiments)

	Mean Squared Error	
	Approach 1	Approach 2
Y2	378.77	379.81
Y3	384.56	383.29

CHAPTER 3

CROP ROTATION MODEL

YIELD AND PRICE VOLATILITY IMPACTS ON PRODUCERS' CROPPING PATTERNS: A DYNAMIC OPTIMAL CROP ROTATION MODEL[5]

[5] Cai, R., J. Bergstrom, and M. Wetzstein. To be submitted to *Journal of Agribusiness.*

3. 1 Abstract

This chapter presents a dynamic crop rotation model that shows how crop yield and price volatility could impact crop mix and acreage response under crop rotation considerations. Specifically, a discrete Markov decision model is utilized to optimize producers' crop rotation decision within a finite horizon. By maximizing net present value of expected current and future profits, a modified Bellman equation helps develop optimum planting decisions. This model is capable of simulating crop rotations with different lengths and structures. Specifically, the corn-soybeans rotations were simulated using the crop rotation model.

Key words: Crop rotation, Acreage response, Bellman equation.

3.2 Introduction

In the United States, crop rotation has been a very popular agricultural practice for many decades. Crop rotation is a practice of planting different crops on the same farm land for sequential seasons. Agronomically speaking, crop rotation could reduce the risk of disease and pest damage while maintaining soil quality for crop growth. In other words, crop rotation is a substitute to some external inputs such as fertilizers or pesticides. For economic considerations, crop rotation helps reduce input costs and improve soil productivity, therefore increasing expected profit which dominates acreage response. Crop rotation benefit is believed to be induced by the agronomic interrelationship between different field crops. A prevalent example is the corn-soybeans rotation, where soybeans provide a key nutrient for corn growth. Furthermore, crop rotation also helps reduce greenhouse gas emissions, since it is a substitute for nitrogen fertilizer. Overall, crop rotation can maintain or improve crop yield by controlling for disease and pests and promoting soil nutrients.

Agricultural producers' acreage response is an important determinant of agricultural supply. Acreage response is largely constrained by crop rotation considerations. Switching from a crop rotation scheme to continuous cropping to take advantage of high crop prices could make farmers worse off in the long run since yield loss due to continuous cropping could decrease profit. For example, in recent years many producers have allocated more acreage to corn planting in response to the corn price boom due to ethanol demand. Even though an immediate short run profit could be gained in some cases, the gain in corn price might not be able to offset the yield loss from continuous cropping in the long run. Therefore, crop choice and acreage response are complex decisions with both agronomic and economic considerations. Without considering the effects of crop rotations on long-term crop yields and profit, producers' planting decision models may be misspecified and misinformed. An interesting research question is: Considering crop rotation effects, how will a profit-maximizing producer's acreage response be altered by crop price volatility? This research question is expected to be of current interest because of increased crop price volatility in recent years.

3.3 Literature Review

Crop rotation has been of great interests to both agricultural producers and policy makers for many decades. This topic has also been intensively investigated by researchers. Crop rotation studies generally focus on two major categories: agronomic and economic modeling.

Agronomists concentrate on estimating yield response to crop rotation, and sometimes, the tradeoff between yield response and external inputs. Agronomists conduct these studies by controlling external factors such as soil type, fertilizer level and some other agronomic factors. The agronomic literature generally indicates that crop rotation practices could enhance crop yield while reducing input demand. Therefore, crops grown during last season could alter this season's crop yield and input demand depending on if producers decide to stay with a rotation scheme or skip it. Johnson et al. (1998) estimated that cotton and peanut yields from the cotton-peanut rotation were 26% and 10% greater, respectively, than those from monoculture over a 7-year study in Georgia. In an agronomic study based in Michigan, Roberts and Swinton (1995) demonstrated that crop rotation could increase corn yields by 16 percent comparing to continuous cropping. Vyn (2006) reported that in Indiana, corn-soybeans rotation enhanced corn yields by about 6%. Overall, yield response results vary across almost all agronomic studies. Disagreement of agronomic results indicates that crop rotation is largely affected by various external factors such as soil type and fertilizer input, therefore increasing the difficulty of developing an economic crop rotation model.

Acreage response is largely constrained by crop rotation considerations. Expected profitability will be altered by crop rotation effects of reducing input demand and improving productivity. However, crop rotation effects were surprisingly omitted by most previous acreage response studies.

Even for acreage response models considering crop rotation, crop rotation was usually used as an additional variable to help estimate acreage response. For example, many researchers incorporate a lagged acreage variable in the econometric acreage response model trying to represent the effects of crop rotation (Bewley, Young, and Colman 1987; Weersink, Cabas, and Olale 2010). This lagged acreage variable only captures rotational constraints, while the mechanism of the crop rotation effects to acreage response behavior was not represented, such as how producers' acreage responses were dynamically altered by price and yield volatility under crop rotation considerations. The reason for this inactive incorporation of crop rotation into acreage response studies is believed to be the lack of a mature economic structural model of crop rotation. Without a usable and correct crop rotation model, it is hard for researchers to incorporate these effects into an acreage response study correctly.

Some researchers have incorporated dynamic considerations into crop rotation and acreage response models. Orazem and Miranowski (1994) estimated a dynamic model to study price effects on acreage response. The effects of current crop choice on future soil productivity were also considered. However, this research focused on how future prices affected current acreage allocations. Dynamically speaking, there is indeed a connection between future prices and current acreage allocations. However, following most economic models of crop rotation in the literature, we argue that previous acreage allocations and current prices should dominate current acreage allocations.

In general, previous studies have not adequately incorporated crop rotation into acreage response models. The reason for this gap in the literature, we believe, is that previous studies have lacked a structural model of crop rotation based on economic theory. Without a usable and theoretically-correct crop rotation model, it is hard for researchers to effectively incorporate crop rotation into acreage response models.

Economic studies of crop rotation are relatively limited compared to agronomic studies. Economic studies may be more limited because of the complexity of crop rotation effects which include interconnections between various factors. Furthermore, many effects of rotations are not completely understood by agronomists. Many economic techniques have been applied for crop rotation modeling. Among various economic modeling approached for crop rotation, linear programming has been one of the most prevalent approaches.

An early study of crop rotation using linear programming was conducted by El-Naze and McCarl (1986). The major contribution of their research is allowing the model to determine freely the optimal long run rotation while most other researchers modeled predetermined rotations. Multiple year crop rotations were modeled using an annual equilibrium linear programming. It assumes sequential crops planting on the same land for continuous seasons. However, most producers actually plant all crops in crop rotation simultaneously in the same season with the purpose of reducing production risk and balancing labor load.

Detlefsen (2004) modeled crop rotation with network modeling. Detlefsen's model provides a visual representation of the crop rotation problem. While it shows an alternative to previous linear programming approaches with certain advantages, it is still limited in only optimizing a one year return.

Hennessy (2006) developed a crop rotation economic model to analyze and separate the interconnected crop rotation effects of yield-enhancement and input-saving carry-over effects. The model was developed by considering both one-year rotation effects and multi-year rotation effects. However, this model does not consider how producers' sequential decision making will be altered by crop rotation effects. Also, Hennessy's model focuses on choosing among rotations instead of allocating acreage to crops within one rotation. Switching between rotations has higher input costs; therefore it is unrealistic for most small producers.

Livingston, Roberts and Rust (2009) examined crop choice as a dynamic optimization problem over an infinite time horizon. Their work is believed to be the first in the literature to consider crop rotations in a dynamic optimization framework. A simple crop rotation model was developed to analyze farmers' response to expected revenue given crop rotation considerations. However, only the simple corn-soybeans rotation was modeled. The whole model was based on one field grown either in corn or soybeans for sequential seasons. In a real farm, producers would prefer to grow all crops in rotation simultaneously which helps to reduce production risk. The situation with both crops planted is more complicated. Another limitation of their model is that it is calibrated by specific agronomic data from Northeast Iowa. The model they develop is most salient to that region of the country and nearby regions with similar soils and climate. It is not apparent that their model could be easily applied to other regions with different external environments. The final results were the optimal choice of crops given previous crops grown and current fertilizer use. This result provides useful decision rules for corn-belt farmers trying to decide between planting corn or soybeans in any given year, however, a multi-period decision analysis was not delivered.

3.4 Methodology

Economic analysis of crop rotation schemes plays a dominant role in acreage response studies. Various approaches developed in recent decades have broadly expanded people's knowledge about economic modeling of crop rotation. However, due to the complexity of crop rotation systems, economic models generally have various limitations, and therefore it is difficult to utilize these models in actual case studies. This study attempts to contribute to the literature by providing a dynamic optimization crop rotation model with a general structure. This model was designed to have minimum agronomic restrictions, such as soil type, yield response, and previous crops grown so that future research could easily adjust the model for use on any crop rotation system with various external environments. It also considers multi-year rotation carry-over effects which were barely addressed in previous studies.

To our knowledge, no literature exists pertaining to crop rotation structural modeling incorporating a Bellman equation to maximize net present value of returns. Therefore, in this study, we focus on the overall research question: What is the optimal cropping plan over multiple periods considering the economics of crop rotation in a dynamic framework?

In the remainder of this chapter, we will first develop a dynamic theoretical model with one-year carry-over effects. This model will then be extended to include two-year carry-over effects, followed by a case study with application to the corn-soybeans rotation.

In our model, we study three types of rotation systems. A-B denotes the rotation with crop A and crop B repeatedly planted after each other on the same farm land for sequential seasons. A-A-B denotes the rotation with repeated schemes of crop A planted for two seasons and crop B planted for one season on the same farm land. A-B-C denotes the rotation with repeated schemes of crop A planted during the first season, crop B planted during the second season, crop C planted during the third season on the same farm land. Agricultural producers are assumed to be price-takers and profit-maximizers. Considering crop rotation effects on yield response, producers intend to maximize net present value of returns for an infinite horizon by allocating crop acreage for each season.

In this study, the discrete time and discrete state Markov decision model is modified to simulate the crop rotation optimization process. The original Markov decision model has the following structure: in every period t, an agent observes an economic state s_t, takes an action x_t, and earns a reward $f(s_t, x_t)$ which depends on both the state of the system and the action (Miranda and Fackler 2002). This process could be converted into the crop rotation process as follows. In the beginning of a planting season, a producer observes the crops planted on the land during last season and decides which crops to plant on the same land for the current season. Producers are making discrete decisions assuming that each field could only plant one type of crop. The expected crop yield depends on both the previous planting state and current planting decision. For example, if corn and soybeans were each planted on two equally sized farm land tracts during last season, and a producer decides to follow the corn-soybeans rotation by flipping the crop planted on the two tracts, then expected corn yields could be maintained at the original level. However, if the producer decides to plant corn on both tracts due to increased corn price, one of the expected corn yields will be reduced due to continuous cropping (see figure 3.1).

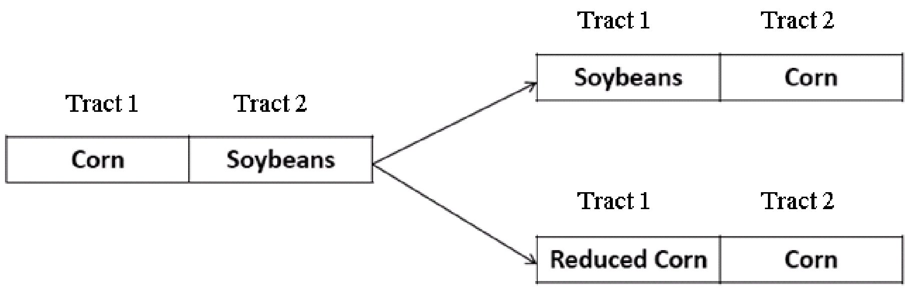

Figure 3.1. Two current planting scenarios based on previous crops planted

Expected input and output prices are assumed to be exogenous. Even expected yields are assumed to be exogenous; only the yield response level (the yield under continuous cropping compared to the yield under rotation) is assumed endogenous to current and previous crop choices. Since crop rotation practices are adopted by most producers, we assume that exogenous expected yields are the yield under rotation. The yield under continuous cropping will depend on the yield response level.

The discrete Markov decision model used in this study is analyzed using the dynamic programming methods developed by Richard Bellman (Bellman 1957). The Bellman equation helps to optimize sequential decisions to balance an immediate reward against expected future rewards. With a finite horizon, the Bellman equation is written as:

(3.1) $$V_t(s) = \max_{x \in X(s)}\{f(s,x) + \delta \sum_{s' \in S} P(s'|s,x)V_{t+1}(s')\}, \; s \in S, t = 1, 2, \ldots, T$$

where, $V_t(s)$ is the maximum attainable sum of current and expected future rewards, given that the system is in state s in period t, x is the control variable. $f(s,x)$ is the immediate reward:

(3.2) $$\delta \sum_{s' \in S} P(s'|s,x)V_{t+1}(s')$$

is the expected future reward. δ is the discount factor, $\boldsymbol{P(s'|s,x)}$ represents the distribution of next period's state.

The objective function for the producer is maximizing the sum of current and expected future farm returns considering the crop rotation for T years. It is also assumed that the current season's crop yield will be known with certainty once both the last and current season's planting decisions are known. Therefore, the crop rotation is considered to be a finite horizon, deterministic problem in this study.

The producer makes planting decisions by looking at the crops planted during last season; therefore, we take crop yield at time *t-1* as the state variable at time *t*. This state variable includes both the crop choice and crop yield. We assume that the yield response level during last season has no impact on this season's yield response level, only the crop choice matters. To be specific, the actual state variable in this model is the profit where exogenous input and output prices are included. To simplify the notation, we say that the combined crop choice and the yield response level is our state variable:

(3.3) $$y_{t-1} \in \{y, ym\}$$

where y denotes the yield of crop *y* under crop rotation, and ym denotes the yield of crop *y* reduced yield under continuous cropping.

We assume that the producer plants alternative crops simultaneously during the same season and switch crops for the next season. Therefore, the size of state space varies according to rotation length. For a rotation with two crops such as A-B, the number of elements in the state space is nine which includes all possible combinations of yield and reduced yield for crop A and crop B. AM-BM is not considered as an element of the state space for rotation A-B. AM-BM indicates that both A and B are harvested with reduced yield due to continuous cropping, so the crops planted for the last season must be A and B. While both crop A and crop B were planted for two sequential seasons, a rational producer will switch the lands for A and B and obtain crop rotation yield A-B, but not continuous cropping yield AM-BM. Therefore, AM-BM is not a possible yield scenario, thus:

(3.4) $y_{t-1} \in (\mathrm{A-B, A-BM, AM-B, A-A, A-AM, AM-AM, B-B, B-BM, BM-BM})$.

For crop rotations with longer length or more crops, the number of elements in the state space will be more. A-A-B has 16 elements and A-B-C has 100 elements in their state spaces. The control variable is:

(3.5) $x \in \{A, B, \dots, N\}$

where $A, B, \dots, N$ denotes alternative crops in a crop rotation scheme.

Based on the state variable and the control variable denoted above, the modified Bellman equation for crop rotation could be written as:

(3.6) $V_t(y_{t-1}) = \max_{x \in X(\pi(y_{t-1}))}\{\pi(y_{t-1}, x) + \delta V_{t+1}(g(y_{t-1}, x))\}, y_{t-1} \in Y, t = 1, 2, \dots,$

where $V_t(y_{t-1})$ is the maximum attainable sum of current and expected futures farm returns, given that system is in state y_{t-1}in period t, x is the crop choice for the current season, $\pi(y_{t-1}, x)$ is the current season farm return, and $\delta V_{t+1}(g(y_{t-1}, x))$ is the expected future farm returns.

The state transition function $g(y_{t-1}, x)$ denotes how the current state y_{t-1} transits in the state space based on the current season crop choice x. $g(y_{t-1}, x)$ in this model could be better understood by visually inspecting figure 3.2. Again, the simplest crop rotation A-B was chosen to demonstrate the state transition process for this model.

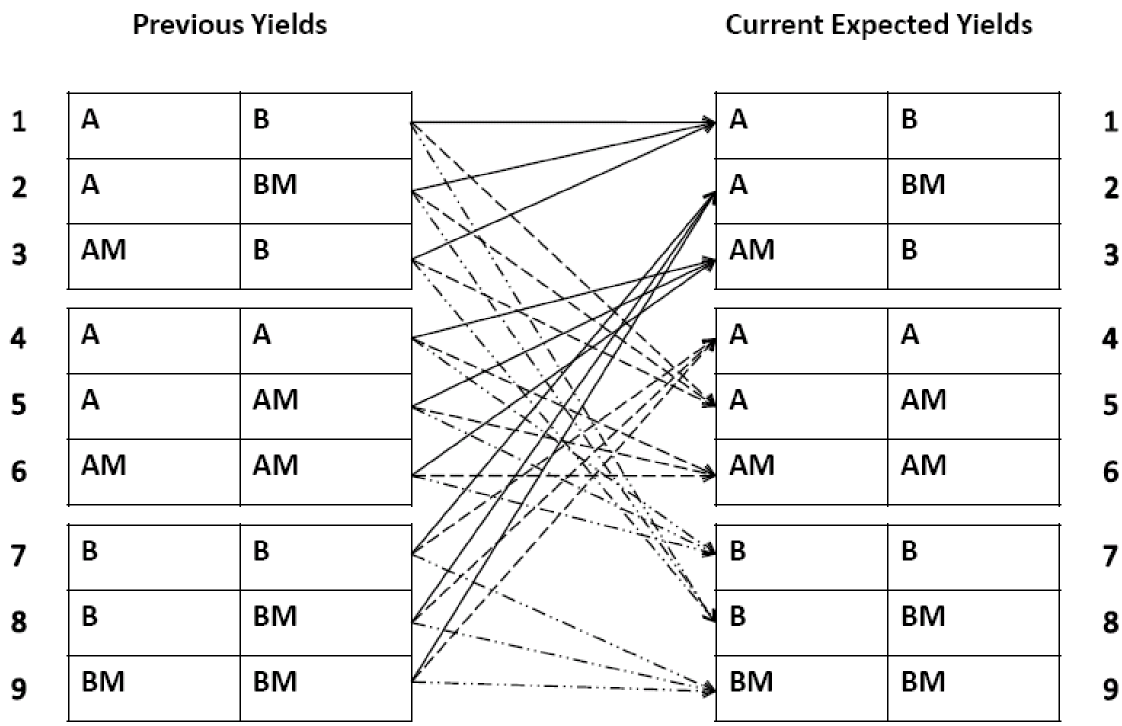

Figure 3.2. Illustration of the transition function of A-B rotation

Each of the two crops is planted on two tracts denoted by cells. The left column denotes the current state, which is the crop choice and yield response level during the last season. The right column denotes the next state depending on the current planting decision. Lines connecting the two columns denote planting decisions. Solid lines denote crop rotations, long dash lines denote growing crop A on both tracts, long dash dot-dot lines represent growing crop B on both tracts. This figure illustrates how the state variables (crop choice and yield response level during last season) transit with the control variables (planting decisions).

