Essays on Applied Resource Economics
Using Bioeconomic Optimization Models

by

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Abstract

With rising demographic growth, there is increasing interest in analytical studies that assess alternative policies to provide an optimal allocation of scarce natural resources while ensuring environmental sustainability. This dissertation consists of three essays in applied resource economics that are interconnected methodologically within the agricultural production sector of Economics.

The first chapter examines the sustainability of biofuels by simulating and evaluating an agricultural voluntary program that aims to increase the land use efficiency in the production of biofuels of first generation in the state of Alabama. The results show that participatory decisions may increase the net energy value of biofuels by 208% and reduce emissions by 26%; significantly contributing to the state energy goals.

The second chapter tests the hypothesis of overuse of fertilizers and pesticides in U.S. peanut farming with respect to other inputs and address genetic research to reduce the use of the most overused chemical input. The findings suggest that peanut producers overuse fungicide with respect to any other input and that fungi resistant genetically engineered peanuts may increase the producer welfare up to 36.2%.

The third chapter implements a bioeconomic model, which consists of a biophysical model and a stochastic dynamic recursive model that is used to measure potential economic and environmental welfare of cotton farmers derived from a rotation scheme that uses peanut as a complementary crop. The results show that the rotation scenario would lower farming costs by 14% due to nitrogen credits from prior peanut land use and reduce non-point source pollution from nitrogen runoff by 6.13% compared to continuous cotton farming.

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"Nissuna umana investigazione si pò dimandare vera scienzia s'essa non passa per le matematiche dimostrazioni."

Leonardo Da Vinci, Trattato Della Pittura (1651)

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Table of Contents

List of Figures

List of Tables

List of Abbreviations

AAEA	Agricultural and Applied Economics Association
ADF	Augmented Dickey Fuller
AIC	Akaike Information Criteria
ARMS	Agricultural Resource Management Survey
BFGS	Broyden–Fletcher–Goldfarb–Shanno
BTU	British Thermal Units
DCP	Direct and Counter-cyclical Payment
DOE	Department of Energy
DP	Dynamic Programming
DSP	Discrete Stochastic Programming
EISA	Energy Independence and Security Act
EMP	Econometric Mathematical Programming
ENSO	El Niño Southern Oscillation Phases
ERS	Economic Research Service
EVS	Expected Value Solution
EWG	Environmental Working Group
FDA	Food and Drug Administration

GE Genetically Engineered

GHG Green House Gasses

HRU Hydrological Response Unit

ILUC Indirect Land-Use Change

MB Mitscherlich-Baule

NASS National Agricultural Statistics Service

NCI National Cancer Institute

NEG Net Energy Gain

NOAA National Oceanic and Atmospheric Administration

ORNL Oak Ridge National Laboratory

PMP Positive Mathematical Programming

Q_{WML} Weighted Quasi-Likelihood Function

RFS Renewable Fuel Standard

RPS Recursive Problem Solution

SDP Stochastic Dynamic Programming

SWAT Soil and Water Assessment Tool

US-EPA United States Environmental Protection Agency

USDA United States Department of Agriculture

VSS Value of Stochastic Solution

WESML Weighted Exogenous Sampling Estimator

Chapter 1

A model for integrated and participatory decisions of optimal land use in biofuel production: An application to the State of Alabama

⋆⋆⋆

"Use of [liquid transportation] fuels has given rise to energy security concerns, contributions to climate change and other environmental challenges."

- National Biofuels Action Plan (2008)

1.1 Introduction

In 2008, the total US demand for transportation fuel accounted for 179% of the total oil produced in the country. The total consumption of fossil fuel was 22,606.7 trillion BTU. (Davis *et al.*, 2010)[1]. The Renewable Fuel Standard (RFS), a key provision of the Energy Independence and Security Act of 2007 (EISA), aims to replace imported oil with 36 billion gallons of biofuels by 2022. According to RFS, these renewable fuels produced by modern biorefineries, will reduce the emissions of green house gasses (GHG) relative to the life cycle emissions from gasoline and diesel by at least 20%. As a consequence of the development of clean energy substitutes for fossil fuels, energy crops are becoming increasingly popular in the United States accounting for 12 billion gallons of corn ethanol and 0.60 billion gallon of soybean biodiesel production annually. The United States became the top world producer of bioethanol followed by Brazil (Renewable Fuel Association, 2011)[2].

As energy crops gain importance, their efficiency and environmental impact are becoming an issue that is hotly debated by the scientific community. The RFS mandate may have a significant impact on land-use change. Searchinger *et al.* (2008)[3] estimated that land-use change associated with corn-based ethanol production would double GHG emissions over 30 years rather than reduce it by 20% as suggested by EISA.

Soils and plant biomass are the largest natural sources for carbon sequestration containing almost 2.7 times the carbon content of the atmosphere. Conversion of rainforests, peat lands, savannas and grasslands would release CO_2 as a result of microbiological processes resulting in decomposition of organic carbon naturally stored in plant biomass and soils. Consequently, a phenomenon called carbon emissions from indirect land-use change (ILUC) will occur. Fargione *et al.* (2008)[4] defined the carbon debt of land conversion as the amount of CO_2 released during the first 50 years after conversion, from the decay processes of organic matter. Over time, the biofuel produced from converted land would repay the carbon debt; however, the authors estimated an increase of 420 times in GHG emissions in the atmosphere instead of a reduction as found by previous studies.

