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Assessing the Effects of Climate Change on Farm Production and Profitability: Dynamic Simulation Approach

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Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2011 AAEA & NAREA Joint Annual Meeting, Pittsburgh, Pennsylvania, July 24-26, 2011

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Abstract

In this paper, a dynamic optimization model was developed to simulate how farm-level realized price and profitability respond to yield change which was induced by climate change. Producers' acreage response was included in the dynamic model considering crop rotation effect. In the crop rotation model, a modified Bellman equation was used to dynamically optimize the net present value of farm profit for a five-year interval. This simulation process was repeated through the year 2050. Then yield, price, and acreage response were compiled to generate realized profit. Results generally indicated that reduction in crop yields due to climate change results in reduced farm profitability for most of the states studied. Predicted climate change is more likely to pose a problem for agricultural production and profitability in the southern U.S. states as compared to the northern U.S. states. 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.

The results of this research are expected to provide a foundation for future related research to aid producers' crop rotation decisions in an unstable price environment.

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

Introduction and Background

In this paper, predicted crop yields and the crop rotation model are incorporated into a dynamic process to simulate farm profit response considering farmers' adaptation practices. We assume that acreage response is the only adaptation practice that producers used to adapt to climate change.

Previous studies have developed different kinds of 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 Halt 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 usually do not show climate change effects. Thus, the numerical simulation approach is used in this study. Compared to empirical acreage response models estimated in previous studies, relatively less work has been using the simulation approach. Our model focuses on how acreage allocation responds to profit expectations.

Price expectation is one of the major factors deciding producers' acreage responses. Producers develop expected prices at the beginning of a planting season, while realized prices won't be revealed until harvest time. Even for well-educated producers who can consider most relevant information, expected prices are still likely to deviate from realized prices.

In previous studies, many approaches have been used to construct expected prices. In the early studies, 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 price. An obvious limitation with using lagged prices is missing current market information. Gardner (1976) used futures price to develop expected price. Futures prices are determined by the interaction of the expected supply and demand for a commodity. Futures price is the market's expectation of actual price. Many researchers believe that futures price is an appropriate proxy for price expectation, since an efficient futures market should provide an unbiased estimate of the actual price at contract maturity (Just and Rausser 1981; Thomson, McNeill, and Eales 1990; Kastens, Jones, and Schroeder 1998). Overall, futures price is thought to be the best measure of actual price.

However, futures price is a national-based price, and local information is missing. Local price variation might deviate from national futures price. As a result, many researchers used "basis" to adjust futures price 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 delivery date. Basis tends to be more stable or predictable than either current price or futures price.

Basis is used by many researchers with the purpose to predict local price from 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 further adjusted by a state-specific, 5-year average basis. Tronstad and Bool (2010) calculated expected price using the December futures price in February plus the 'November state basis' to incorporate state level supply and

demand conditions. They also incorporated the expected loan deficiency payment (LDP) into the basis value to capture the effect of government price support programs on expected prices for the producer. However, since the difference between the nation and a local area could change with future climate change, basis could also change under climate change in long-run. Therefore, it is inappropriate to use a presumably constant basis in climate change studies. As a result, we do not use basis to offset this drawback of futures price in this study.

Another drawback of using futures price as an agricultural price expectation is the timing issue. Futures price is the best estimate during planting months of what realized price will be during harvest months. However, futures price 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 price and harvest month realized price could be observed.

Alternatively, price expectations can be developed using the rational expectations model. The rational expectations 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 are 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.

In this paper, a rational expectation model was used. We assume that producers adjust their price expectations according to changes in relevant information. Base expected price was the weighted average between lagged price and futures price. This base price will be improved by considering yield change which was induced by climate change.

Some researchers consider government policies as constraints for price expectations. Government subsidizes producers to stabilize their incomes. 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, we focus on commodity loans which we expect to have direct impact on producers' expected price.

The mechanism for the federal commodity loan program is briefly described as follows. Producers may receive a commodity loan from the government 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 (LDP), which is the difference between the loan rate and the repayment rate. The LDP was first authorized by the U.S. Congress in 1985. 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 LDP encourages producers to sell their crops on the market (Westcott and Price 2001).

Overall, the commodity loan program provides benefits to producers through LDP or loan gains when the loan repayment rate is less than the loan rate. Therefore, effective expected prices are simply the loan rate if the expected price is lower than the loan rate. In this paper, we assume the loan rates to be the effective support prices for corn, soybeans, cotton and peanuts.

Figure 1 illustrates the relationship between the loan rate, LDP, and additional loan gain. Additional loan gain could be obtained when cash price is higher than the repayment rate.

When crop prices are below loan rates, LDP or loan gains could affect acreage response. On the other hand, when loan rates are below crop prices, acreage response could also be affected since loan rates truncate the expected price distribution which reduces the risk for risk averse producers, although this effect could be negligible when the loan rate is much lower than the market price (Lin et al. 2000). Although a full range adjustment may maximize profit, most producers still do partial adjustments in acreage response hinged by both risk perceptions and adaptation ability.