Figure 3.2 visually demonstrates the state transition function for the simplest crop rotation A-B. The previous crop choice and yield response level transits to the specific current yield response level, depending on the current planting decision. At the beginning of the current season, a producer considers crops planted during the last season, making the choice between three alternative planting decisions: planting A on both tracts, planting B on both tracts or planting both A and B on both tracts.

In order to maximize the net present value of the return, the producer optimizes his or her planting decision based on the crop planted during last season and this season's expected yield. For example, row 2 of the left column means both A and B were planted during the last season, while A was harvested with rotational yield, and B was harvested with continuous yield. If the producer decides to plant A on both tracts during the current season, the expected current yield level will transit to row 5 on the right column where A was harvested with rotational yield on one tract and continuous yield on the other tract.

The state transition function, the reward function and the Bellman equation for the A-B rotation are listed in the Appendix B (take Corn-Soybeans rotation as an example). The above illustration of state transition could also extend to other crop rotation types such as A-A-B and A-B-C. As alternative crops in the crop rotation increases, the number of elements in the state space also largely increases. Compared to nine elements for the A-B rotation, the A-A-B rotation has 16 elements and the A-B-C rotation has 40 elements in their state spaces. Their structure figure, the state transition function, the reward function and the Bellman equations are listed in the Appendix as well.

It should be noted that the above dynamic optimization models derived for A-B, A-A-B and A-B-C rotations have one strong assumption: the crop yield response level at time *t* only depends on the crop planted at time *t-1* and the planting decision at time *t*. However, this assumption is unlikely to be valid for some crops, for which the crop yield response level depends on crops planted at both time *t-1* and time *t-2* and the planting decision at time *t*.

Therefore, we extend the previous model by considering the last two crops grown instead of just the last crop grown.

The control variable for the new model is still the current crop choice. The state variable now changes from last season's crop choice and yield response level to the same two variables for the last two seasons. As mentioned earlier, the yield response level is still not completely understood by agronomists. Although agronomic yield response level results are available in many previous studies, their values vary by area, by crop and some other unknown agronomic factors. In the model only considering last season's impact, the crop planted in the same land for two sequential seasons could be categorized into either the same crop or a different crop for the A-B rotation.

For the model considering the last two seasons' impact, the crop on the same land for three sequential seasons could be categorized into four scenarios: A-B-A, B-A-A, A-A-A, B-B-A (assuming crop A will be planted for the current season). The yield response level for A is believed to be different for all these four scenarios. However, we are not able to value these four yield response levels due to the lack of agronomic evidence. We will assign different appropriate values to these yield response levels for the model simulation.

Since the state variable is now more complicated, the number of elements in the state space also greatly increased. Take the A-B rotation as an example. There were nine elements in the state space for the old model only, while there will be 27 elements in the state space for the new model. Specifically, there are nine different states by crops, and each crop has three yield response level scenarios, combining into a total of 27 states. For example, the crop state A-B|A-B could come from three possible previous states: A-B|A-B, A-A|A-B, and B-B|A-B. Therefore, given the fact that A and B are planted during this season, there are three possible yield response level scenarios depending on previous states. The state transition figure for the A-B rotation with two-season effects is illustrated in figure 3.3.

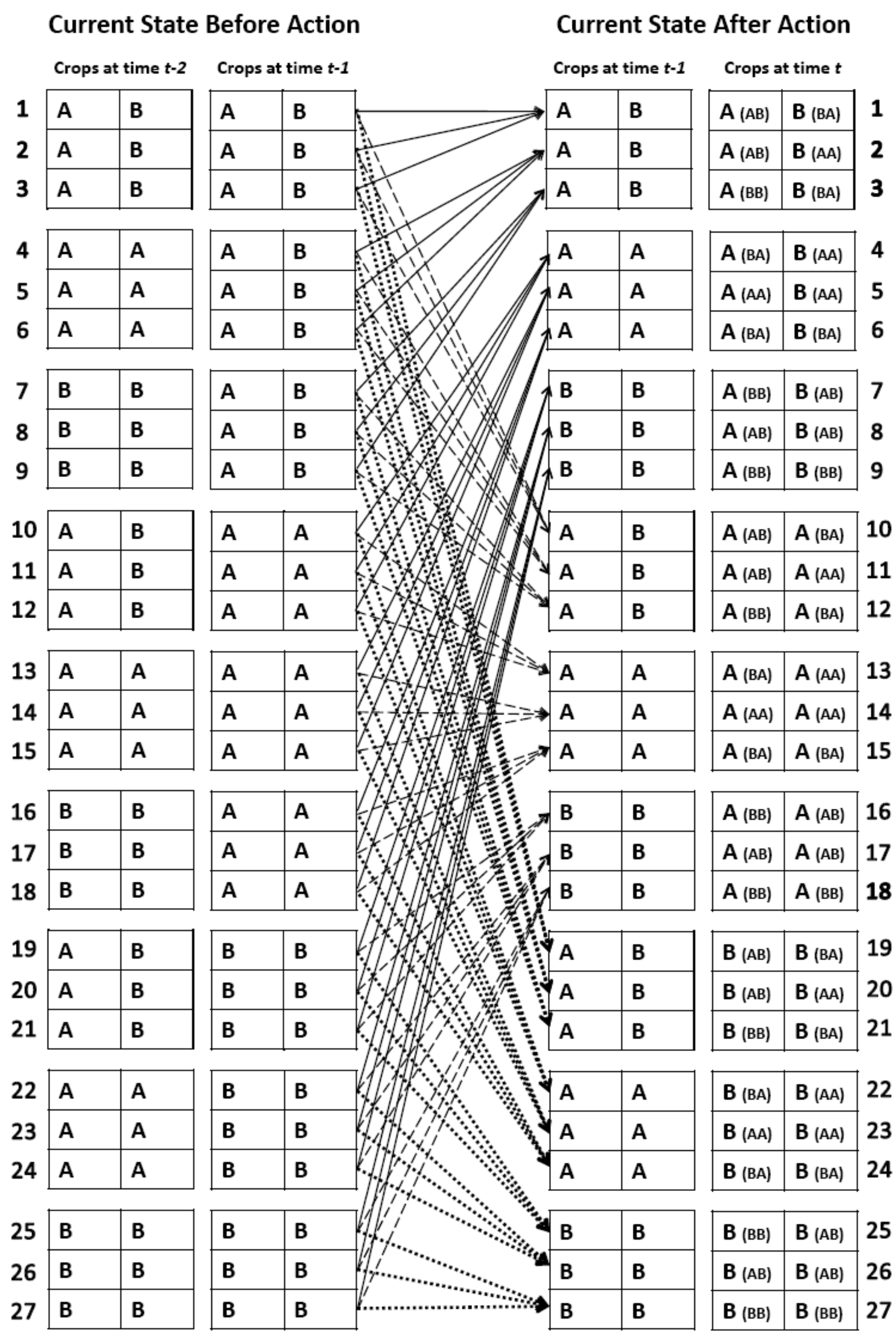

Figure 3.3. **A-B rotation with two-season effects**

Furthermore, the same approach can be applied to other crops rotation types such as A-A-B and A-B-C to extend the model. The number of elements in the state space also greatly increases. It could be summarized that for each rotation type, the number of elements in the state space for the last season is the square of their possible crop combinations, for the last two seasons it is the cubic of their possible crop combinations. A-B has three crop combinations: A-B, A-A and B-B. A-A-B has four combinations: A-A-B, B-B-A, A-A-A and B-B-B. A-B-C has ten combinations: A-B-C, A-A-B, B-B-A, A-A-C, C-C-A, B-B-C, C-C-B, A-A-A, B-B-B and C-C-C. Compared to 27 elements for the A-B rotation, the A-A-B rotation has 64 elements and the A-B-C rotation has 1,000 elements in their state spaces (see Table 3.1). For simplicity, their transition functions, reward functions, and modified Bellman equations will not be demonstrated.

Table 3.1. The Number of Elements in the State Spaces for Different Rotations

	Last Season			Last two seasons		
Rotation Type	A-B	A-A-B	A-B-C	A-B	A-A-B	A-B-C
No. of elements in the state space	9	16	100	27	64	1000

We extend the crop rotation model with one-season effects to two-season effects (if desired, we also could extend the model to three-season effects or even longer). However, we argue that the crops planted at three seasons earlier have insignificant effects on current crop yields. Thus, we only derive the model considering two-season effects in this study.

3.5 Assumptions

As an initial assessment to apply the Bellman equation on acreage response considering crop rotation, several major assumptions have been made in the economic models derived in this study.

This model does not presume any soil types or natural factors that could affect yield response levels. It is designed to be able to apply to various external conditions. Expected yield and expected input and output prices are all exogenous, while yield response levels are endogenous. We assume producers to be price takers. Therefore, their response in acreage will not cause dynamic price responses.

It is assumed that each phase of a rotation system is grown every year. For example, the A-B rotation means producers grows both crop A and crop B in the same season. If the rotation continues the following season, a producer will flip the farm land tracts planted for crop A and crop B. Also, A-A-B means the producer plants crop A on two tracts and crop B on one tract. A-B-C means the producer simultaneously plants crop A, B and C on three different tracts in the same season. This assumption simulates the real situation on most farms. Also, this assumption helps separate the effects of the rotation system on yields from that of variable weather factors.

Two types of dynamic crop rotation models were developed with each assuming the number of previous seasons that could affect this season's yield response level. For the first model, we assume that only last season's crop could impact this season's yield response. As mentioned earlier, that could be false for some crops. Therefore, we develop the second model where we assume that last two seasons' crop could impact this season's yield response.

We assume that the producer uses constant external inputs such as fertilizer and pesticides for different seasons. In reality, farmers could do crop rotations while adjusting external inputs simultaneously in order to maximize returns. Continuous cropping yields could be made similar to yields of rotational crops if producers upgrade inputs such as fertilizer. Crop rotations could thus either improve yields with fixed input, or save inputs with fixed yields. However, the interconnections between fertilizer inputs and yields with crop rotation are relatively complex. As a first attempt to incorporate crop rotation process into the Bellman equation, external inputs were fixed for simplicity. That is, the producer will not change inputs after switching from rotating crops to continuous cropping.

It is assumed that certain tracts of farm land are only used to plant certain crop rotations or continuous crops for that particular rotation. Other crops will not be planted on these tracts. We also assume there is no land use change and producers will not introduce new crop varieties into the system. It is not necessary to use percentage share to represents a producer's acreage response, since his or her response occurs plot by plot.

3.6 Simulation

MATLAB was used to simulate the dynamic crop rotation model developed in this study. MATLAB utilizes the CompEcon toolbox to solve for discrete time/discrete variable dynamic programming problem (Fackler 2010). Given the terminal value of $V_{t+1}(g(y_{t-1}, x))$, the decision is solved recursively by repeated application of the Bellman equation. MATLAB compares the value of $V_{t+1}(g(y_{t-1}, x))$ for each time *t*, and provides the optimal decision for each period.

The value for each $V_{t+1}(g(y_{t-1}, x))$ includes current and discounted future rewards. The current reward for each period is a producers' immediate profit:

(3.7) $$\pi_{it(d)} = \sum_{i=1}^{N}(P_{it}Y_{it(d)} - C_{it})$$

The above profit function is the profit summation for crops planted under planting decision *d*. Take a corn-soybeans rotation as an example. We assume previous crops planted on two farm land tracts were corn and soybeans. There will be three possible decisions *d* for the current season: keeping a rotation system, planting all corn or planting all soybeans. If keeping a rotation system is decided, the current expected profit will be corn profit and soybeans profit, both with rotation yields. If growing all corn is decided, the current expected profit will be corn profit with rotation yields and corn profit with continuous yields. If planting all soybeans is decided, the current expected profit will be soybean profit with rotation yields and soybeans profit with continuous yields. MATLAB will then compare three profit bundles and pick the one with the highest value as the optimal decision for period *t*. However, this will be true only for the last period T where there is no future reward. For any other period *t*, MATLAB compares three profit bundles with each adding their future rewards given by the Bellman equation value at period *t*.

The models developed above were simulated on corn-soybeans for the A-B structure. Specifically, both the one-season effects and two-season effects models were simulated. Yield response levels are summarized from previous empirical studies. The corn-soybeans rotation yield response level is retrieved from a compilation of all known published data comparing corn after corn to a corn-soybeans rotation in the U.S. by Erickson (2008). We simply take the average of all data compiled by Erickson (2008) which is 7.8%, meaning that the continuous corn yield is on average 7.8% lower than the corn rotation yield. The continuous soybeans yield response is 14.5 % lower than the soybeans rotation yield. Since most producers use crop rotation systems, we assume that expected yields are the equal to the rotation yields. Continuous yields are discounted based on this assumption.

The expected input and output prices and expected yields are all retrieved from USDA ten-year agricultural projections. We simulated the individual producers' planting decisions under USDA projections of prices and yields. The producers are assumed to be profit-maximizers and price-takers. It is assumed that the producer owns two equally sized farm land tracts. At the beginning of each period, the producer decides which crop to plant on each cropland based on price expectations, the crop planted last season and related yield expectations.

Based on current USDA projections for the next five years, the producers will plant corn for all tracts. As long as the USDA corn price projections are higher than 98% of the current level, producers produce all corn. The upper and lower bound of corn price percentage changes for all crop rotations are -12% and -16%. If corn prices decreased by over 30%, then producers will not rotate crops and instead grow all soybeans.

Now we run another A-B model simulation with two previous crops considered. Compared to the A-B model only considering the last crop, the yield response level is more complicated. We need to decide the yield response of crop A after A-B for last two periods, or after B-A, A-A, B-B. There are four yield response levels for crop A given different crops combinations for the last two periods which is the same for crop B. To the best of our knowledge, agronomic results for these complicated yield response levels are not available. We therefore make several assumptions. We assume crop A after B-B has the full yield, crop A after A-B has a 5% reduction in yield, crop A after B-A has a 10% reduction in yield, crop A after A-A has a 15% reduction in yield. The same assumption was made for crop B. We use USDA yield projections for the next five years again. As long as USDA corn price projections are higher than 108% of current level, producers produce all corn. If corn prices decreased by over 30%, then producers will not rotate crops and instead grow all soybeans. No level of corn price change can be found for pure crop rotation practices. It should be noted that the above two case studies were only used to test the performance of the derived rotation model, and it has nothing to do with the analysis in the rest of this dissertation.

3.7 Conclusions

In this chapter, a dynamic crop rotation model was developed to connect expected profit to acreage response. Specifically, a modified Bellman equation was used for dynamic optimization, and the crop rotation model is actually a part of its transition function.

The crop rotation model was developed for both the one-season effects and two-season effects. The simulation results indicate that by considering the one-season effects, continuous corn cropping is the optimized choice. For the two-season effects, corn-soybeans rotation is the optimized choice. These results indicate that two-season effects are more stable and producers should prefer to choose a mixed cropping scheme.

The complexity of interactions is inherent in a crop rotation system. This crop rotation ignored the interactions between crop yield and fertilizer usage by using empirical yield responses. Future research could improve this model by including fertilizer usage. Furthermore, while it is commonly agreed that rotational effects varied by region, the effect of differences in soil types and other natural factors were not considered. Again, an improvement of this crop rotation model should allow the input of soil types and other natural factors.