Behavioral researches indicate that producers' responses to planting decisions are greatly influenced by risk perceptions (Xu et al. 2005). Many previous acreage response studies include risk effects (Just 1975; Thompson and Abbott 1982; Holt and Chavas 2002). We argue that actual risk effects should be considered as the joint effects of both risk and risk perceptions. Variance of profit is usually used as a proxy for risk.

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). A risk aversion coefficient represents the marginal rate at which an investor is willing to sacrifice expected return in order to lower variance by one unit. Risk aversion can be categorized into three types: risk averse, risk neutral and risk loving. Generally, a risk averse producer prefers higher profit with low variance (Anderson et al. 1977).

To simplify the analysis, we use values between zero and one to represent risk perceptions. A risk averse producer has a coefficient of risk close to one, while a risk loving producer has a coefficient of risk close to zero. We assume 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). Therefore, we include another coefficient to penalize monocropping.

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 out 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 we use realized price in this study which is affected by acreage response, we also need to set up a relationship between realized price and acreage response. 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 a study of climate change, it is important to consider how changes in production (supply) impact price, since climate change mostly affects supply rather than demand.

Edwards (1985) studied how Georgia crop prices are affected by Georgia crop yield. The covariance between Georgia crop yield and Georgia output price were studied. Edwards (1985) found that prices of corn, cotton, soybeans and peanuts respond to changes in crop yield. We argue that Georgia crop prices are not just affected by overall crop production instead of crop yields. Furthermore, Georgia prices of crops are determined globally, not locally, so the key is the effect of climate on global production. Although a global model would be needed to predict how climate changes would affect crop yields, we have limited information and data to predict

crop supplies in other countries. Besides, a global study includes complex general equilibrium considerations, which are well beyond the scope of this research. Thus, we only consider major producing states production of U.S. instead of global production in this research.

As noted earlier, most previous acreage response studies focused on estimating empirical models based on historical data. The purpose of these studies is usually identifying and weighing major determinants of acreage response. However, in this study, we want to focus on the impact of climate change. It is hard to separate the effects of climate change on acreage response in an empirical model based on historical data. Also, due to changes of various factors in both the natural environment and policy arena, past relationship between climate change and acreage response may not hold in the future. Besides, producers' crop rotation data are not available which makes including crop rotation in empirical modeling difficult. Failing to include crop rotation in the model could lead to misspecification since crop rotation is an important agronomic consideration. Empirical econometric models estimated from historical data also have a limited ability to explain how producers respond. Due to the above reasons, we conduct acreage response analysis using a numerical simulation approach.

The Policy Analysis System (POLYSYS) model is an agricultural policy simulation model. POLYSYS simulates the impacts of policy, economic or environmental change on the agricultural sector (Ray et al. 1998). Using baseline projections from the U.S. Department of Agriculture (USDA), Food and Agriculture Policy Research Institute (FAPRI), or the U.S. Congressional Budget Office (CBO), POLYSYS simulates deviations from the baseline due to exogenous shocks. Using a linear programming (LP) supply framework and facilitating the interaction of demand, supply, and income modules, POLYSYS can be used to analyze allocation of cropland (Ugarte et al. 2003).

Specifically, based on expected prices, the POLYSYS supply module estimates planted and harvested acres, yields, and production costs as maximizing returns. Then the aggregate of production for 305 regions results in national crop production, and together with ending stock and imports provides an estimate of national supply. Supply is then fed into a demand module to generate the market-clearing price. The market-clearing price is then recursively fed into the LP models to solve for planted and harvested acres for the following year and the simulation process continues through the year 2005. 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. The models determines market-clearing prices by adjusting the baseline numbers by multiplying the percentage change in total use by the revised price flexibilities estimated by USDA Economic Research Service (ERS) analysts.

The approach used in this research is similar to the simulation process of POLYSYS. Regional acreage was obtained from expected price, and then regional production was aggregated to national production to obtain the clearing price. However, our study differs in that we relate expected price to acreage via a crop rotation model instead of acreage-price elasticities, and we estimate the market-clearing price from price flexibilities which measure how price responds to production change instead of a demand change. In POLYSYS, the relationship between price and demand was derived from a historical trend. The elasticity of acreage response to price was also derived from a historical trend.

The studies of 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. The Multinomial Logit (MNL) framework was used in their

research to analyze crop selection. However, this model was not built in a dynamic optimization framework; therefore, it is unable 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 the revenue impact on crop area allocation into separate average and variance contributions for both price and yield, yield and price were assumed to be independent. We argue that it is inappropriate to assume the independence between yield and price if we want to study how weather affects yield and price, since aggregate yield change does affect local price through the effect of supply. Furthermore, rotational effects were only captured by using lagged acreage in their study.

A dynamic optimization approach was conducted for our acreage response analysis using a crop rotation model. The fundamental idea of dynamic programming is that the multiple periods' maximization problems are reduced to a sequence of two period problems, in which the producer faces the need to balance an immediate reward with expected future rewards. The dynamic model has obvious advantages over static models of exogenous variables where producers' adaptation practices could not be fully investigated.