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Appendix B

The Reward Functions:

$The\ state\ variable\quad Y \in \{C|S, C|SM, CM|S, C|C, C|CM, CM|CM, S|S, S|SM, SM|SM\},$

$$t \in \{1,2,3, \dots, n\}$$

$The\ action\ variable\quad x \in \{crop\ rotation, all\ corn, all\ soybeans\}$

$$f(Y_{t-1}, x) = \begin{cases} (P_c - C_c)Y_c + (P_s - C_s)Y_s, & if\ Y_{t-1} = (C|S, or\ C|SM, or\ CM|S)\ and\ x = rotation; \\ (P_c - C_c)Y_c + (P_c - C_c)Y_{cm}, & if\ Y_{t-1} = (C|S, or\ C|SM, or\ CM|S)\ and\ x = corn; \\ (P_s - C_s)Y_s + (P_s - C_s)Y_{sm}, & if\ Y_{t-1} = (C|S, or\ C|SM, or\ CM|S)\ and\ x = soybeans; \end{cases}$$

$$f(Y_{t-1}, x) = \begin{cases} (P_c - C_c)Y_{cm} + (P_s - C_s)Y_s, & if\ Y_{t-1} = (C|C, or\ C|CM, or\ CM|CM)\ and\ x = rotation; \\ (P_c - C_c)Y_{cm} + (P_c - C_c)Y_{cm}, & if\ Y_{t-1} = (C|C, or\ C|CM, or\ CM|CM) and\ x = corn; \\ (P_s - C_s)Y_s + (P_s - C_s)Y_s, & if\ Y_{t-1} = (C|C, or\ C|CM, or\ CM|CM) and\ x = soybeans; \end{cases}$$

$$f(Y_{t-1}, x) = \begin{cases} (P_c - C_c)Y_c + (P_s - C_s)Y_{sm}, & if\ Y_{t-1} = (S|S, or\ S|SM, or\ SM|SM) and\ x = rotation; \\ (P_c - C_c)Y_c + (P_c - C_c)Y_c, & if\ Y_{t-1} = (S|S, or\ S|SM, or\ SM|SM) and\ x = corn; \\ (P_s - C_s)Y_{sm} + (P_s - C_s)Y_{sm}, & if\ Y_{t-1} = (S|S, or\ S|SM, or\ SM|SM) and\ x = soybeans; \end{cases}$$

The Transition Functions:

$$g(Y_t, x) = \begin{cases} 9t + 1, & if\ Y_t = (C|S, or\ C|SM, or\ CM|S)\ and\ x = rotation; \\ 9t + 5, & if\ Y_t = (C|S, or\ C|SM, or\ CM|S)\ and\ x = corn; \\ 9t + 8, & if\ Y_t = (C|S, or\ C|SM, or\ CM|S)\ and\ x = soybeans; \end{cases}$$

$$g(Y_t, x) = \begin{cases} 9t + 3, & if\ Y_t = (C|C, or\ C|CM, or\ CM|CM)\ and\ x = rotation; \\ 9t + 6, & if\ Y_t = (C|C, or\ C|CM, or\ CM|CM)\ and\ x = corn; \\ 9t + 7, & if\ Y_t = (C|C, or\ C|CM, or\ CM|CM)\ and\ x = soybeans; \end{cases}$$

$$g(Y_t, x) = \begin{cases} 9t+3, & if\ Y_t = (S|S, or\ S|SM, or\ SM|SM)\ and\ x = rotation; \\ 9t+4, & if\ Y_t = (S|S, or\ S|SM, or\ SM|SM)\ and\ x = corn; \\ 9t+9, & if\ Y_t = (S|S, or\ S|SM, or\ SM|SM)\ and\ x = soybeans; \end{cases}$$

The Bellman Equation:

$V(Y_{t-1}) = \max\{(P_c - C_c)Y_c + (P_s - C_s)Y_s + \delta V(9t+1),\ (P_c - C_c)Y_c + (P_c - C_c)Y_{cm} +$

$\delta V(9t+5)$,

$(P_s - C_s)Y_s + (P_s - C_s)Y_{sm} + \delta V(9t+8)\}, \quad if\ Y_{t-1} = (C|S, or\ C|SM, or\ CM|S)$

$V(Y_{t-1}) = \max\{(P_c - C_c)Y_{cm} + (P_s - C_s)Y_s + \delta V(9t+1),\ (P_c - C_c)Y_{cm} + (P_c - C_c)Y_{cm} +$

$\delta V(9t+5)$,

$(P_s - C_s)Y_s + (P_s - C_s)Y_s + \delta V(9t+8)\}, \quad if\ Y_{t-1} = (C|C, or\ C|CM, or\ CM|CM)$

$V(Y_{t-1}) = \max\{(P_c - C_c)Y_c + (P_s - C_s)Y_{sm} + \delta V(9t+1),\ (P_c - C_c)Y_c + (P_c - C_c)Y_c +$

$\delta V(9t+5)$,

$(P_s - C_s)Y_{sm} + (P_s - C_s)Y_{sm} + \delta V(9t+8)\}, \quad if\ Y_{t-1} = (S|S, or\ S|SM, or\ SM|SM)$

Note: C-Corn S-Soybeans CM-Corn with reduced yield SM-Soybeans with reduced yield

CHAPTER 4

DYNAMIC MODEL

ECONOMIC CONSEQUENCES OF CLIMATE CHANGE EFFECTS ON AGRICULTURE: A DYNAMIC SIMULATION[6]

[6] Cai, R., J. Bergstrom, J. Mullen, and M. Wetzstein. To be submitted to *American Journal of Agricultural Economics.*

4.1 Abstract

A dynamic optimization model was developed to simulate how farm-level realized price and profitability respond to yield change induced by climate change. A modified Bellman equation was used to dynamically optimize the net present value of farm profit for a five-year interval. This process was then repeated through the year 2050. Results indicate that reduction in crop yields due to climate change results in reduced farm profitability. At the state level, predicted climate change is likely to pose a problem for agricultural production and profitability in the southern U.S. states as compared to the northern U.S.. Our results also suggest that acreage response alone is not sufficient to ameliorate the potential negative effects of global climate change on agricultural production and profitability.

Key words: Acreage response, Crop rotation Dynamic simulation model, Expected price, Realized price.

4.2 Introduction

Studies addressing the effects of climate change on acreage response are scarce in the literature. Kurukulasuriya and Mendelsohn (2006) directly studied the relationship between crop choice and climatic variables. A multinomial logit framework was used in their research to analyze crop selection. However, this model was not built in a dynamic optimization framework; limiting its ability to address the essential role of crop rotation in crop selection. Weersink, Cabas and Olale (2010) studied the effect of weather on the distribution of yield and its subsequent impact on the acreage allocation decisions of crop producers in Ontario. While a contribution was made by the decomposition of price and yields into mean and variance revenue impacts on crop area allocation, yield and price were assumed to be independent.

The objective is to extend this previous agricultural climate change research by developing a dynamic crop acreage response model considering both crop rotation and the interdependence between yields and prices. The fundamental idea of dynamic optimization is that the multiple period maximization problem is reduced to a sequence of two-period problems, in which the producer balances an immediate reward with expected future returns.

4.3 Literature Review

Previous studies have developed alternative acreage response models. In a basic empirical acreage response model, planted acreage is viewed as a function of expected prices (Nerlove 1958). Several other exogenous variables were commonly incorporated into previous acreage response models as well including producer's initial wealth, proxies for risk, lagged acreage, and commodity policies (Chavas and Holt 1990; Park and Garcia 1994; Lin and Dismukes 2007).

The acreage response models developed in previous studies generally rely on estimation of empirical models from historical data. However, when evaluating the effects of climate change on agriculture, empirical analysis based on historical data may not be an appropriate approach since historical data do not indicate future climate change effects. Thus, a numerical simulation approach is used in this study. Compared to empirical acreage response models, relatively limited work exists using a simulation approach. Our model focuses on how acreage allocation responds to profit expectations given climate change affects on yields and prices.

In previous studies, various approaches were employed to construct expected prices. Researchers used the simple cobweb theorem where lagged prices were used as proxies for expected price (Ezekiel 1938; Nerlove 1958). Nerlove (1958) used a weighted sum of past prices to develop expected prices. A limitation with using lagged prices is missing current market information. Gardner (1976) used futures prices to develop expected prices. Futures prices are determined by the interaction of the expected supply and demand for a commodity. Futures prices acres the market's expectation of actual price. Many researchers believe that futures prices are an appropriate proxy for price expectation, since an efficient futures market should provide an unbiased estimate of the actual prices at contract maturity (Just and Rausser 1981; Thomson, McNeill, and Eales 1990; Kastens, Jones, and Schroeder 1998).

However, futures prices are a national-based price, and local information is missing. As a result, researchers have used basis to adjust futures prices to incorporate local conditions (Peck 1976; Garbade and Sibler 1983; Moschini and Myers 2002). Basis is the difference between local cash price and futures price for the month closest to the delivery date. Basis tends to be more stable or predictable than either current price or futures price. Lin et al. (2000) derived expected prices from the December corn futures price and the November soybean futures price at the Chicago Board of Trade in mid-March, the time when planting decisions are made for corn. Expected prices were then adjusted by a state-specific, 5-year average basis. Tronstad and Bool (2010) calculated expected prices using the December futures price in February with the November state basis to incorporate state level supply and demand conditions. They also incorporated the expected loan deficiency payment into the basis value to capture the effect of government price support programs on expected prices for the producer. However, the relationship between the national and a local area prices along with the basis could change with future climate change. Thus, using a constant basis in climate change studies is questionable, so a basis correction is not employed in the analysis.

Another limitation of using futures prices as an agricultural price expectation is the timing issue. Futures prices are a good surrogate for expected harvest prices during planting seasons. However, futures prices could change dramatically in three or four months. Producers usually build their price expectations during the beginning of the planting season when futures prices are relatively uncertain and imprecise. Significant differences between planting month futures prices and harvest month realized price could be observed.

Alternatively, price expectations can be developed using a rational expectations model. This model represents mathematical expectations conditional on all relevant information. Chavas, Pope and Kao (1983) recognized the possibility that information from both cash and futures markets might prove useful in understanding the formulation of producer price expectations. Therefore, in their research, expected cash prices, government program payments, and futures prices were used as the components of price expectations used by producers. Their research also aims at estimating the relative importance of these factors. Chavas and Holt (1990) estimated the weights of these prices in forming expected prices.

Producers have diverse price expectations and researchers have not discovered a single dominant specification for price expectations (Pope 1981; Orazem et al. 1986). It is unrealistic to develop a comprehensive price expectation model due to the complexity of market price system. Based on previous literature a rational expectations model was used by assuming producers adjust their price expectations according to changes in relevant information. Base expected prices were determined as the weighted average between lagged prices and futures prices. In a dynamic model, this base price will be adjusted by considering yield change induced by climate change.

Researchers have also considered government policies as constraints for price expectations. Government programs set a minimum guaranteed price for producers and have major impacts on producers' acreage response when market prices are low. Therefore, government programs should not be excluded from any acreage response studies. Among various government commodity programs, commodity loans are considered which are expected to have direct impacts on producers expected prices. Producers may receive a government commodity loan at a loan rate by pledging their crops as collateral. They can obtain a loan gain by repaying the loan at a lower repayment rate during the loan period whenever market prices are below the loan rate. Alternatively, producers can choose to receive a direct loan deficiency payment, which is the difference between the loan rate and the repayment rate. The program makes direct payments, equivalent to marketing loan gains, to producers who agree not to obtain nonrecourse loans, even though they are eligible. The deficiency payments encourage producers to sell their crops on the market (Westcott and Price 2001). Overall, the commodity loan program provides benefits to producers through deficiency payments or loan gains, when the loan repayment rate is less than the loan rate. Therefore, effective expected prices are simply the loan rate if expected prices are lower than the loan rate. The assumption is the loan rates are the effective support prices for corn, soybeans, cotton and peanuts. Behavioral researches indicate that producers' responses to planting decisions are greatly influenced by risk perceptions (Xu et al. 2005). Previous acreage response studies include risk effects (Just 1975; Thompson and Abbott 1982; Holt and Chavas 2002). Actual risk effects should be considered as the joint effects of both risk and risk perceptions. In previous research variance of profit is employed as a proxy for risk (Ref.). A profit distribution may be valued differently due to producer's risk perception. Therefore, risk aversion coefficients were introduced to represents producer's risk perceptions (Arrow 1965). For the analysis it is assumed that individual producers' risk aversion coefficient is exogenous in the dynamic model. Furthermore, producers identify diversification as an effective strategy to reduce production risks (Knutson et al., 1998).

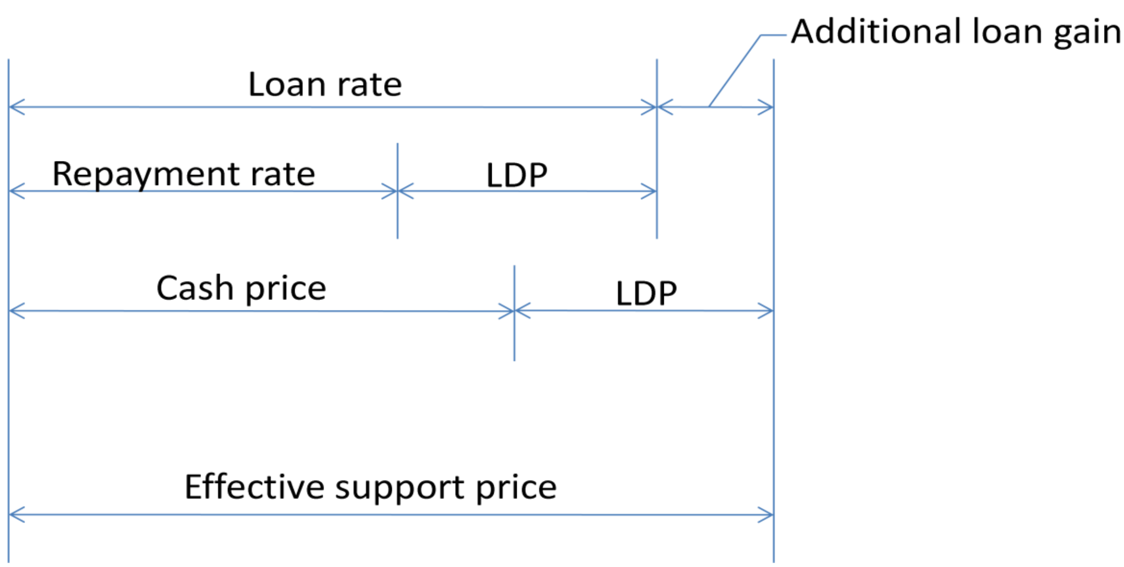

Figure 4.1. The relationship between the loan rate, LDP and effective support price

The perception of risk does not directly relate to actions. Smit, Mcnabb and Smithers (1996) found that, while most producers reported being significantly affected by abnormal weather conditions over a 6-year period, only 20% of producers responded to climate change.

Brklacich et al. (1997) found that, while 90% of producers have noticed climate change for the past two decades, only 18% of producers have adopted practices to adapt to climate change. Therefore, in this study, producers' ability and response speed will be represented by a partial adjustment coefficient.

Since using realized prices in this study which is affected by acreage response, a relationship between realized price and acreage response is required. Most past studies have focused on how supply or production responds to price changes, while little has been contributed to the opposite relationship; i.e., how prices respond to changes in supply or production. In climate change studies, it is important to consider how changes in production (supply) impact prices, since climate change mostly affects supply rather than demand. Edwards (1985) investigated how Georgia crop prices are affected by Georgia crop yields through the covariance between Georgia crop yields and Georgia output prices. He determined that prices of corn, cotton, soybeans and peanuts respond to changes in crop yield. Georgia crop prices are affected by overall crop production instead of just crop yields. Furthermore, Georgia prices of crops are determined globally, not locally, so the key is the effect of climate on global production. Thus, consideration is given to the major U.S. production states.

The approach used in this research is similar to the simulation process of POLYSYS[7] (Ray et al. 1998). Regional acreage was obtained from expected price, and then regional production was aggregated to national production to obtain the market clearing prices. However, our study differs in that we relate expected price to acreage via a crop rotation model instead of acreage-price elasticities and estimate the market-clearing prices from price flexibilities.

[7] POLYSYS simulates the impacts of policy, economic or environmental change on the agricultural sector POLYSYS uses farm prices lagged by 1 year as expected prices for the current year, and determines planted acreage for the current year by the change in expected prices and acreage price elasticities.

4.4 Methodology

Equation (4.1) presents a basic farm-level profit function which includes input and output prices, crop yields and crop acreage.

(4.1) $$\pi = \mathrm{PAY} - \mathrm{CA}$$

where P denotes output price, A denotes acreage, Y denotes yield, and C denotes input price.

We assume that producers use relative expected profitability between crops as decision criteria for acreage response. Suppose a representative producer has N alternative crops, indexed by N= 1, 2, …,N. Producers maximize net present value of total expected profits by selecting crops and deciding crop acreage for a certain period. Equation (4.2) represents an objective function considering only one year, and we will extend it to a multi-year form later.