Methodology

Equation (1) presents a basic farm-level profit function which includes input and output prices, crop yields and crop acreage.

$$\pi = \mathrm{PAY} - \mathrm{CA} \tag{1}$$

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 (2) represents an objective function considering only one year, and we will extend it to a multi-year form later.

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

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 (3) represents the overall objective function for maximizing present value of profit for period T:

$$\text{(3)} \qquad \text{Max}\{\sum_{i=1}^{N} [\Psi_{i1} + \frac{\Psi_{i2}}{1+\tau} + \cdots + \frac{\Psi_{iT}}{(1+\tau)^T}]\}$$

where

$$\text{(4)} \qquad \Psi_i = \sum_{i=1}^{N} a_i * [\Pi_i - \theta * V(\Pi_i)] - \delta \sum_{i=1}^{N} (\frac{a_i}{A})^2$$

The detail formula for parameters in equation (4) is as follows:

$$\text{(5)} \qquad \Pi_i = P_i Y_i - C_i$$

$$\text{(6)} \qquad V(\Pi_i) = (EP_i)^2 V(Y_i) + (Y_i)^2 V(EP_i) + V(Y_i) V(EP_i)$$

$$\text{(7)} \qquad V(EP_{it}) = 0.5\left[EP_{i(t-1)} - P_{i(t-1)}\right]^2 + 0.33\left[EP_{i(t-2)} - P_{i(t-2)}\right]^2 + 0.17[EP_{i(t-3)} - P_{i(t-3)}]^2.$$

Figure 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

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 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 paper. 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 3.

The crop rotation model developed by Cai et al. (2000a) 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 by Cai et al. (2011a). As described by Cai et al. (2011a), 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 by Cai et al. (2011a) transferred the input of expected profits to the output acreage response. Therefore, in this paper, 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 original acres to be reallocated as shown in figure (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.

As indicated by Cai et al. (2011a), 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 by Cai et al. (2011a) 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 by Cai et al. (2011a) 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 paper. 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.

In this study, 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 foresting 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:

$$P_{it} = [\alpha P_{i(t-1)} + (1-\alpha)F_{it}]\left[1 + \frac{Y_{it}-Y_{i(t-1)}}{Y_{i(t-1)}}\frac{\partial P}{\partial Y}\frac{Y}{P}\right]. \quad (8)$$

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 (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.

Data

Yield, price, cost and harvested acreage for corn, soybeans, cotton and peanuts were retrieved from the USDA-National Agricultural Statistical Service (NASS) 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 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.

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 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.

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 3 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).

Results and Discussion

Price flexibilities are obtained by relating historical crop price to crop production. Flexibilities are reported in Table 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.

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 4-8.

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 low partial adjustment level results in a 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.

Crop profitability from several representative counties are reported in figures 6-11: corn profitability from a northern county and a southern county; soybeans profitability from a northern county and a southern county; cotton profitability from a southern county; and peanuts profitability from a southern county. Furthermore, we construct Climate Change Impact Index (CCII) for profitability which is similar to the one used in Cai et al. (2011b), but using profitability instead of yields. Table 9 shows the results of CCII for profitability for selected northern and southern states. The results show that the northern states have a lower CCII value compared to a southern state (Georgia) in terms of corn and soybeans (profitability for Texas was not simulated). The results also indicate that corn and soybeans' profitability 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 profitability results are very similar to the yields results using a static model reported in Cai et al. (2011b).

The results reported in Table 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.

Conclusions

This paper 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 for this study.

To apply the crop rotation model developed by Cai et al. (2011a), 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 profitabilities in several northern and southern U.S. states. Realized prices for crops were generated under crop yield shocks derived from the three climate models. A producer's profitability calculation uses this realized price 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 the southern U.S. states as compared to the 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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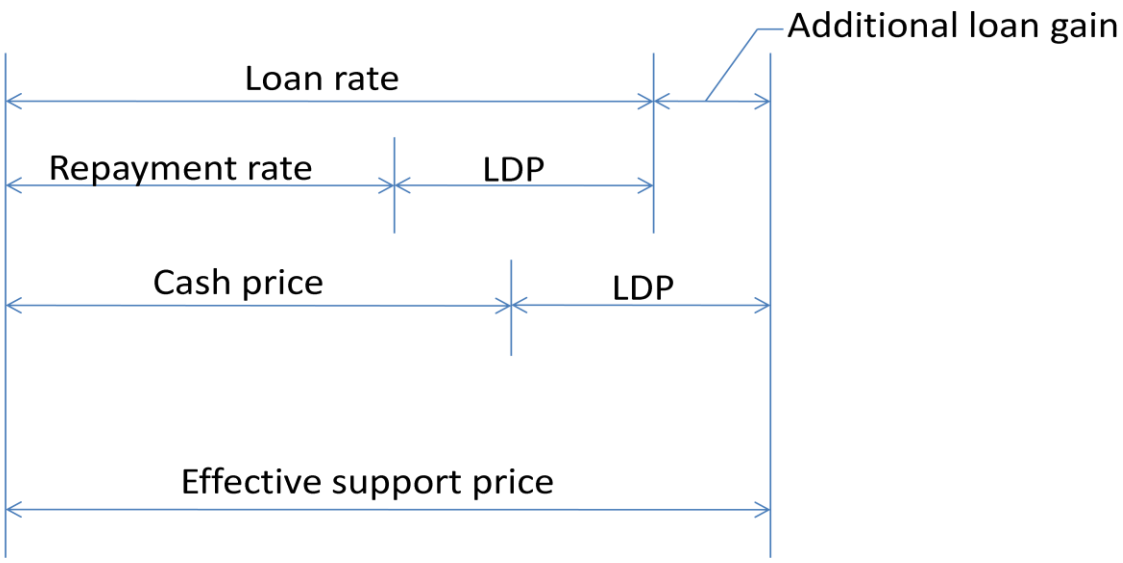

Figure 1. The relationship between the loan rate, LDP and effective support price

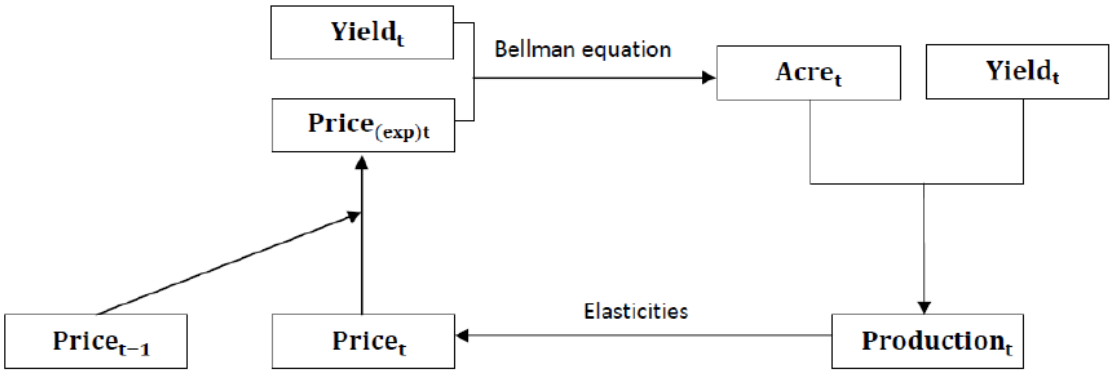

Figure 2. A basic dynamic simulation process

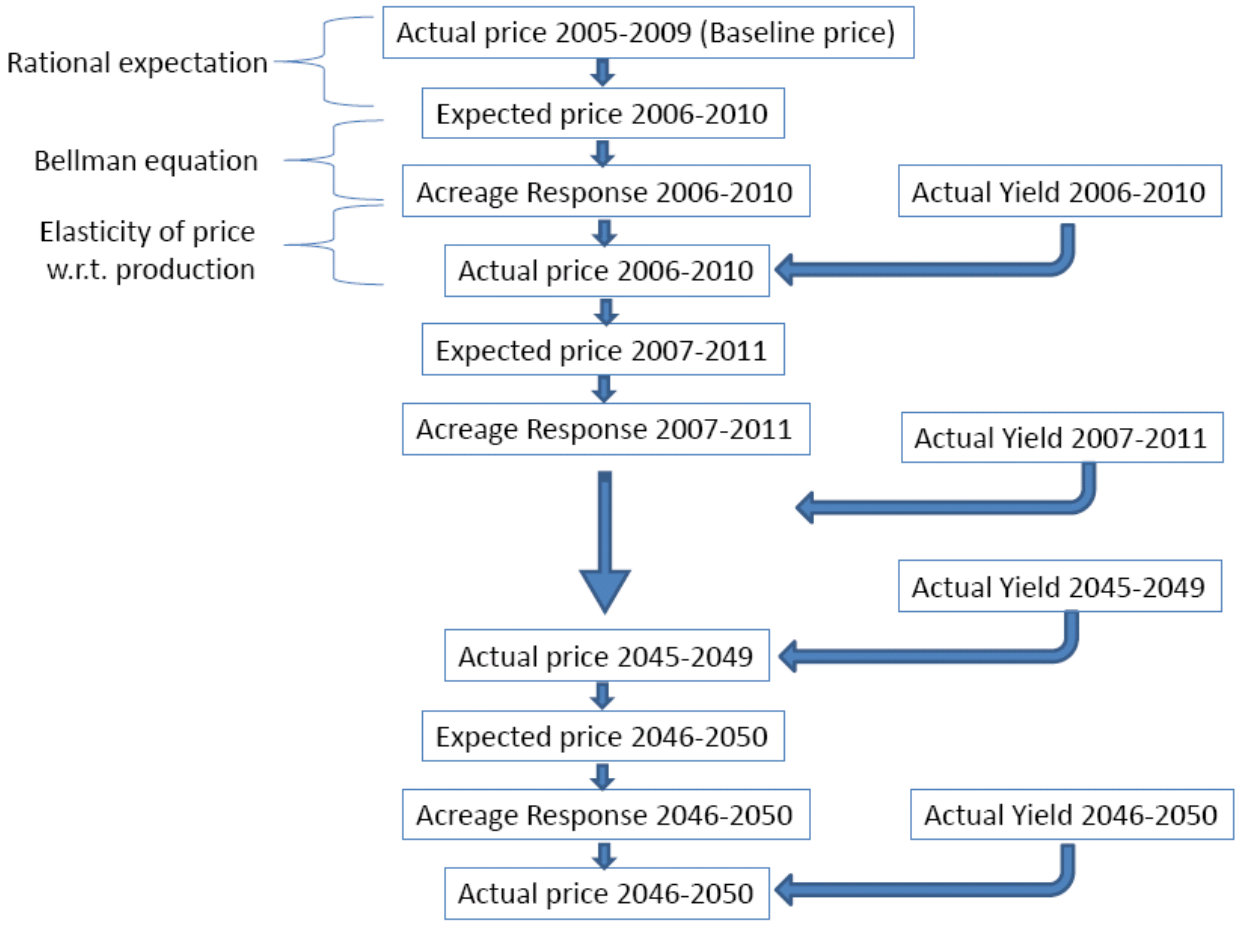

Figure 3. The dynamic simulation process illustrated with specific years

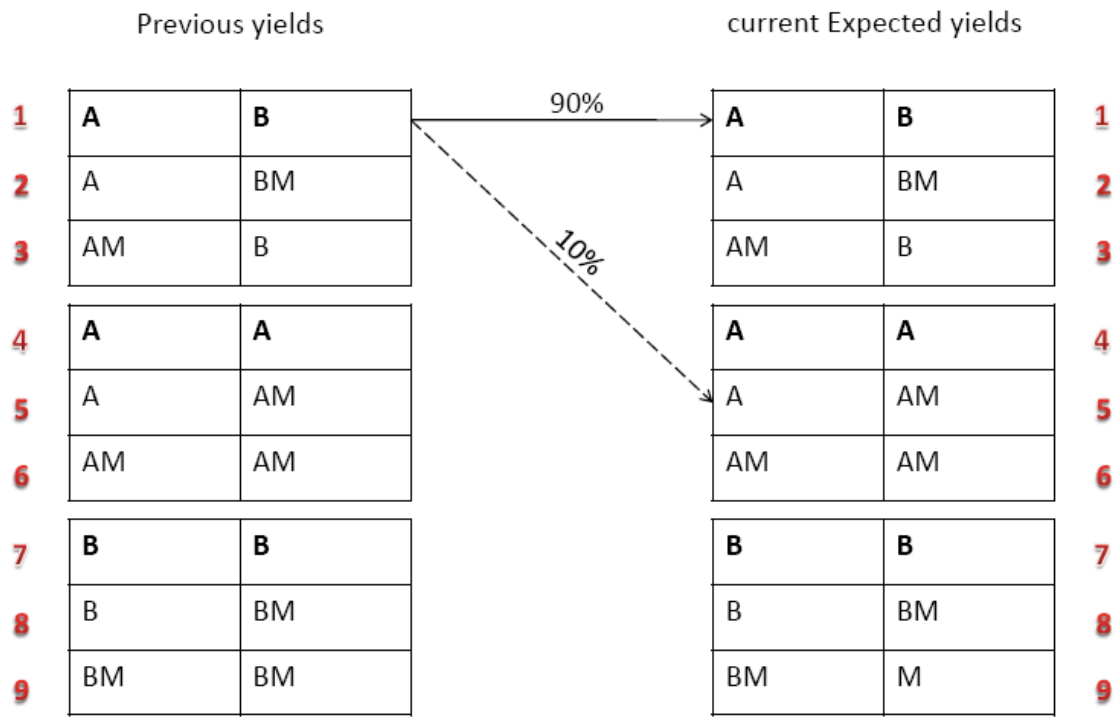

Figure 4. A 10% partial adjustment in A-B rotation

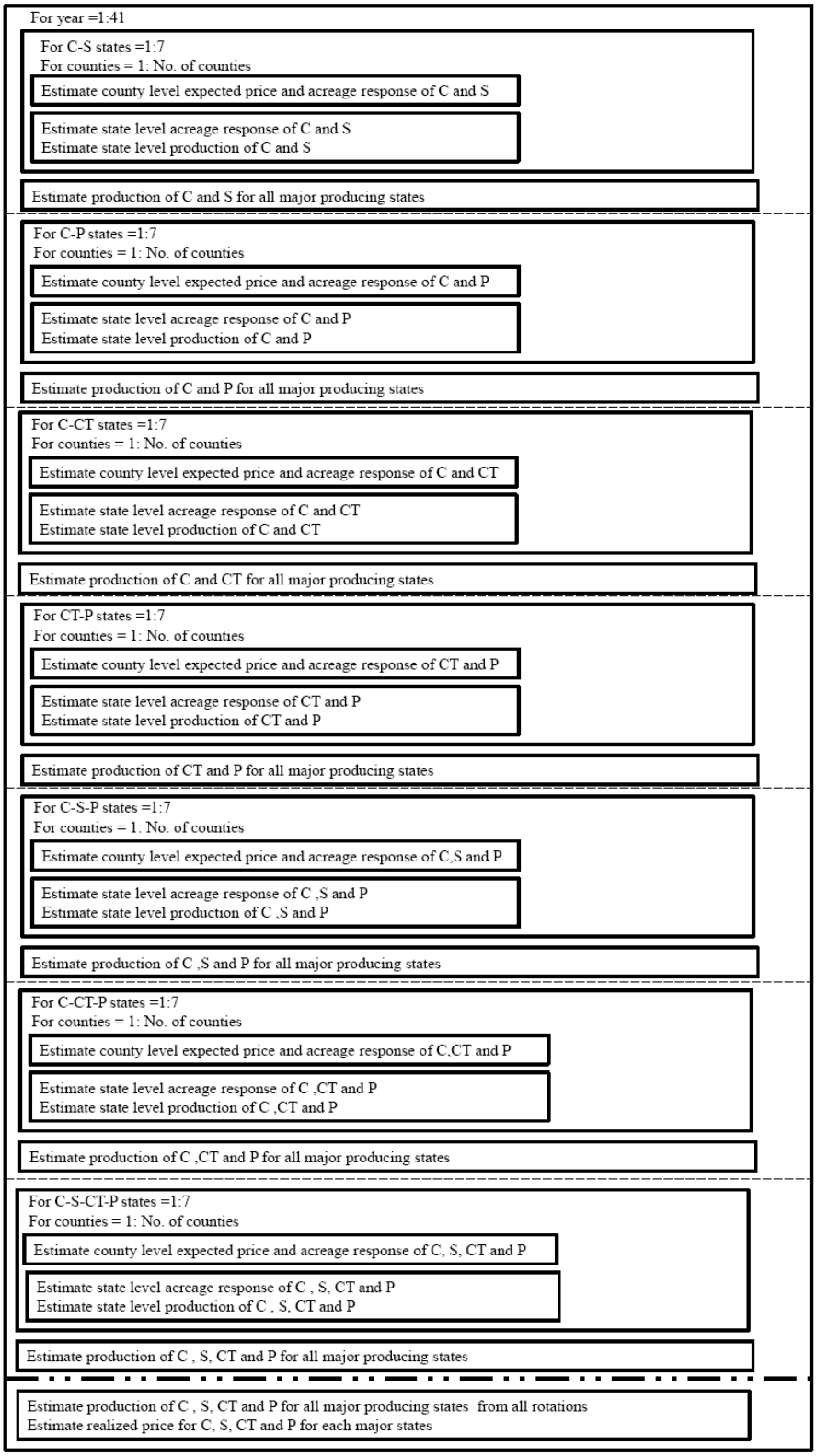

Figure 5. The overall algorithms for the dynamic simulation process