(4.2) $$\mathrm{Max}\{\sum_{i=1}^{N} \mathrm{a_i} * [\Pi_i - \theta * \mathrm{V}(\Pi_i)] - \delta \sum_{i=1}^{N} (\frac{\mathrm{a_i}}{\mathrm{A}})^2\}$$

where a_i denotes acres of crop i, Π_i denotes profit per acre of crop i, θ denotes the risk aversion coefficient, $V(\Pi_i)$ denotes the variance of total profit of crop i, and δ is a coefficient to penalize the situation with fewer crops planted. This equation was incorporated into the Bellman equation to optimize the present value of total farm profit balancing current and future rewards. We assume producers maximize discounted expected profit for T years. Equation (4.3) represents the overall objective function for maximizing present value of profit for period T:

(4.3) $$\mathrm{Max}\{\sum_{i=1}^{N}[\Psi_{i1} + \frac{\Psi_{i2}}{1+\tau} + \cdots + \frac{\Psi_{iT}}{(1+\tau)^{T}}]\}$$

(4.4) $$\Psi_i = \sum_{i=1}^{N} \mathrm{a_i} * [\Pi_i - \theta * \mathrm{V}(\Pi_i)] - \delta \sum_{i=1}^{N} (\frac{\mathrm{a_i}}{\mathrm{A}})^2$$

The detail formula for parameters in equation (4.4) is as follows:

(4.5) $$\Pi_i = P_i Y_i - C_i$$

(4.6) $$V(\Pi_i) = (EP_i)^2 V(Y_i) + (Y_i)^2 V(EP_i) + V(Y_i)V(EP_i)$$

(4.7) $\quad V(EP_{it}) = 0.5\left[EP_{i(t-1)} - P_{i(t-1)}\right]^2 + 0.33\left[EP_{i(t-2)} - P_{i(t-2)}\right]^2 + 0.17[EP_{i(t-3)} - P_{i(t-3)}]^2.$

Figure 4.2 illustrates the basic structure of the dynamic model. At the beginning of the growing season, a representative producer is assumed to have crop yield expectations. Based on the expected relationships between crop yields (e.g., supply) and exogenous demand factors, the representative producer then develops price expectations based on yield expectations and lagged prices. Next, the producer determines acreage response from profit expectations based on yield and price expectations of multiple crops. At the end of growing season, realized prices are determined by crop yields and acreage responses. A producer's profit calculation then uses this realized price instead of the price expectation.

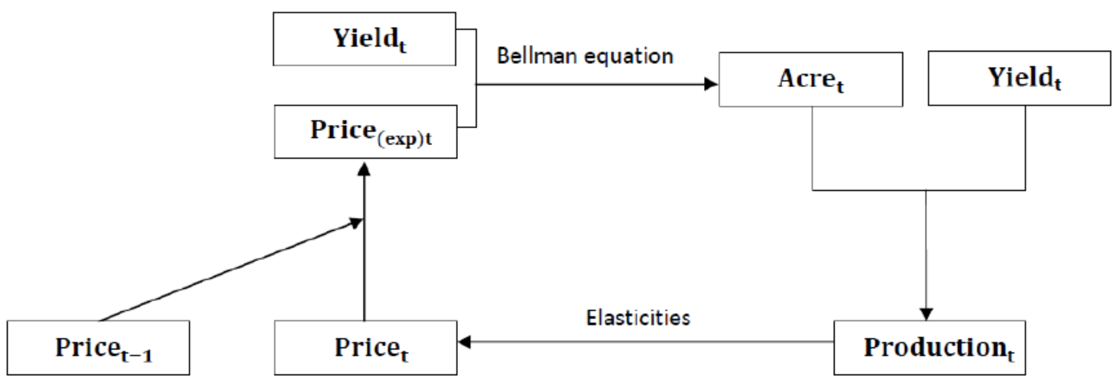

Figure 4.2. A basic dynamic simulation process

Suppose producers develop current expected price at time t based on a lagged price. With predicted yield for the current season, we used the above Bellman equation to simulate acreage response using a crop rotation model. Aggregate crop production was then estimated, and then realized price was estimated based on the elasticity of price with respect to production. This realized price was then be used as the lagged price for the next year.

The unique, dynamic process illustrated in figure 4.2 was applied to corn, soybeans, cotton, and peanuts at the county-level in eight northern and southern U.S. states which are major producers of these crops. Five years was selected as a planning period for profit optimization, which we denote as "round" for the rest of this chapter. Years 2005-2009 were selected as the baseline years. We assumed that a representative producer has yield expectations for the five year period 2005-2009. The average value of lagged price and future prices was used to calculate the base price expectations. Next, price expectations were adjusted by the percentage change in crop yields and the elasticity of price changes to production changes.

By using a Bellman equation in the crop rotation model, optimized acreage responses among multiple crops were determined based on their relative profitability. Then, in each state, county-level expected production levels for the current season were estimated based on expected yields and acreage responses for each county. State-level expected production levels then determined realized prices which were different from expected prices derived earlier.

Using realized price instead of expected price has the advantage of accounting for the effects of adaptation. We used realized prices, expected yields and acreage responses to calculate farm profits for 2011-2015. We assumed that expected yields were the same as realized yields. We also considered input prices to be exogenous. Producers usually decide the planting plan for the next few growing seasons. For each new season, producers adjust the previous planting plan based on updated expectations. Motivated by this fact, we only recorded 2011 profit derived from estimated 2011-2015 profits. Similarly, 2012 profit was derived by repeating the above process for the 2012-2016 data. Realized prices for 2011-2015 were used as lagged prices for 2012-2016. The same dynamic process was repeated through 2050. This process is illustrated in figure 4.3.

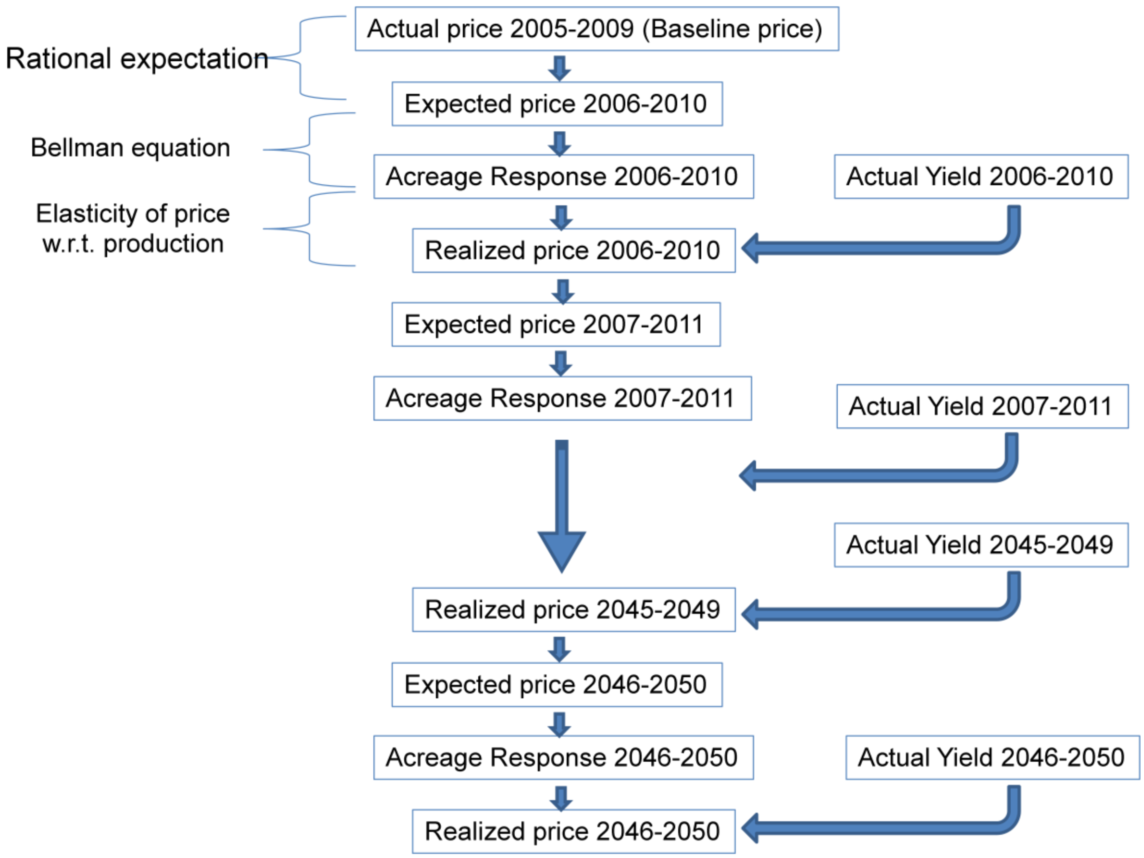

Figure 4.3. The dynamic simulation process illustrated with specific years

The crop rotation model developed in Chapter 3 was incorporated into this dynamic simulation model to simulate acreage response. MATLAB was used to build the above dynamic model and run simulations. Although the basic structure of dynamic process could be described in short, the detail of the model will not be fully revealed without discussing algorithms used in MATLAB. When putting a theoretical model into MATLAB for simulation, we came across multiple issues in the details. One contribution of this study is accomplishing the dynamic acreage response simulation using MATLAB. Therefore, the rest of the methodology section will focus on our algorithms used in MATLAB.

The algorithms used for MATLAB in the dynamic simulation process were based on the crop rotation model developed in Chapter 3. The crop rotation model was programmed in

MATLAB using the CompEcon toolbox which can solve for discrete time/discrete variable dynamic programming problems (Fackler 2010). For the Bellman equation, the state variable is the current and previous year's crop yield while the control variable is producer's action. Each year, the producer faces the possible previous year's yields combinations and current price expectations.

By having both expected prices and yields, producers respond by allocating acreage with the purpose of maximizing the present value of expected profit for the following five years. The previous year's yield and current year's expected profit jointly influence a producers' current acreage response decision. The MATLAB algorithms designed in Chapter 3 transferred the input of expected profits to the output acreage response. Therefore, in this chapter, algorithms should be designed to use the expected price as an input and then estimate the realized price from the acreage response output.

Producers take into account the previous year's realized price and this year's futures price to develop their base price expectations, and finalize these expectations according to the predicted change in annual yield. Programming expected price into MATLAB is straightforward; therefore, its algorithms will not be described here. Instead, we focus on algorithms of estimating realized price from the acreage response output. The acreage response output from a basic crop rotation model has certain limitations. First, it assumes that producers take advantage of the full range of adaptation; in other words, partial adjustment is not allowed. Second, the model only allows for the acreage allocation across the crops within the original rotation; therefore, new crops are not allowed to be introduced. Algorithms were designed to relax the above two major limitations.

Partial adjustment is realized by the following algorithm. For example, to allow partial adjustment of 0.1, we assume that producers only switch 10% of acres according to what the crop rotation model suggests. For example, if the crop rotation model shows that it is better to assign crop A to both plots for the next season for dynamic optimization, our new algorithms will only allow 10% of the original acres to be reallocated as shown in figure 4.4. It is apparent that the new algorithm breaks the previous season's acres into two parts: one part keeps the original planting pattern, the other part goes to a new planting pattern as suggested by the model. One dilemma could be caused by the above algorithm; for example, suppose we have a plot at season 1, this plot will be divided into two parts during season 2, and will further be divided into four parts; thus, there will be 16 parts at season 5. Obviously, this could make the model extremely complicated when we need to increase the optimization period to 10 or more seasons. The above issue could be solved by adjusting the algorithm.

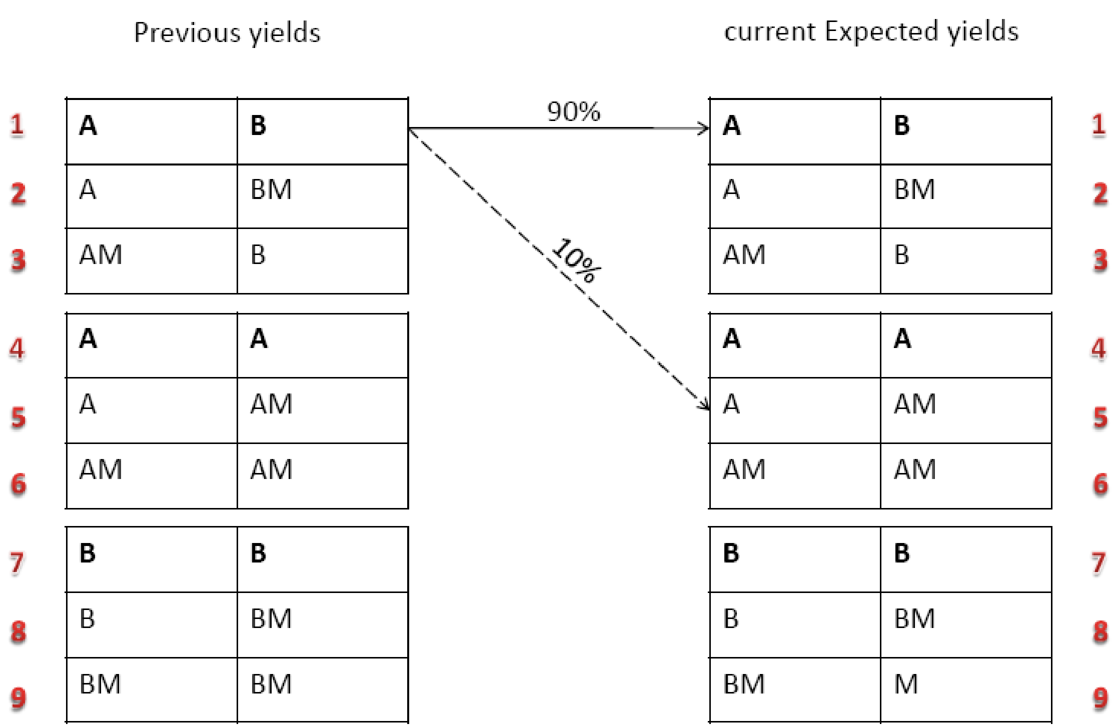

Figure 4.4. A 10% partial adjustment in A-B rotation

As indicated in Chapter 3, a crop rotation with two crops considering two-season effects has 27 scenarios (i.e., the state space has 27 elements). No matter how many parts the original plot is divided into, each part will still be one of 27 scenarios. Therefore, instead of continuing to divide the original plot and increase the number of plots from year to year, we will assign a fixed number of 27 possible plots for each season, and acres will be allocated between these 27 plots. By using this adjusted algorithm, the crop rotation model designed in Chapter 3 is now improved to be able to solve partial adjustment. This adjustment in theoretical design is motivated by the reality that producers are usually not able to conduct perfect adaptation according to constraints such as capital, machinery, or labor.

The crop rotation model developed in Chapter 3 was based on one rotation. Acres could only be allocated between the crops within a rotation. In reality, for a corn-soybeans rotation, producers could introduce cotton in the next year to switch the rotation from corn-soybeans to corn-cotton. Therefore, this design deviates from reality. To enable the crop rotation model to be able to switch between rotations, another adjustment in the algorithm was made. Suppose county i has two possible crop rotations A-B and C-D. Crop rotation A-B has 27 possible states from state ab1 to state ab27, while rotation C-D has 27 possible states from state cd1 to state cd27. From season t to season t+1, the crop rotation model results indicate that the state variable should jump from ab1 to ab10 for profit optimization. To allow acres to switch across rotations, profit for state ab10 will be compared to profit for state cd1 from rotation C-D. If state cd1 is more profitable than state ab10, acres will be allocated to state cd1 instead of ab10. This results in acres switching from rotation A-B to rotation C-D. We assume that a new rotation always has full yield without yield penalties.

County level acreage responses were obtained after simulation using crop rotation with the two improvements made above. Then aggregate acres for each crop are calculated. By combining realized acreage response with expected yield, realized total production can be generated. With an elasticity obtained from the historical relationship between crop production and crop price, realized price could be estimated. Expected yield is assumed to be the same as realized yield in this chapter. Using the above algorithms, we are able to simulate realized crop price from the acreage response results. Realized crop price was used to generate price expectations for the next season. Overall, the value for expected price, realized price and acreage response are interactively affecting each other.

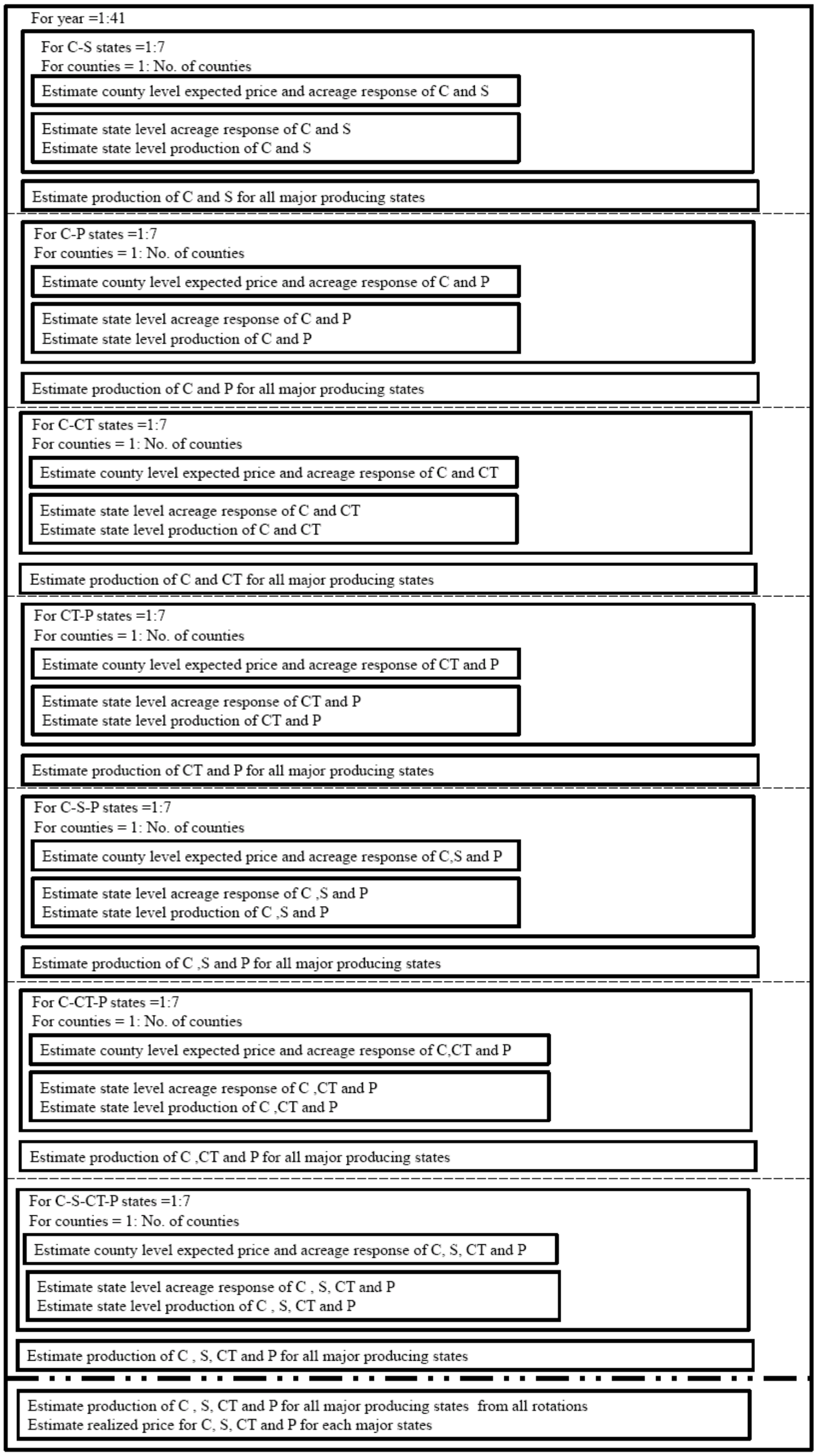

Figure 4.5. The overall algorithms for the dynamic simulation process

In this dissertation, producers' price expectations are defined as producers' expectations of realized price. We argue that producers' expectation is not equivalent to the term "expected value" in statistics. Expected value is based on a predetermined random variable. Producers' expected price is a random variable; however, it is not predetermined. It should be noted that we are not attempting to develop the price expectation model that has the best forecasting of realized price; instead, we are trying to develop producers' price expectations.

Expected price was developed as a rational expectation. Specifically, futures price and lagged cash price constitute the baseline price. Expected price could be formed as the weighted average between lagged price and futures price. This baseline price is then adjusted by yield change to reflect producers' price expectations:

$$\text{(4.8)} \qquad P_{it} = [\alpha P_{i(t-1)} + (1-\alpha)F_{it}]\left[1 + \frac{Y_{it} - Y_{i(t-1)}}{Y_{i(t-1)}}\frac{\partial P}{\partial Y}\frac{Y}{P}\right].$$

Since no peanut futures price is available, baseline expected peanut price will only be constructed by lagged price and the constraint from the loan rate. We use the loan rate as a support price. If expected price is larger than the loan rate, expected price has the formula shown by equation (4.8). If expected price is smaller than the loan rate, expected price will equal the loan rate.

Changes in crop prices result from multiple factors. One substantial factor is ending stock. Since demand is assumed to be constant, supply changes are equivalent to production change. Therefore, in this research, we use production as an indicator for crop output price. A standard multiple linear regression model is used where state level de-trended crop price is the dependent variable and total crop production from major producing states are the independent variables. To account for the effect of the farm bill in 1996 and 2002, we create dummy variables for all regression models. A log-log form of the regression model is used and elasticity is derived for each crop in each state. The estimated coefficients of the above model are denoted as price flexibilities. Price flexibilities measure the percentage change in realized price caused by a percentage change in production. Price flexibilities are used to predict realized price based on production change.

Another important part of the profit function is cost. Here, we only study variable cost and assume fixed costs do not exist. Costs are assumed to be exogenous.

4.5 Data

Price, cost, and planted acreage for corn, soybeans, cotton and peanuts were retrieved from the USDA-National Agricultural Statistical Service (NASS)[8] for the past 50 years for Minnesota, Nebraska, Illinois, Indiana, Iowa, Texas and Georgia at the county level. Crop price is the annual average price received by producers. Crop prices were deflated using the CPI for all goods and are in 2009 dollars. We assumed that harvested acreage is equal to planted acreage.

Historical futures prices were obtained from the DATASTREAM software. They are observations of the New York Mercantile Exchange (NYMEX). Futures prices for corn, cotton and soybeans were available from February 1979. Each year, the planting month's average price for the harvest month's contract was used. Futures contracts may not coincide with the timing of planting or harvest. Futures contracts for corn are available for September and December, futures contracts for soybeans are available for September and November, and futures contracts for cotton are available for October and December. The following table shows usual planting and harvesting dates for corn, soybeans, cotton and peanuts in Georgia. Based on the dates in the table and availability of futures contracts, the following futures contracts were used: average

[8] Price, cost, and planted data were retrieved from:
http://quickstats.nass.usda.gov/ (last accessed on May, 2011)

price between the September contract for corn, November contract for soybeans, and December contract for cotton. Specifically, for the September corn futures contract, we used its futures price in March. For the December cotton futures contract, we used its futures price in April. For the November soybeans futures contract, we used its futures price in May.

Table 4.1. Usual Planting and Harvesting Dates – Georgia[9]

	Usual planting dates			Usual harvesting dates		
	Begin	Most active	End	Begin	Most active	End
Corn	Mar 14	Mar 22 - Apr 21	May 4	Aug 6	Aug 16 - Sep 22	Oct 7
Soybeans	May 5	May 17 – Jun 26	Jul 5	Oct 11	Oct 25 - Dec 8	Dec 17
Cotton	Apr 23	May 2 - May 31	Jun 11	Sep 23	Oct 10 - Dec 2	Dec 18
Peanuts	Apr 27	May 6 – May31	Jun 7	Sep 15	Sep 25 - Oct 31	Nov 11

It should be noted that there is no futures contract for peanuts; therefore, we only use lagged cash price as the baseline expected price for peanuts. Also, because there is no forecasted futures price projection data available, future futures price were estimated by ARIMA.

Crop loan rates may change from one U.S. Farm Bill to another U.S. Farm Bill. Loan rates used in this research are based on the 2008 U.S. Farm Bill. In contrast to previous legislation, commodity loan rates for each year are specified in the 2008 Farm Act. The 2008 Farm Act governs U.S. agricultural programs through 2012. Table 4.2 lists national loan rates for corn, cotton, soybeans and peanuts. We noticed that loan rates from 2008 to 2012 stayed constant for all above crops. We assume that loan rates after 2012 are the same as 2012 loan rates.

[9] Data source: Usual planting and harvesting dates for U.S. field crops

Table 4.2. Historical and Current National Loan Rates

	National Loan Rates				
	Previous Farm Bill		2008 Farm Bill		
	CY 2002-03	CYs 2004-07	CY 2008	CY 2009	CYs 2010-12
Corn	$1.98/bu	$1.95/bu	$1.95/bu	$1.95/bu	$1.95/bu
Soybeans	$5.00/bu	$5.00/bu	$5.00/bu	$5.00/bu	$5.00/bu
Upland cotton	$0.52/lb	$0.52/lb	$0.52/lb	$0.52/lb	$0.52/lb
Peanuts	$355/ton	$355/ton	$355/ton	$355/ton	$355/ton

Acreage share data for crop rotations are not available. Suppose planted acreage for corn in a specific county is 10,000 acres; we will not be able to find out how many acres are in which rotation unless we conducted a survey. Therefore, we make certain assumptions about rotation acres for the baseline year.

The yield difference between rotational cropping and continuous cropping is also not available for most rotations. A corn-soybeans rotation is extremely prevalent in the Corn Belt states; therefore, we retrieve yield differences for corn-soybeans from previous empirical studies (Erickson 2008). For other less prevalent rotations, say A-B, we use the yield response level assumed as follows. There are four yield response levels for crop A given different crops combinations for the last two periods which is the same for crop B. To the best of our knowledge, agronomic results for these complicated yield response levels are not available. We therefore make several assumptions. We assume crop A after B-B has the full yield, crop A after A-B has a 5% reduction in yield, crop A after B-A has a 10% reduction in yield, crop A after A-A has a 15% reduction in yield. The same assumption was made for crop B.

We applied the dynamic model described above to assess agricultural production and profitability under three climate change scenarios developed by the USDA Forest Service (Coulson et al. 2010). These climate change scenarios were based on general circulation models driven by greenhouse gas emission scenarios documented in the Special Report on Emissions Scenarios (SRES) of the Intergovernmental Panel on Climate Change (Nakicenovic et al. 2000; IPCC 2007; Coulson et al. 2010). For our analysis, we used climate projections based on the CGCM 3.1, CSIRO 3.5, and MIROC 3.2 general circulation models and the A1B socio-economic scenario.

All three general circulation models project a warming future global climate. The MIROC 3.2 model predicts the relatively warmest future climate and the CSIRO 3.5 model predicts the relatively coolest future climate (but still warmer than the present). The CGCM 3.1 model predicts moderate warming in-between the MIROC 3.2 and CSIRO 3.5 models. The A1B scenario assumes a growing world population that peaks in the mid-century and a global economy supported by introduction of new and more efficient technologies. This scenario emphasizes balanced technological growth, which does not rely too heavily on one particular energy source (Nakicenovic et al. 2000; IPCC 2007; Coulson et al. 2010).

4.6 Results and Discussion

Price flexibilities are obtained by relating historical crop price to crop production. Flexibilities are reported in Table 4.3. As expected, crop prices have a negative response to crop production (e.g., assuming competitive markets, an increase in supply depresses market price). These generated flexibilities are then used in the dynamic simulation process to estimate realized crop prices.

Table 4.3. Price flexibilities (by crops, by states)[10]

	Corn	Soybeans	Cotton	Peanuts
MN	-0.58737	-0.92857		
IA	-0.57285	-0.91381		
NE	-0.59466	-0.92617		
IL	-0.61159	-0.90937		
IN	-0.61167	-0.91762		
GA	-0.67622	-0.88607	-0.65791	-1.09119
TX	-0.52308	-0.90069	-0.5887	-1.11486

Dynamic simulation results are reported in this section. Partial adjustment factors are varied to check the sensitivity of the simulation results. The three climate models are compared at the different partial adjustment levels: 0.0, 0.1, 0.2, 0.5, and 1.0. As noted earlier, a high level for the partial adjustment factor denotes a quicker and higher acreage response, while a low level for the partial adjustment factor denotes a slower and lower acreage response. Specific production projections for crops are reported in tables 4.4-8.8.

[10] See Table C.1 for regression statistics

Table 4.4. Crop Production with Three Climate Models-Partial Adjustment=0

	Corn[11]			Soybeans			Peanuts			Cotton		
	H[12]	M	C	H	M	C	H	M	C	H	M	C
2011	4.17	4.04	3.98	8.35	8.35	8.56	0.86	0.87	1.02	2.13	1.8	2.3
2012	4.11	4.01	4.09	8.35	8.3	8.24	0.93	0.82	0.87	2.23	1.61	2.17
2013	4.23	4.19	4.2	8.45	8.49	7.96	0.88	1.01	0.94	1.66	2.16	1.97
2014	3.9	4.04	4.38	8.01	7.96	8.2	0.87	0.72	0.8	1.82	1.97	2.33
2015	3.99	3.92	4.11	8.06	8.29	8.2	1.03	0.84	0.95	1.44	1.56	2.64
2016	4.29	3.99	4.26	8.71	8.18	8.23	0.87	0.92	0.92	2.46	1.85	2.18
2017	4.18	3.79	4.09	8.45	7.79	8.5	0.84	0.79	0.99	1.58	2.08	1.76
2018	4.04	3.99	3.83	8.53	8.08	8.08	0.83	0.92	1.04	1.58	1.78	1.67
2019	3.93	4.12	4.03	7.89	8.5	8.15	0.88	0.94	0.84	1.55	1.87	2.23
2020	4.05	3.98	3.96	8.24	8.13	7.98	0.93	0.9	0.98	2.15	1.87	2.45
2021	4.19	4.05	3.75	8.46	8.4	7.99	0.94	0.98	1.01	2.21	2.23	2.1
2022	4.22	4.12	3.94	8.71	8.27	7.94	0.91	0.78	0.95	1.63	1.83	1.82
2023	3.92	4.14	4.17	8.26	8.33	8.12	0.93	0.93	0.94	1.61	1.86	1.83
2024	3.94	4.09	3.88	8.27	8.29	8.07	0.91	0.84	0.98	1.81	2.05	1.94
2025	3.77	4.08	4.27	8.17	8.48	8.39	0.83	0.86	0.88	1.94	1.58	1.91
2026	4.01	4.1	3.96	8.24	8.52	8.09	0.82	0.94	1	1.55	1.93	2.1
2027	4.02	3.95	3.93	8.19	8.03	8.14	0.9	0.88	0.9	1.42	1.61	1.92
2028	4.02	3.85	4.1	7.94	7.85	8.19	0.91	0.88	1	1.77	1.93	1.99
2029	4.1	4.09	3.98	8.14	8.41	8.24	0.97	0.94	0.88	1.58	2.07	1.89
2030	4.03	4.2	4.31	8.34	8.5	8.66	0.84	0.9	0.88	1.68	1.87	1.8
2031	4.06	4.15	3.95	8.48	8.43	7.92	0.94	0.82	0.92	1.23	1.98	1.84
2032	3.85	4.01	4.04	8.12	8.41	8.1	0.85	0.93	0.88	1.7	2.33	2.19
2033	3.81	4.23	4.32	8.17	8.56	8.43	0.98	0.82	0.89	1.41	2.9	2.41
2034	3.95	4.07	4.44	8.22	8.28	8.3	0.81	0.84	0.91	1.89	2.07	2.04
2035	4.09	4.07	3.82	8.45	8.31	8.12	0.93	0.86	1.02	1.63	2.54	1.99
2036	3.89	3.98	4.04	8.12	8.08	8.2	0.83	0.82	0.9	2.28	2.08	1.9
2037	4.12	4.11	4.42	8.68	8.38	8.51	0.97	0.93	0.9	1.66	1.78	2.54
2038	3.9	3.99	3.91	8.17	8.26	8.44	0.83	0.93	0.97	1.85	1.5	1.84
2039	3.89	4.13	4.03	7.86	8.47	8.08	0.97	0.92	0.96	1.41	1.71	1.66
2040	4.03	4.16	3.95	8.37	8.37	8.17	0.99	0.72	0.89	1.13	2.14	2.02
2041	3.99	4.11	4.19	8.49	8.45	8.3	0.88	0.86	0.86	1.44	2.49	1.92
2042	3.92	3.95	3.97	8.2	7.82	8.02	0.85	0.93	0.9	1.87	1.5	2.17
2043	4.03	4.18	3.83	8.38	8.29	7.88	1.06	0.85	0.87	1.7	1.61	2.06
2044	3.97	3.97	4.06	8.43	8.05	8.35	0.79	0.85	0.92	1.41	1.97	2.16
2045	4.02	4.19	4.37	8.4	8.49	8.38	0.87	0.78	0.9	1.68	1.78	1.67
2046	3.87	4.04	4.41	8.32	8.35	8.8	0.82	0.85	0.86	1.01	1.8	1.83

[11] The Units for corn, soybeans, peanuts and cotton are billion bushels, hundred million bushels, billion pounds, and million pounds
[12] H, M, and C denote MIROC 3.2, CGCM 3.1 and CSIRO 3.5

Table 4.5. Crop Production with Three Climate Models-Partial Adjustment=0.1

	Corn			Soybeans			Peanuts			Cotton		
	H	M	C	H	M	C	H	M	C	H	M	C
2011	3.08	2.96	3.02	1.15	1.16	1.15	2.19	2.08	2.52	1.63	1.34	1.64
2012	3.03	2.91	3.02	1.16	1.16	1.13	2.56	2.32	2.47	1.62	1.1	1.44
2013	3.13	3.02	3.06	1.17	1.19	1.11	2.78	3.16	2.97	1.08	1.36	1.2
2014	2.78	2.83	3.19	1.14	1.15	1.15	2.4	2.08	2.19	1.24	1.33	1.49
2015	2.75	2.77	3.01	1.17	1.18	1.14	3.05	2.57	2.66	0.97	0.96	1.64
2016	2.99	2.8	3.13	1.25	1.18	1.14	2.97	2.94	2.88	1.47	1.06	1.23
2017	2.95	2.63	3.05	1.21	1.13	1.17	2.88	3.01	3.42	0.91	1.08	0.95
2018	2.88	2.75	2.77	1.21	1.19	1.13	3.01	3.41	3.86	0.81	0.87	0.84
2019	2.72	2.87	2.84	1.14	1.22	1.17	3.58	3.74	3.32	0.72	0.87	1.08
2020	2.81	2.77	2.82	1.2	1.17	1.14	3.73	3.71	3.86	0.95	0.79	1.09
2021	2.91	2.84	2.63	1.22	1.21	1.14	3.89	4.15	4.13	0.97	0.85	0.89
2022	3.01	2.89	2.72	1.24	1.19	1.15	3.99	3.75	4.23	0.66	0.67	0.72
2023	2.79	2.97	2.93	1.18	1.19	1.16	4.35	4.22	4.2	0.58	0.66	0.64
2024	2.79	2.92	2.76	1.18	1.19	1.16	4.24	4.11	4.59	0.62	0.62	0.62
2025	2.63	2.93	3.01	1.18	1.21	1.19	4.2	4.16	4.06	0.66	0.46	0.59
2026	2.78	2.95	2.88	1.2	1.21	1.15	4.24	4.52	4.69	0.53	0.58	0.55
2027	2.81	2.8	2.83	1.19	1.14	1.15	4.34	4.54	4.46	0.52	0.45	0.53
2028	2.8	2.72	2.92	1.16	1.13	1.17	4.68	4.44	4.7	0.56	0.52	0.52
2029	2.89	2.89	2.84	1.18	1.21	1.18	4.46	4.75	4.36	0.5	0.5	0.47
2030	2.87	2.97	3.06	1.19	1.22	1.23	4.65	4.53	4.59	0.58	0.46	0.49
2031	2.92	2.99	2.85	1.21	1.19	1.13	4.44	4.38	4.51	0.49	0.46	0.46
2032	2.75	2.89	2.86	1.16	1.2	1.16	4.61	4.82	4.51	0.57	0.5	0.47
2033	2.67	3.02	3.03	1.19	1.23	1.21	5.17	4.23	4.49	0.52	0.54	0.5
2034	2.74	2.91	3.2	1.21	1.19	1.18	4.38	4.56	4.72	0.65	0.4	0.42
2035	2.79	2.91	2.82	1.24	1.2	1.13	4.67	4.53	5.08	0.58	0.42	0.41
2036	2.7	2.83	2.9	1.19	1.17	1.17	4.69	4.45	4.7	0.54	0.38	0.35
2037	2.87	2.92	3.14	1.26	1.21	1.21	4.98	5.06	4.76	0.44	0.32	0.47
2038	2.72	2.85	2.85	1.19	1.18	1.18	4.56	4.49	5.02	0.49	0.3	0.35
2039	2.71	2.94	2.87	1.17	1.21	1.16	4.99	4.73	5.2	0.44	0.36	0.33
2040	2.85	2.97	2.8	1.21	1.2	1.18	5.15	4.36	4.65	0.41	0.4	0.29
2041	2.81	2.96	2.96	1.22	1.21	1.19	4.76	4.59	4.52	0.48	0.43	0.34
2042	2.77	2.82	2.83	1.19	1.13	1.15	4.67	4.82	4.63	0.54	0.29	0.36
2043	2.84	3.01	2.74	1.21	1.18	1.14	5.22	4.68	4.62	0.45	0.33	0.33
2044	2.8	2.9	2.83	1.22	1.15	1.21	4.68	4.9	4.92	0.56	0.32	0.33
2045	2.8	3.01	3.08	1.22	1.21	1.21	4.52	4.49	4.83	0.42	0.33	0.25
2046	2.72	2.93	3.21	1.21	1.2	1.24	4.7	4.76	4.97	0.48	0.38	0.25