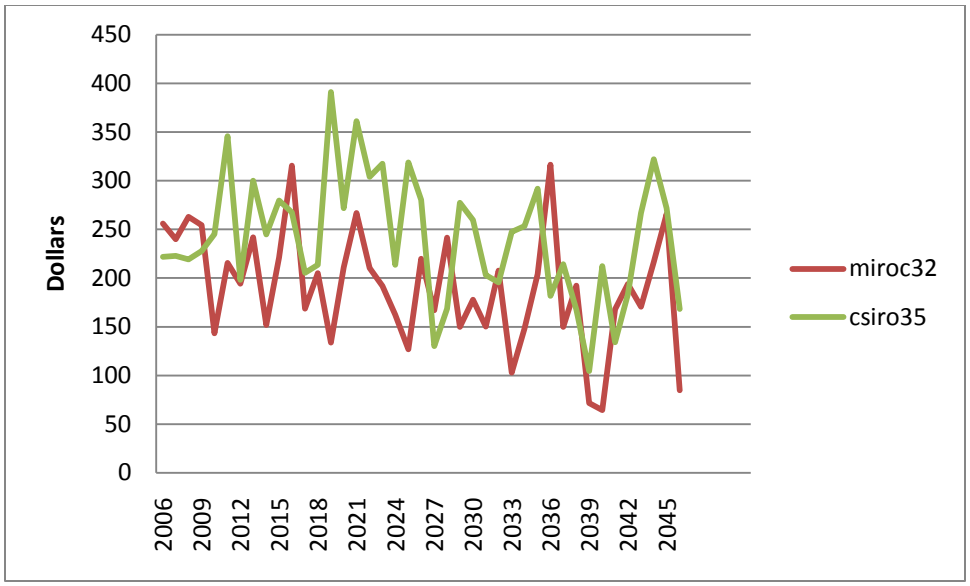

Figure 6. Corn profitability, Bulloch County, Georgia

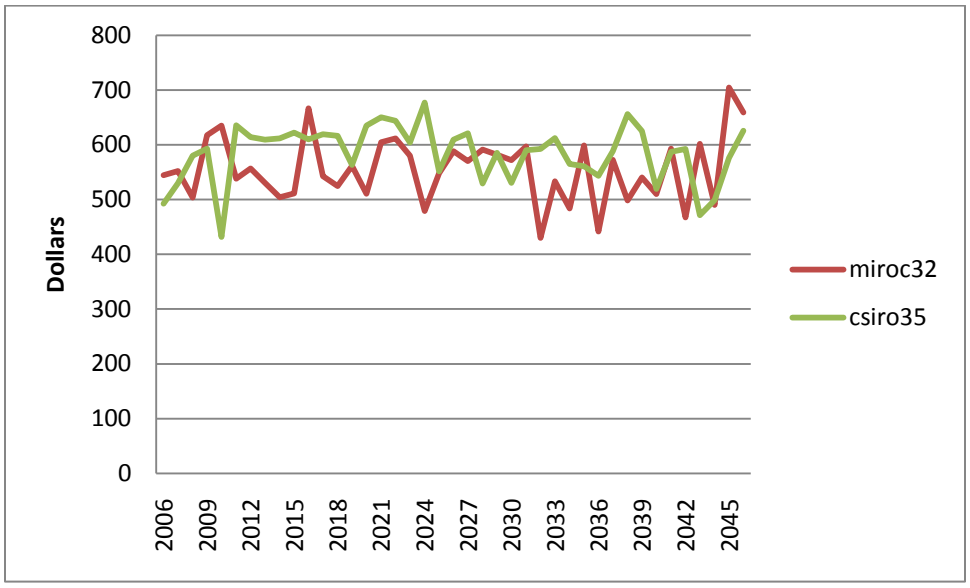

Figure 7. Corn profitability, Benton County, Iowa

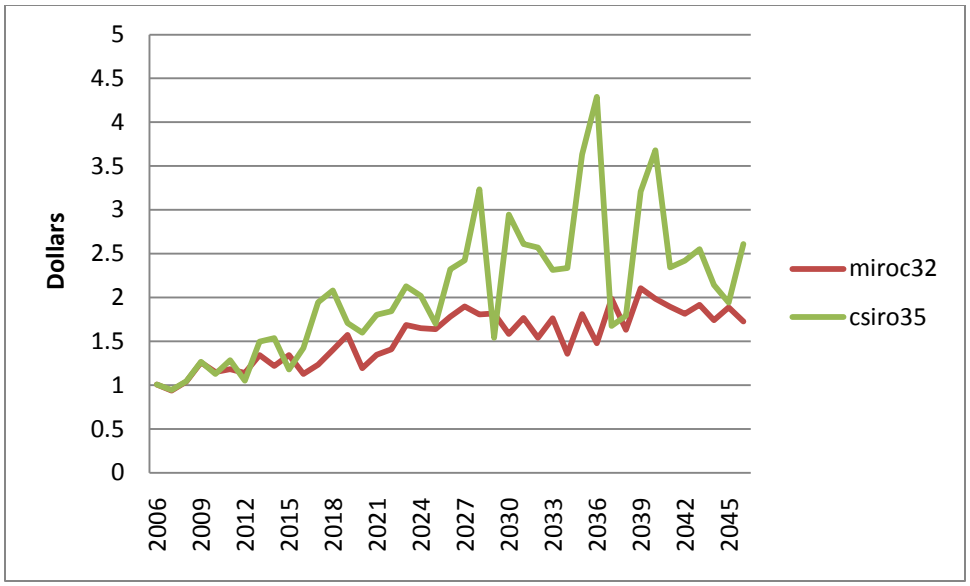

Figure 8. Cotton profitability, Worth county, Georgia

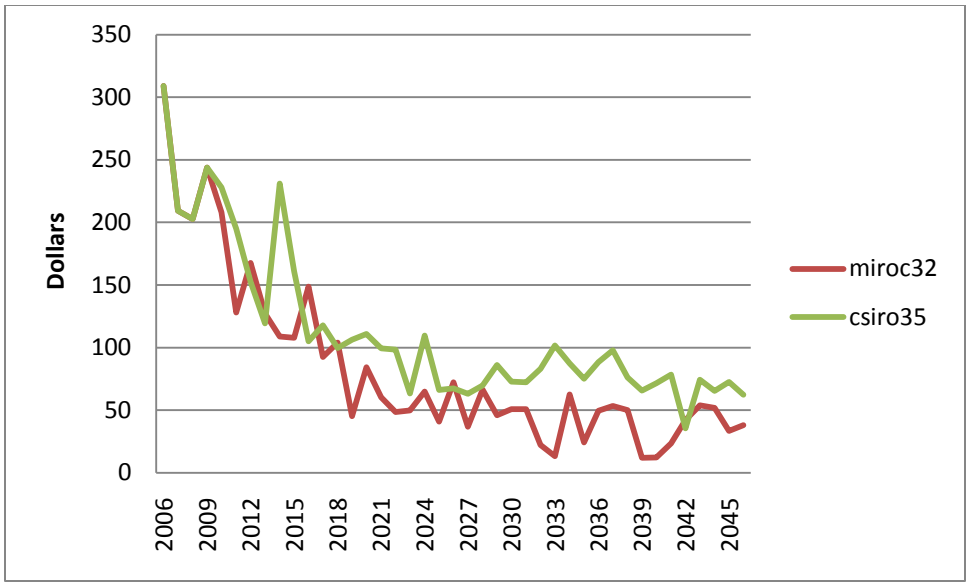

Figure 9. Peanuts profitability, Decatur county, Georgia

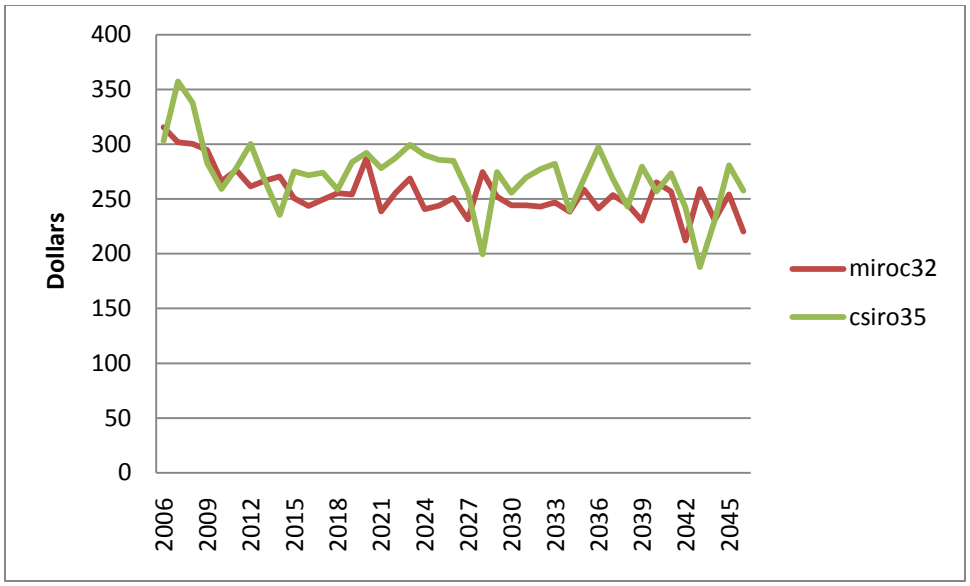

Figure 10. Soybeans profitability, Yellow Medicine county, Minnesota