Table 4.6. Crop Production with Three Climate Models-Partial Adjustment=0.2

	Corn			Soybeans			Peanuts			Cotton		
	H	M	C	H	M	C	H	M	C	H	M	C
2011	2.72	2.6	2.75	1.25	1.27	1.24	2.83	2.66	3.16	1.39	1.12	1.34
2012	2.83	2.7	2.79	1.22	1.23	1.2	3.37	3.08	3.24	1.32	0.85	1.08
2013	3.04	2.91	2.88	1.2	1.23	1.17	3.7	4.18	3.89	0.78	0.96	0.82
2014	2.67	2.75	3.14	1.17	1.17	1.16	2.83	2.46	2.55	1.04	1.11	1.23
2015	2.59	2.75	3.01	1.22	1.19	1.15	3.72	3.07	3.04	0.81	0.74	1.36
2016	2.9	2.78	3.13	1.28	1.19	1.15	3.68	3.59	3.42	1.1	0.79	0.93
2017	2.97	2.59	3.07	1.21	1.15	1.17	3.57	3.74	4.15	0.65	0.75	0.71
2018	2.91	2.71	2.69	1.21	1.2	1.16	3.71	4.17	4.71	0.54	0.59	0.59
2019	2.66	2.85	2.69	1.16	1.23	1.21	4.29	4.54	4.04	0.49	0.58	0.78
2020	2.72	2.76	2.74	1.22	1.18	1.17	4.44	4.47	4.56	0.59	0.48	0.76
2021	2.84	2.85	2.56	1.24	1.21	1.16	4.58	4.94	4.85	0.64	0.49	0.6
2022	3	2.86	2.62	1.24	1.2	1.18	4.66	4.42	4.94	0.46	0.39	0.46
2023	2.75	2.99	2.92	1.19	1.18	1.17	5.01	4.77	4.87	0.35	0.42	0.37
2024	2.7	2.91	2.75	1.21	1.19	1.16	4.81	4.6	5.25	0.41	0.36	0.35
2025	2.5	2.87	3.01	1.23	1.23	1.19	4.72	4.62	4.57	0.43	0.28	0.32
2026	2.65	2.89	2.92	1.24	1.23	1.14	4.7	4.97	5.17	0.4	0.42	0.28
2027	2.73	2.74	2.78	1.21	1.16	1.17	4.71	4.96	4.89	0.44	0.31	0.31
2028	2.74	2.61	2.84	1.18	1.16	1.19	5.03	4.81	5.07	0.43	0.36	0.33
2029	2.87	2.81	2.74	1.18	1.23	1.2	4.71	5.04	4.6	0.41	0.35	0.33
2030	2.86	2.91	3	1.19	1.24	1.25	4.93	4.78	4.83	0.49	0.32	0.38
2031	2.9	3	2.79	1.21	1.19	1.14	4.61	4.6	4.71	0.49	0.31	0.33
2032	2.68	2.85	2.79	1.19	1.21	1.18	4.82	4.94	4.69	0.53	0.35	0.33
2033	2.5	2.95	2.92	1.23	1.25	1.24	5.34	4.35	4.63	0.51	0.36	0.37
2034	2.55	2.83	3.25	1.26	1.21	1.16	4.47	4.7	4.86	0.62	0.29	0.31
2035	2.68	2.82	2.82	1.27	1.22	1.13	4.74	4.63	5.16	0.53	0.27	0.34
2036	2.62	2.74	2.77	1.21	1.2	1.21	4.79	4.55	4.8	0.41	0.28	0.27
2037	2.87	2.86	3.05	1.25	1.23	1.23	4.99	5.17	4.86	0.4	0.24	0.39
2038	2.67	2.79	2.75	1.2	1.2	1.21	4.59	4.56	5.11	0.44	0.24	0.3
2039	2.61	2.9	2.75	1.19	1.23	1.19	5.05	4.7	5.29	0.41	0.37	0.28
2040	2.81	2.92	2.72	1.21	1.21	1.2	5.17	4.37	4.71	0.44	0.36	0.21
2041	2.77	2.92	2.88	1.23	1.22	1.21	4.79	4.63	4.55	0.52	0.36	0.28
2042	2.65	2.7	2.78	1.22	1.17	1.17	4.68	4.88	4.65	0.57	0.26	0.29
2043	2.76	2.96	2.68	1.23	1.2	1.16	5.15	4.74	4.62	0.48	0.31	0.27
2044	2.71	2.86	2.74	1.24	1.16	1.23	4.67	4.94	4.92	0.6	0.3	0.27
2045	2.71	2.96	3.01	1.24	1.22	1.23	4.49	4.45	4.83	0.4	0.34	0.2
2046	2.62	2.87	3.26	1.24	1.21	1.22	4.59	4.73	4.98	0.5	0.41	0.19

Table 4.7. Crop Production with Three Climate Models-Partial Adjustment=0.5

	Corn			Soybeans			Peanuts			Cotton		
	H	M	C	H	M	C	H	M	C	H	M	C
2011	2.23	2.02	2.54	1.38	1.42	1.29	3.59	3.32	4.12	1.19	0.98	0.98
2012	3.05	2.85	2.5	1.16	1.18	1.27	4.51	4.16	4.37	0.97	0.54	0.56
2013	2.92	3	2.55	1.24	1.21	1.25	4.79	5.34	5.04	0.43	0.57	0.33
2014	1.77	1.99	2.91	1.43	1.37	1.22	2.3	1.97	2.08	1.23	1.27	1.54
2015	1.57	2.2	2.65	1.49	1.34	1.24	4.12	3.09	2.75	0.82	0.58	1.6
2016	2.62	2.07	2.58	1.34	1.38	1.28	4.37	4.15	3.88	0.87	0.62	0.77
2017	3.03	2.05	2.87	1.18	1.3	1.22	4.2	4.46	4.96	0.37	0.66	0.74
2018	2.45	2.2	1.96	1.34	1.33	1.37	4.27	4.81	5.63	0.37	0.55	0.55
2019	1.54	2.43	2.04	1.45	1.34	1.4	4.46	5.13	4.62	0.57	0.49	0.74
2020	1.79	2.32	2.49	1.46	1.29	1.23	4.77	4.96	4.74	0.47	0.38	0.74
2021	2.26	2.42	2.17	1.39	1.32	1.28	4.87	5.34	5.17	0.63	0.36	0.52
2022	2.77	2.07	2.09	1.29	1.4	1.32	4.96	4.67	5.31	0.53	0.28	0.26
2023	1.85	2.49	2.51	1.43	1.32	1.27	5.26	4.51	5.17	0.36	0.4	0.27
2024	1.52	2.31	2.31	1.53	1.36	1.28	4.92	4.53	5.46	0.48	0.39	0.25
2025	1.42	2.25	2.55	1.52	1.39	1.3	4.84	4.68	4.65	0.41	0.27	0.22
2026	1.81	2.25	2.45	1.45	1.4	1.26	4.71	5.07	5.1	0.48	0.56	0.3
2027	1.99	2.17	1.99	1.39	1.32	1.39	4.6	5.02	4.93	0.64	0.32	0.43
2028	2.04	1.95	2.22	1.35	1.33	1.35	5.01	4.9	5.01	0.58	0.36	0.52
2029	2.05	2.39	2.31	1.38	1.33	1.31	4.57	4.93	4.38	0.56	0.35	0.49
2030	1.86	2.41	2.74	1.45	1.37	1.31	4.96	4.73	4.77	0.66	0.28	0.46
2031	1.78	2.5	2.23	1.52	1.33	1.28	4.56	4.61	4.64	0.71	0.26	0.33
2032	1.56	2.08	2	1.48	1.43	1.4	4.87	4.62	4.65	0.65	0.42	0.42
2033	1.29	2.2	2.2	1.55	1.45	1.42	5.31	4.33	4.62	0.7	0.38	0.57
2034	1.71	2.2	3.39	1.48	1.38	1.12	4.38	4.78	4.88	0.81	0.33	0.36
2035	2.13	2.25	2.39	1.39	1.38	1.26	4.7	4.64	5	0.65	0.27	0.44
2036	1.82	2.07	1.74	1.41	1.37	1.49	4.84	4.52	4.86	0.59	0.4	0.32
2037	1.86	2.33	2.24	1.52	1.36	1.44	4.83	5.15	4.94	0.71	0.32	0.5
2038	1.25	2.08	1.97	1.57	1.39	1.42	4.67	4.52	5.12	0.6	0.42	0.33
2039	1.33	2.32	2.07	1.5	1.38	1.38	5.18	4.45	5.32	0.56	0.62	0.27
2040	2.11	2.35	1.92	1.38	1.36	1.42	5.14	4.38	4.74	0.69	0.41	0.31
2041	1.83	2.36	2.05	1.47	1.37	1.41	4.84	4.79	4.46	0.74	0.27	0.43
2042	1.41	1.78	1.95	1.52	1.4	1.38	4.68	5.05	4.57	0.68	0.22	0.38
2043	1.43	2.45	1.83	1.58	1.33	1.38	4.99	4.84	4.58	0.62	0.32	0.43
2044	1.38	2.28	2.05	1.59	1.3	1.4	4.69	4.95	4.95	0.83	0.36	0.31
2045	1.41	2.38	2.18	1.57	1.36	1.42	4.5	4.24	4.85	0.56	0.52	0.33
2046	1.47	1.97	3.15	1.54	1.46	1.25	4.28	4.63	5.02	0.66	0.56	0.3

Table 4.8. Crop Production with Three Climate Models-Partial Adjustment=1

	Corn			Soybeans			Peanuts			Cotton		
	H	M	C	H	M	C	H	M	C	H	M	C
2011	3.35	2.37	3.62	1.05	1.32	0.94	5.76	5.37	6.07	0.42	0.41	0.2
2012	4.07	4.18	2.72	0.89	0.81	1.26	5.13	4.86	4.95	0.62	0.19	0.14
2013	4.77	3.98	4.6	0.68	0.92	0.69	4.89	5.27	5.01	0.14	0.45	0.17
2014	2.84	2.69	5.23	1.17	1.24	0.57	0	0	0	1.94	2	2.86
2015	3.49	3.78	3.51	0.97	0.88	1.03	5.85	4.03	3.16	0.64	0.09	1.28
2016	5.08	2.94	3.88	0.62	1.16	0.93	5.09	5.05	5.11	0.54	0.47	0.29
2017	4.08	3.06	4.77	0.91	1.05	0.68	4.33	4.7	5.48	0.06	0.67	0.75
2018	3.32	3.06	2.15	1.09	1.1	1.37	4.31	4.87	5.9	0.64	0.4	0.51
2019	2.3	3.77	3.62	1.29	0.96	0.96	3.85	5.25	4.56	0.87	0.36	0.41
2020	4.85	3.22	4.37	0.59	1.08	0.72	5.09	5.02	4.13	0.13	0.26	0.91
2021	3.9	3.14	2.05	0.98	1.12	1.37	4.92	5.27	5.53	0.72	0.35	0.45
2022	4.07	2.86	2.47	0.91	1.2	1.22	5.04	4.72	5.53	0.57	0.05	0
2023	3.16	4.47	4.56	1.11	0.8	0.73	5.27	3.68	5.21	0.18	0.46	0.34
2024	3.51	2.87	2.61	0.99	1.2	1.21	4.77	4.99	5.35	0.67	0.49	0.23
2025	3.29	2.67	2.37	1.05	1.31	1.39	4.91	4.93	4.58	0.21	0.24	0.07
2026	3.18	3.41	3.65	1.09	1.11	0.91	4.6	5.1	4.87	0.47	0.69	0.44
2027	4.16	2.77	2.61	0.81	1.19	1.27	4.49	5.03	5.13	0.85	0.3	0.71
2028	3.64	2.6	2.85	0.96	1.19	1.22	5.12	4.95	4.86	0.48	0.34	0.68
2029	3.51	3.41	2.71	1	1.06	1.21	4.37	4.65	4.15	0.59	0.37	0.51
2030	3.74	3.22	3.02	0.95	1.18	1.26	5.13	4.8	4.96	0.51	0.18	0.63
2031	3.79	3.21	2.5	0.96	1.16	1.25	4.45	4.73	4.65	0.89	0.44	0.17
2032	2.84	2.59	2.23	1.16	1.31	1.36	4.96	4.07	4.64	0.62	0.42	0.57
2033	2.7	3.07	2.75	1.18	1.21	1.28	5.4	4.58	4.66	0.72	0.34	0.64
2034	3.63	2.87	5.26	1.04	1.2	0.64	4.21	4.91	4.91	0.89	0.34	0.36
2035	3.98	3.06	1.68	0.87	1.18	1.53	4.78	4.52	4.68	0.57	0.21	0.54
2036	2.66	2	1.39	1.21	1.41	1.6	5.01	4.62	5.14	0.31	0.44	0.32
2037	3.56	3.72	4.06	1.04	0.95	0.97	4.94	5	4.89	0.7	0.31	0.56
2038	2.92	2.75	2.02	1.13	1.26	1.42	4.88	4.37	5.02	0.43	0.55	0.28
2039	3.02	2.45	2.1	1.1	1.34	1.42	5.28	4.24	5.36	0.64	0.82	0.19
2040	3.47	3.34	2.8	1	1.11	1.2	4.89	4.73	4.76	0.85	0.3	0.47
2041	3.14	3.22	2.13	1.14	1.14	1.4	4.84	5.04	4.27	0.8	0.28	0.5
2042	2.34	1.62	2.4	1.32	1.48	1.28	4.68	5.04	4.43	0.53	0.23	0.33
2043	3.82	3.98	2.05	0.95	0.94	1.35	4.74	4.78	4.79	0.77	0.68	0.32
2044	2.76	2.85	2.5	1.22	1.15	1.28	4.83	4.86	5.05	0.62	0.43	0.16
2045	2.82	2.85	2.08	1.24	1.25	1.45	4.48	3.88	4.86	0.47	0.67	0.46
2046	2.69	2.48	4.21	1.23	1.37	0.98	3.7	4.88	5.06	0.78	0.48	0.24

Major observations with respect to the dynamic simulation results are discussed in this section. At the partial adjustment level of zero, no significant production trend could be observed for all four crops, since production is exclusively driven by crop yields. Under any nonzero partial adjustment levels, aggregate corn production decreased over the next 40 years, while aggregate soybeans production increased over the next 40 years. Aggregate peanuts production increased over the next 40 years, while aggregate cotton production decreased over the next 40 years under all three climate scenarios.

Due to the negative effect of increases crop production (e.g., supply) on prices, the realized prices have the opposite trend for each crop. Increased production induces decreased realized prices, while decreased crop production induces increased realized prices. However, the changes in production and prices are in fact mostly caused by an initial difference of profitability between the crops in the baseline year, which is considerably larger than the effects of climate change. Therefore, the effects of climate change are investigated by comparing three future climate scenarios instead of comparing past and future. Specifically, we compare the results between the warmest scenario (MIROC 3.2) and the coldest scenario (CSIRO 3.5). We also compare the results under different partial adjustment levels in order to investigate the role of farm adaptation.

Compared to CSIRO 3.5, the warmer MIROC 3.2 scenario predicts low corn production, while it predicts high soybean production under low partial adjustment levels for the most of next 40 years. These results are expected since corn and soybeans are strong substitute crops for the Corn Belt states. These results also indicate that the MIROC 3.2 scenario is likely to decrease corn production more than soybeans production in the future.

Compared to the relatively cooler CSIRO 3.5 scenario, the warmer MIROC 3.2 scenario predicts lower production for both cotton and peanuts at the zero partial adjustment level, indicating the adverse effects of global warming. However, at the partial adjustment levels of 0.1 and 0.2 where farm adaptations are allowed, the MIROC 3.2 scenario predicts higher production for both cotton and peanuts. This result can be explained as follows. Due to the decreased corn and soybean yields in the southern states and the no agricultural land use change assumption, producers switch land from corn and soybeans to cotton and peanuts which raises cotton and peanuts production under the MIROC 3.2 scenario.

High partial adjustment level results in extremely unstable crop production, while a low partial adjustment level results in relatively stable crop production. It could be explained that a producer with a quicker and higher acreage response will switch more acres from year to year in order to optimize overall profits, thus creating unstable production from year to year. All crops have the characteristic that production increases or decreases for the first several years, and then gets to a relatively stable state. It is also observed that a high partial adjustment factor makes crop production go to this relatively stable state more quickly.

Revenue per acre from several representative counties are reported in figures 4.6-4.11: revenue per acre for corn from a northern county and a southern county; revenue per acre for soybeans from a northern county and a southern county; revenue per acre for cotton from a southern county; and revenue per acre for peanuts from a southern county. Furthermore, we construct Climate Change Impact Index (CCII) for revenue per acre which is similar to the one used in Chapter 2, but using revenue per acre instead of yields. Table 4.9 shows the results of CCII for revenue per acre for selected northern and southern states. The results show that the northern states have a lower CCII value compared to the southern states in terms of corn and soybeans. The results also indicate that corn and soybeans' revenue per acre generally display a mild decrease due to predicted global climate change in the northern U.S. states studied, and a relatively more pronounced negative effect in the southern U.S. states studied. These results are very similar to the yield results using a static model reported in Chapter 2.

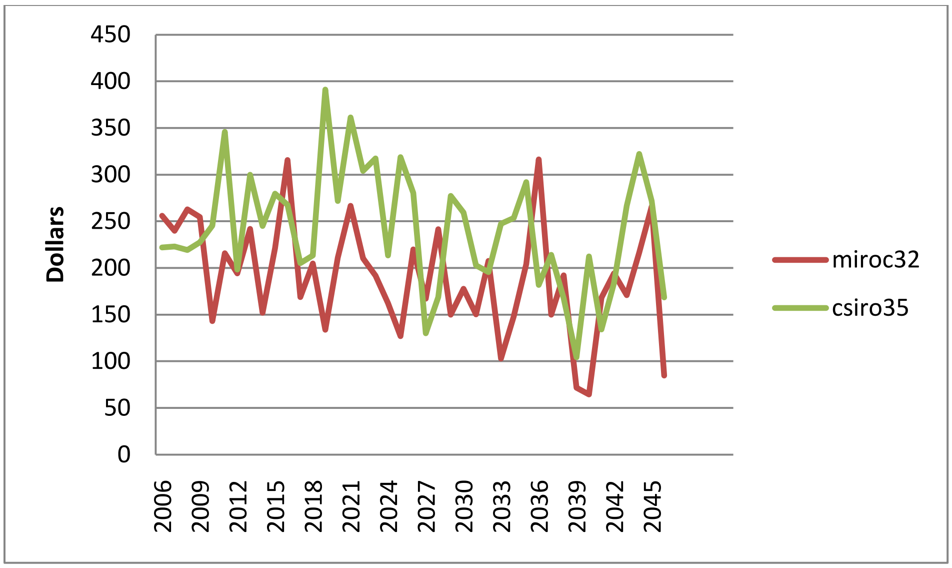

Figure 4.6. Revenue per acre for Corn, Bulloch County, Georgia

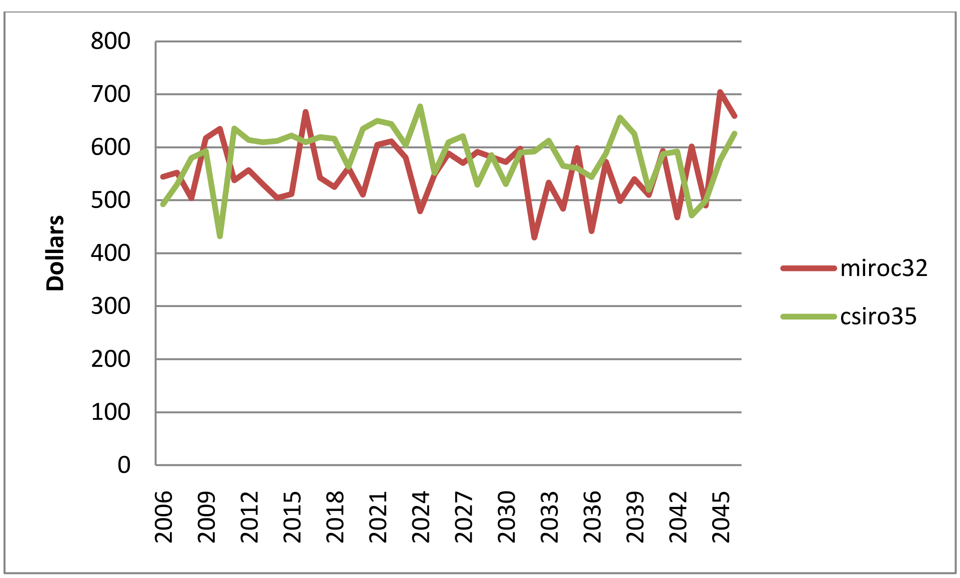

Figure 4.7. Revenue per acre for Corn, Benton County, Iowa

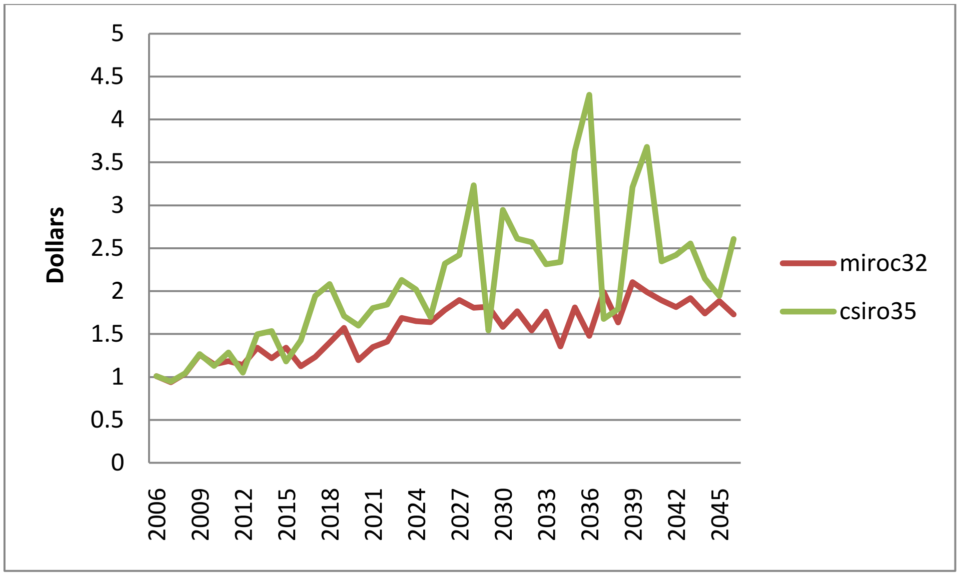

Figure 4.8. **Revenue per acre for Cotton, Worth county, Georgia**

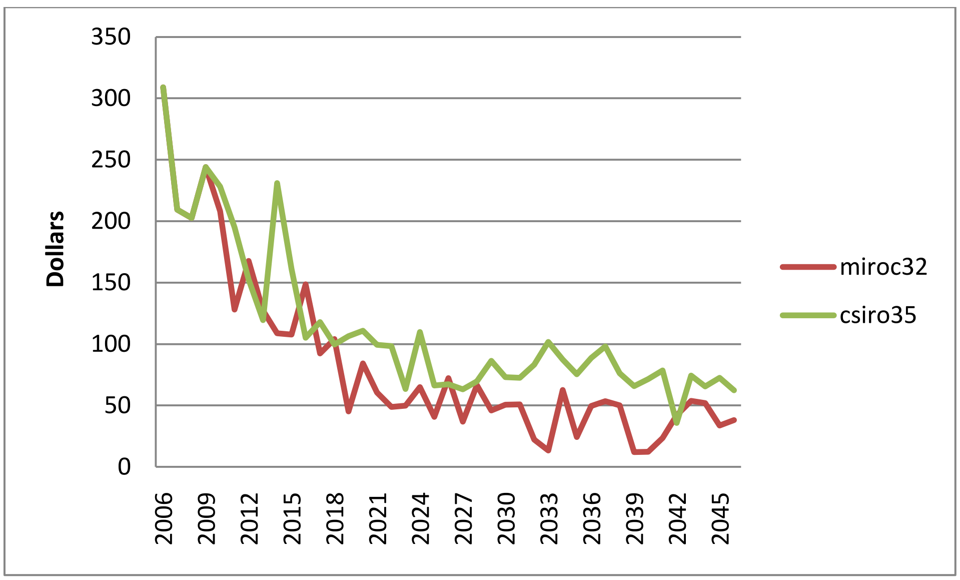

Figure 4.9. **Revenue per acre for Peanuts, Decatur county, Georgia**

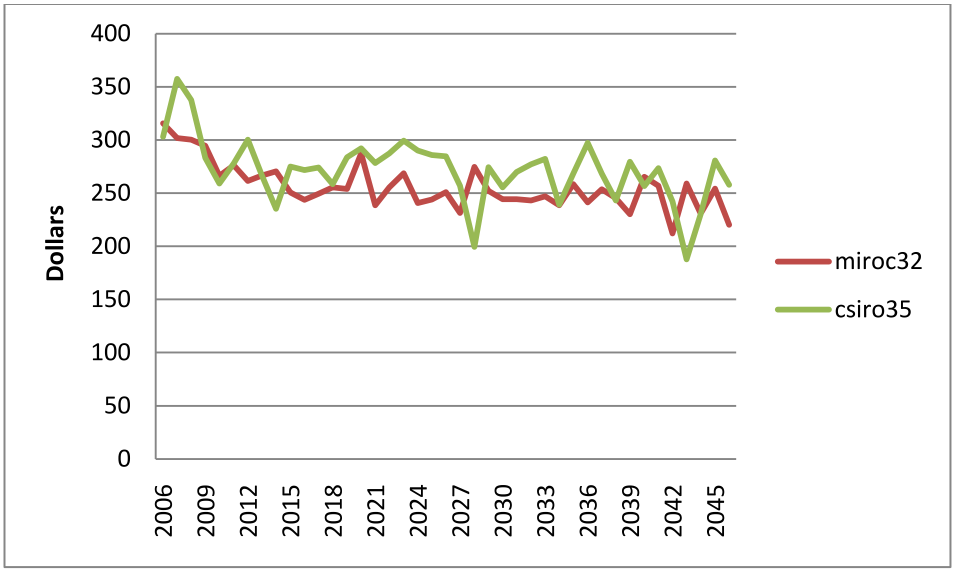

Figure 4.10. Revenue per acre for Soybeans, Yellow Medicine county, Minnesota

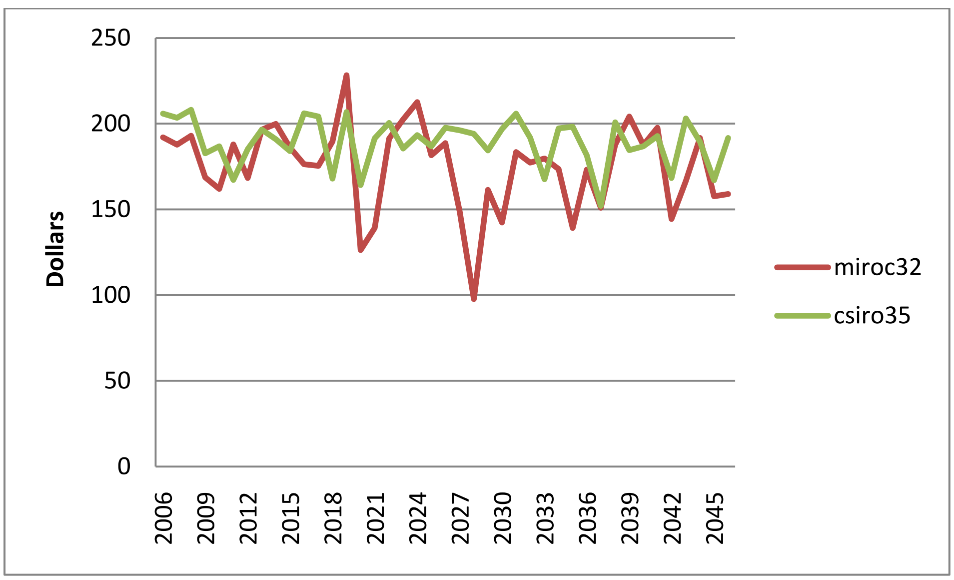

Figure 4.11. Revenue per acre for Soybeans, Appling county, Georgia

The results reported in Table 4.9 also show the unresponsiveness of the CCII to a change in the partial adjustment level. The results indicate that, although producers respond by reallocating acreage, a warmer climate scenario still generates lower profitability compared to a cooler climate scenario for Georgia. In this research, acreage response is assumed to be the only adaptation practice employed by farmers. Therefore, based on our simulation results, acreage response alone is not able to fully offset the adverse effects of climate change. Other adaptation options such as fertilizer adjustments and changing planting dates should be considered by farmers in order to better adapt to possible future climate change scenarios.

Tables 4.10-4.12 show the CCII derived by comparing total revenues for which varied yield penalties are considered. The results indicate that the CCII are not sensitive to the change of yield penalty. The CCII increase with the increasing partial adjustment factors for most of the states, which indicates that CSIRO 3.5 outperforms MIROC 3.2 more when producers increase acreage response. Tables 4.13-4.15 show the differences for total revenues between CSIRO 3.5 and MIROC 3.2. The results indicate that average total revenues over next 40 years for MIROC 3.2 are higher than that of CSIRO 3.5 for the southern states, while the same relationships are not observed for the northern states.

Table 4.9. Climate Change Impact Index for Profitability (by states, by crops)

Crops		Corn	Soybeans	Cotton	Peanuts
State	Partial Adjustment				
	0	0.42	0.43		
MN	0.1	0.42	0.44		
	0.2	0.42	0.44		
	0.5	0.79	0.91		
	0	0.50	0.48		
IA	0.1	0.49	0.51		
	0.2	0.48	0.50		
	0.5	0.04	0.94		
	0	0.46	0.52		
NE	0.1	0.45	0.54		
	0.2	0.44	0.54		
	0.5	0.81	0.89		
	0	0.49	0.56		
IL	0.1	0.49	0.58		
	0.2	0.49	0.58		
	0.5	0.77	0.92		
	0	0.50	0.54		
IN	0.1	0.49	0.56		
	0.2	0.50	0.56		
	0.5	0.77	0.92		
	0	0.55	0.58	0.68	0.49
TX	0.1	0.54	0.60	0.74	0.44
	0.2	0.56	0.59	0.63	0.58
	0.5	0.75	0.88	0.80	0.88
	0	0.58	0.63	0.80	0.47
GA	0.1	0.57	0.66	0.73	0.44
	0.2	0.57	0.64	0.80	0.57
	0.5	0.78	0.90	0.83	0.83

Table 4.10. Climate Change Impact Index[13] for Total Revenue with Yield Penalty =0.025 (by states, by crops)

State	Partial Adjustment	Corn	Soybeans	Cotton	Peanuts	Overall
MN	0	0.39	0.29			0.32
	0.1	0.56	0.15			0.44
	0.2	0.59	0.10			0.46
	0.5	0.68	0.85			0.78
IA	0	0.56	0.37			0.51
	0.1	0.83	0.20			0.68
	0.2	0.80	0.17			0.59
	0.5	0.63	0.90			0.80
NE	0	0.39	0.66			0.39
	0.1	0.49	0.46			0.59
	0.2	0.44	0.49			0.51
	0.5	0.51	0.90			0.80
IL	0	0.56	0.78			0.68
	0.1	0.41	0.93			0.63
	0.2	0.46	0.93			0.56
	0.5	0.51	0.95			0.76
IN	0	0.49	0.66			0.51
	0.1	0.61	0.61			0.59
	0.2	0.54	0.51			0.51
	0.5	0.41	0.93			0.80
TX	0	0.56	0.71	0.98	0.49	0.56
	0.1	0.73	0.24	0.73	0.10	0.73
	0.2	0.71	0.32	0.44	0.07	0.71
	0.5	0.83	0.56	0.66	0.17	0.83
GA	0	0.83	0.71	0.95	0.51	0.78
	0.1	0.98	0.83	0.98	0.24	1.00
	0.2	0.98	0.80	0.56	0.17	1.00
	0.5	0.95	0.93	0.78	0.17	0.93

[13] Climate Change Impact Index represents the percentage of the number of years for which MIROC 3.2 generates lower revenue compared to CSIRO 3.5 over 40 years.