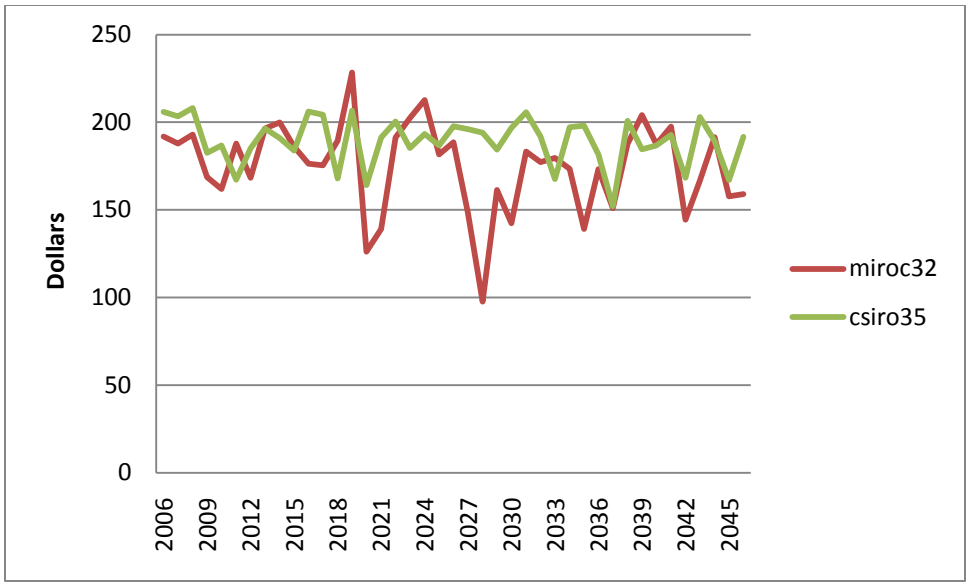

Figure 11. Soybeans profitability, Appling county, Georgia

Table 1. Usual Planting and Harvesting Dates – Georgia

	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

Table 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

Table 3. Price Flexibilities (by crops, by states)

	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

Table 4. Crop Production with Three Climate Models-Partial Adjustment=0 (2010-2046)

	Corn[1]			Soybeans			Peanuts			Cotton		
	H[2]	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

[1] The Units for corn, soybeans, peanuts and cotton are billion bushels, hundred million bushels, billion pounds, and million pounds

[2] H, M, C denotes MIROC 3.2, CGCM 3.1 and CSIRO 3.5

Table 5. Crop Production with Three Climate Models-Partial Adjustment=0.1 (2010-2046)

	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 6. Crop Production with Three Climate Models-Partial Adjustment=0.2 (2011-2046)

	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 7. Crop Production with Three Climate Models-Partial Adjustment=0.5 (2011-2046)

	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 8. Crop Production with Three Climate Models-Partial Adjustment=1 (2011-2046)

	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

Table 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			0.68	0.49
TX	0.1			0.74	0.44
	0.2			0.63	0.58
	0.5			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