Table 4.11. Climate Change Impact Index for Total Revenue with Yield Penalty =0.05 (by states, by crops)

Crops		Corn	Soybeans	Cotton	Peanuts	Overall
State	Partial Adjustment					
MN	0	0.39	0.29			0.32
	0.1	0.39	0.24			0.39
	0.2	0.46	0.22			0.37
	0.5	0.85	0.88			0.90
IA	0	0.56	0.37			0.51
	0.1	0.80	0.17			0.68
	0.2	0.80	0.15			0.61
	0.5	0.80	0.95			0.93
NE	0	0.39	0.66			0.39
	0.1	0.46	0.54			0.56
	0.2	0.46	0.63			0.56
	0.5	0.83	0.95			0.85
IL	0	0.56	0.78			0.68
	0.1	0.44	0.90			0.68
	0.2	0.46	0.88			0.66
	0.5	0.73	0.95			0.88
IN	0	0.49	0.66			0.51
	0.1	0.56	0.63			0.56
	0.2	0.54	0.54			0.51
	0.5	0.73	0.93			0.90
TX	0	0.56	0.71	0.98	0.49	0.56
	0.1	0.73	0.39	0.73	0.15	0.76
	0.2	0.76	0.29	0.44	0.10	0.73
	0.5	0.83	0.63	0.54	0.17	0.85
GA	0	0.83	0.71	0.95	0.51	0.78
	0.1	1.00	0.80	0.95	0.12	0.98
	0.2	1.00	0.78	0.56	0.07	1.00
	0.5	0.95	0.98	0.46	0.20	0.90

Table 4.12. Climate Change Impact Index for Total Revenue with Yield Penalty =0.10 (by states, by crops)

Crops		Corn	Soybeans	Cotton	Peanuts	Overall
State	Partial Adjustment					
MN	0	0.39	0.29			0.32
	0.1	0.51	0.17			0.39
	0.2	0.54	0.24			0.41
	0.5	0.93	0.76			0.90
IA	0	0.56	0.37			0.51
	0.1	0.80	0.17			0.66
	0.2	0.73	0.12			0.63
	0.5	0.93	0.90			0.93
NE	0	0.39	0.68			0.39
	0.1	0.49	0.59			0.61
	0.2	0.54	0.56			0.66
	0.5	0.93	0.95			0.95
IL	0	0.56	0.78			0.68
	0.1	0.37	0.90			0.63
	0.2	0.37	0.88			0.61
	0.5	0.88	0.93			0.98
IN	0	0.49	0.66			0.51
	0.1	0.51	0.68			0.51
	0.2	0.46	0.73			0.56
	0.5	0.85	0.95			0.95
TX	0	0.56	0.71	0.98	0.49	0.56
	0.1	0.73	0.46	0.88	0.34	0.76
	0.2	0.73	0.49	0.68	0.73	0.73
	0.5	0.98	0.78	0.27	0.12	0.98
GA	0	0.83	0.71	0.95	0.51	0.78
	0.1	0.98	0.80	0.95	0.32	1.00
	0.2	0.98	0.85	0.71	0.41	1.00
	0.5	1.00	0.90	0.39	0.17	1.00

Table 4.13. Difference[14] in Total Revenue between MIROC 3.2 (Warmest) and CSIRO 3.5 (Coolest) Climate Change Scenarios with Yield Penalty = 0.025 (by states, by crops)

Crops		Corn	Soybeans	Cotton	Peanuts	Overall
State	Partial Adjustment	Billion Dollars	Billion Dollars	Hundred Thousand Dollars	Ten Million Dollars	Billion Dollars
MN	0	-0.034	-0.041			-0.076
	0.1	0.015	-0.061			-0.047
	0.2	0.029	-0.078			-0.050
	0.5	0.061	0.317			0.378
IA	0	0.013	-0.020			-0.007
	0.1	0.128	-0.060			0.068
	0.2	0.143	-0.086			0.057
	0.5	0.192	0.552			0.744
NE	0	-0.020	0.027			-0.019
	0.1	0.004	-0.036			0.000
	0.2	-0.008	-0.007			-0.009
	0.5	0.002	0.203			0.201
IL	0	0.007	0.051			0.067
	0.1	-0.065	0.098			0.033
	0.2	-0.049	0.080			0.031
	0.5	-0.031	0.443			0.412
IN	0	0.018	0.026			0.045
	0.1	0.041	0.011			0.052
	0.2	0.039	0.002			0.042
	0.5	-0.043	0.395			0.352
TX	0	0.003	0.000	1.976	0.023	0.004
	0.1	0.045	-0.002	0.617	-0.063	0.043
	0.2	0.053	-0.001	-0.040	-0.080	0.052
	0.5	0.050	0.001	0.097	-0.069	0.051
GA	0	0.003	0.001	0.762	0.053	0.005
	0.1	0.029	0.001	0.196	-0.312	0.027
	0.2	0.032	0.001	0.012	-0.476	0.028
	0.5	0.011	0.002	0.075	-0.304	0.010

[14] Difference is the revenue for CSIRO 3.5 minus the revenue for MIROC 3.2.

Table 4.14. Difference in Total Revenue between MIROC 3.2 (Warmest) and CSIRO 3.5 (Coolest) Climate Change Scenarios with Yield Penalty = 0.05 (by states, by crops)

Crops		Corn	Soybeans	Cotton	Peanuts	Overall
State	Partial Adjustment	Billion Dollars	Billion Dollars	Hundred Thousand Dollars	Ten Million Dollars	Billion Dollars
	0	-0.034	-0.041			-0.075
MN	0.1	-0.026	-0.042			-0.068
	0.2	-0.017	-0.049			-0.066
	0.5	0.200	0.273			0.473
	0	0.012	-0.019			-0.007
IA	0.1	0.130	-0.066			0.064
	0.2	0.121	-0.067			0.054
	0.5	0.451	0.498			0.950
	0	-0.019	0.027			-0.019
NE	0.1	-0.005	0.035			-0.002
	0.2	-0.009	0.071			-0.002
	0.5	0.978	1.699			0.268
	0	0.006	0.050			0.056
IL	0.1	-0.032	0.077			0.049
	0.2	-0.014	0.067			0.047
	0.5	0.159	0.369			0.528
	0	0.018	0.026			0.044
IN	0.1	0.041	0.087			0.045
	0.2	0.037	0.098			0.053
	0.5	0.103	0.327			0.430
	0	0.056	0.001	0.601	-0.580	0.057
TX	0.1	0.049	-0.001	0.597	-0.576	0.047
	0.2	0.059	-0.002	0.029	-0.780	0.057
	0.5	0.056	0.001	0.601	-0.580	0.057
	0	0.003	0.001	0.754	0.051	0.005
GA	0.1	0.003	0.001	0.184	-0.328	0.022
	0.2	0.003	0.001	0.010	-0.443	0.024
	0.5	0.002	0.002	0.000	-0.390	0.017

Table 4.15. Difference in Total Revenue between MIROC 3.2 (Warmest) and CSIRO 3.5 (Coolest) Climate Change Scenarios with Yield Penalty = 0.10 (by states, by crops)

Crops		Corn	Soybeans	Cotton	Peanuts	Overall
State	Partial Adjustment	Billion Dollars	Billion Dollars	Hundred Thousand Dollars	Ten Million Dollars	Billion Dollars
MN	0	-0.033	-0.039			-0.073
	0.1	-0.012	-0.049			-0.061
	0.2	-0.002	-0.055			-0.057
	0.5	0.204	0.052			0.255
IA	0	0.011	-0.019			-0.008
	0.1	0.119	-0.060			0.059
	0.2	0.117	-0.062			0.054
	0.5	0.436	0.119			0.555
NE	0	-0.019	0.026			-0.018
	0.1	-0.007	0.077			0.001
	0.2	-0.001	0.064			0.005
	0.5	0.107	0.052			0.158
IL	0	0.005	0.049			0.054
	0.1	-0.040	0.078			0.038
	0.2	-0.039	0.080			0.040
	0.5	0.199	0.132			0.331
IN	0	0.017	0.026			0.042
	0.1	0.008	0.026			0.034
	0.2	0.002	0.029			0.031
	0.5	0.149	0.099			0.247
TX	0	0.003	0.000	0.187	0.019	0.004
	0.1	0.041	0.000	0.918	-0.149	0.041
	0.2	0.044	0.000	0.456	0.126	0.044
	0.5	0.078	0.001	-0.036	-0.316	0.078
GA	0	0.003	0.001	0.732	0.045	0.005
	0.1	0.002	0.001	0.150	-0.094	0.024
	0.2	0.003	0.001	0.015	-0.002	0.028
	0.5	0.003	0.001	-0.028	-0.194	0.024

4.7 Conclusions

This Chapter assesses the effects of climate change on agricultural profitability. A basic farm-level profit function includes input and output prices, crop yields, and crop acreage. Crop yields directly impact profit. Crop yields also indirectly influence profit by influencing crop prices and acreage. The yields from multiple crops grown were expected to show a combined effect on a farmer's acreage response. Motivated by these connections, a dynamic simulation approach was developed in this chapter

To apply the crop rotation model developed in Chapter 3, two improvements were made. First, partial adjustment is allowed; second, acreage switching between rotations is allowed. These two improvements greatly improved the crop rotation model and allowed it to be able to address more practical issues. A dynamic approach, motivated by POLYSYS, was used to simulate agricultural profitability in several northern and southern U.S. states. Realized prices for crops were generated under crop yield shocks derived from the three climate models. This realized price was used to calculate a producer's profitability instead of price expectations. The results indicate that global warming will generate lower profitability in the southern U.S. states even when producers' adaptation practices such as acreage response is considered. Thus, our results suggest that acreage response alone is not sufficient to ameliorate the potential negative effects of global climate change on agricultural production and profitability. Predicted climate change is more likely to pose a problem for agricultural production and profitability in southern U.S. states as compared to northern U.S. states. This result is consistent with the expectation that a probable impact of global climate change, should it occur as predicted, would be to shift some cropping patterns from the southern U.S. to the northern U.S.

Our model and results provide farmers in different regions of the country with useful guidance for future planting decisions under uncertain weather and economic conditions. Our results also suggest that federal and state governments can help reduce the potential negative effects of predicted climate change on agricultural production and profitability by facilitating farmer response to changing weather patterns; for example, by providing up-to-date, localized climate change predictions that farmers can use to develop crop yield, price and acreage expectations.

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Appendix C

Table C.1. Regression Results for Production Elasticities of Price (by states, by crops)

		Corn	Soybeans	Cotton	Peanuts
	elasticity	-0.58737	-0.92857		
MN	standard error	0.20149	0.16481		
	p-value	0.0069	<.0001		
	adjusted R-square	0.2054	0.5146		
	elasticity	-0.57285	-0.91381		
IA	standard error	0.20156	0.16506		
	p-value	0.0083	<.0001		
	adjusted R-square	0.1962	0.5055		
	elasticity	-0.59466	-0.92617		
NE	standard error	0.19648	0.16144		
	p-value	0.0053	<.0001		
	adjusted R-square	0.2196	0.5239		
	elasticity	-0.61159	-0.90937		
IL	standard error	0.18283	0.15894		
	p-value	0.0024	<.0001		
	adjusted R-square	0.26	0.5225		
	elasticity	-0.61167	-0.91762		
IN	standard error	0.18682	0.15921		
	p-value	0.0028	<.0001		
	adjusted R-square	0.251	0.5263		
	elasticity	-0.52308	-0.90069	-0.5887	-1.11486
TX	standard error	0.18364	0.17525	0.13773	0.30691
	p-value	0.0081	<.0001	0.0002	0.0011
	adjusted R-square	0.197	0.467	0.3732	0.296
	elasticity	-0.67622	-0.88607	-0.65791	-1.09119
GA	standard error	0.17572	0.1676	0.13078	0.3262
	p-value	0.0006	<.0001	<.0001	0.0024
	adjusted R-square	0.3226	0.4817	0.456	0.26

Table C.2. Comparing Total Acres and Acres Used in Simulation (by states, by crops)[15]

		Corn	Soybeans	Cotton	Peanuts
MN	Total Acres	7300000	6900000		
	Used Acres	4475000	3777200		
	Used/Total Ratio	61.30%	54.74%		
IA	Total Acres	12800000	10050000		
	Used Acres	8180800	6549500		
	Used/Total Ratio	63.91%	65.17%		
NE	Total Acres	8500000	4700000		
	Used Acres	4559000	3154000		
	Used/Total Ratio	53.64%	67.11%		
IL	Total Acres	12100000	9500000		
	Used Acres	4917000	3613000		
	Used/Total Ratio	40.64%	38.03%		
IN	Total Acres	5900000	5400000		
	Used Acres	3982600	3591500		
	Used/Total Ratio	67.50%	66.51%		
TX	Total Acres	2030900	258100	5950000	262700
	Used Acres	389600	41800	2365500	180800
	Used/Total Ratio	19.18%	16.20%	39.76%	68.82%
GA	Total Acres	270000	176400	1216600	755000
	Used Acres	144000	87150	849900	454800
	Used/Total Ratio	53.33%	49.40%	69.86%	60.24%

[15] This table demonstrates that the portion of acres that actually used in the analysis compared to the total acres. The unit is Acres. These are acres in the year 2005 which is the baseline year of the analysis.

CHAPTER 5

SUMMARY AND CONCLUSIONS

5.1 Summary and Conclusions

This dissertation assesses the effects of climate change on agricultural production and profitability. A basic farm-level profit function includes input and output prices, crop yields, and crop acreage. Crop yields directly impact profit. Crop yields also indirectly influence profit by influencing crop prices and acreage. The yields from multiple crops grown were expected to show a combined effect on a farmer's acreage response. Motivated by these connections, a dynamic simulation approach was developed in this dissertation.

In Chapter 2, a historical relationship between weather and crop yields was estimated using a Principal Components Regression (PCR) model. Three General Circulation Models (GCMs) under the IPCC SRA1B emissions scenario were incorporated into the estimated PCR model to predict crop yields through 2050. The PCR model were applied to corn, cotton, peanuts and soybeans at the county-level in eight northern and southern U.S. states who are major producers of these crops. Predicted yield results indicated that future climate change is likely to shift corn and soybeans pattern northwards.

In Chapter 3, a crop rotation model was developed as the transition function of a modified Bellman Equation. MATLAB was used to program the model. The rotation model dynamically connects expected profits with acreage response, and it became an essential part for the dynamic simulation approach in Chapter 4.

In Chapter 4, to apply the crop rotation model developed in Chapter 3, two improvements were made. First, partial adjustment is allowed; second, acreage switching between rotations is allowed. These two improvements greatly improved the crop rotation model and allowed it to be able to address more practical issues. A dynamic approach, motivated by POLYSYS, was used to simulate profits in several northern and southern U.S. states. Realized prices for crops were generated under crop yield shocks derived from the three general circulation climate models. A farmer's profitability calculation should use this realized price instead of price expectations. The results indicate that global warming would generate lower profitability in the southern U.S. states even when producers' acreage response is considered. Thus, our results suggest that acreage response alone is not efficient to ameliorate the potential negative effects of global climate change on agricultural production and profitability. These results support our assertion that previous climate change studies which do not include farmer adaptation likely overestimate the potential negative effects of global climate change on the agricultural sector.

Our results indicate that crop yields generally show a mild decrease due to predicted global climate change in the northern U.S. states studied, and a relatively more pronounced negative effect in the southern U.S. states studied, where warm temperatures and periodic drought already pose significant constraints to crop production. For most of the states studied, the reduction in crop yields due to climate change resulted in reduced farm profitability.

Predicted climate change is more likely to pose a problem for agricultural production and profitability in southern U.S. states as compared to northern U.S. states. This result is consistent with the expectation that a probable impact of global climate change, should it occur as predicted, would be to shift some cropping patterns from the southern U.S. to the northern U.S.

Our model and results provide farmers in different regions of the country with useful guidance for future planting decisions under uncertain weather and economic conditions. Our results also suggest that federal and state governments can help reduce the potential negative effects of predicted climate change on agricultural production and profitability by facilitating farmer response to changing weather patterns; for example, by providing up-to-date, localized climate change predictions that farmers can use to develop crop yield, price and acreage expectations.

5.2 Limitation and Future Research

The approaches used in this dissertation research do have certain limitations. Climate change projections include an increased likelihood of both floods and droughts which will make U.S. agriculture increasingly unstable and make it difficult for U.S. agricultural producers to make a profit. For the PCR model, only temperature and precipitation were included as weather conditions, while these extreme events which could have huge impacts on agriculture were ignored.

Because extreme weather events do not have a monthly value, it is difficult to combine extreme weather events with temperature and precipitation into the PCR model. For future research, a PCR model correctly including extreme weather events would be a great improvement.

For the crop rotation model, the interaction between fertilizer input and crop yields were not included. We assumed producers' only response option is crop rotation. However, in actual crop planting decisions, producers could change the input of fertilizer and pesticide, while simultaneously making a change in crop rotations. In future research, the crop rotation model could be modified by adding in fertilizer and pesticide input assumptions and responses. Although the crop rotation model was improved to allow switching between rotations, no new crop varieties are allowed in the acreage response. This limitation is not due to the constraints of the crop rotation model; rather, we did not allow new crop varieties since we did not have values for their respectable crop yields.

Because climate change may affect various sectors of the economy directly or indirectly, interactions between different sectors should be included in future studies to assess the entire effects of climate change on agriculture. However, the dynamic simulation process in Chapter 4 only addresses the direct effects of climate change.

This dissertation research also greatly depends on current government programs. For future research, if there are changes in government programs, the approach developed in this dissertation may have to be revised.