A GHG federal cap-and-trade program may benefit the US agricultural sector and may increase social welfare if the improvement in air and water quality and wildlife conservation derived from agricultural and forestry mitigation activities are considered (Baker *et al.*, 2010)[5]. However, there may be some issues in the implementation of such a policy if the ILUC emissions are included in the regulation. Khanna *et al.* (2011)[6] argue that the large variability of ILUC estimates within studies and between different studies may produce subjective policies rather than policies designed according to scientific evidence. Moreover, if such a policy would promote the production of biofuels with a lower ILUC factor, it will not guarantee global reductions in GHG emissions. Whether or not biofuels are a possible solution to climate change mitigation is strongly dependent on the type of biofuel or even the mix of biofuels considered. The authors conclude that an alternative policy approach would be

> "[...]creating incentives for sustainable land management practices, such as land zoning regulations and payments to landowners for environmental protection"[1]

[1]Khanna, M., C. L. Crago, and M. J. Black. 2011. "Can Biofuels be a Solution to Climate Change? The Implications of Land Use Change Related Emissions for Policy", *Interface Focus*, 1, p. 245

that may produce global reductions of GHG.

Based on their conclusion, an interesting question would be whether participatory decisions on land management, made by landowners and institutions, would lead to sustainable production of biofuels. The objective of this study is to test this hypothesis in the State of Alabama where the State Energy Program was awarded with $55.57 million from the American Recovery and Reinvestment Act (2009) by the Department of Energy (DOE) to invest in public and private sectors aimed at building a sustainable energy economy and reducing GHG emissions in the state.

To my knowledge, there is no other study that has attempted to examine the above hypothesis. This study is unique in the literature of biofuels and bioenergy for several reasons. First, the current research presents the first normative analysis that quantitatively assesses the potential environmental benefits deriving from a cooperative outcome. Secondly, in this study the hypothesis is tested simulating a voluntary program that could promote a sustainable land use to produce biofuels in Alabama. Finally, the simulation of the voluntary program in this study is performed using an original multidisciplinary integrated model that differs from any other model used in the bioenergy and applied economics literature.

This article is organized as follows. Section two reviews previous research; section three presents the theoretical model; section four explains the source of data used in this study; section five focuses on the econometric calibration of the model; and section six presents and discusses the results of the empirical analysis. Lastly section seven gives some concluding remarks.

1.2 Review of previous research

In order to ensure a sustainable economic growth, subject to an improvement in resource efficiency and pollution reduction, voluntary environmental programs became increasingly popular in Europe and in the U.S. in the past two decades. These programs are based on voluntary agreements among firms that cooperate in reducing pollution associated with their production processes to a level that is regulated by the government. For example, "EPA 33/50" was a voluntary program that aimed to reduce the toxic release of U.S. chemical industrial sector. Khanna and Damon (1999)[7] evaluated the impact of this program over the period 1991-1993 and they found a significant decline of toxic release among the participants. In Europe voluntary environmental initiatives are more popular than in the U.S. Voluntary agreements that aimed to increase energy efficiency while reducing carbon dioxide have been examined by Krarup and Ramesohl (2002)[8] in five countries of the European Union during the 1990s. The authors argue that voluntary agreements are more effective when are integrated in a broader climate policy mix with regular monitoring, support, and economic incentives. In the forestry sector, Auld *et al.* (2008)[9] found that voluntary initiatives in sustainable forest management, that involve the cooperation of government, non-governmental organizations, and private stakeholders, led to substantial GHG emission reductions.

Environmental Planners have the unique role to bridge the gap between the technical knowledge of the environment and the understanding of the sociopolitical context of communities (Ali, 2002)[10]. Consequently, implementing a program that aims to increase land use efficiency would require the integration of other technical factors such as the knowledge of yield growth that is an important determinant of land conversion for production of biofuels.

If forest land conversion has a negative environmental effect, if one considers the uncertain but non-null ILUC factor, then a research analysis would consist of finding the best combination of energy crops to grow restrictively in cropland areas that would provide the largest energy supply. While the demand for ethanol increased by 235% in the past five years, demand for biodiesel registered the most rapid growth of approximately 1,680% (Davis *et al.*, 2010)[1] ; therefore, investigations should not be restricted solely to corn-based ethanol.

The impact of energy crops on land-use change plays a significant role in choosing between different crops in biofuels production. Bioenergy productivity of land should be the key element of a participatory program that intends to promote sustainable practices of land management. Each energy crop has a unique energy yield that can be expressed in British thermal units (BTU) per unit of land. The most efficient energy crop is the one that supplies the largest value of energy per unit of land at the same amount of energy required to produce the energy supplied. A better way to assess the bioenergy efficiency of energy crops is by using the net energy value or net energy gain (NEG) of biofuels, which is the difference between the energy produced and the energy expended in the stages of production. Net energy gain also has an environmental meaning; it can be considered as the net quantity of fossil fuel avoided during the production stages of biofuels. Crops that have large NEG also have a lower carbon footprint[2].

There are some studies that have dissenting opinions regarding the efficiency of biofuels. While Shapouri *et al.* (2002)[11] report 34% energy gain for corn ethanol, Pimentel and Patzek (2005)[12] found 29% energy deficit; however, these studies either used state aggregated yield data or did not include crop residues. Certainly they ignored phenological parameters that vary from place to place and in general determine the growth and yield of crops. Crop yield variation plays a significant role in the assessment of the net energy balance. An assessment of the variability of climate and soil characteristics in the calculation of NEG of corn-based ethanol has been made by Persson *et al.* (2009)[13]. The research conducted in four regions of Southeast U.S. found that different soils and different climate conditions impact consistently the net energy values.

However, all the previous studies are conducted in the realm of pure agronomy and engineering and they all ignore the important economic agents, such as public decision makers and landowners that make the ultimate decision on land use. Public decision makers design agricultural policies that may affect land allocation choices made by landowners who wish to maximize their future returns by choosing among alternative energy crops at their present value.

[2] There would be a low positive emission of GHG during the production stage.

In the current debate, a continuum between the hard and the social sciences is missing. Therefore, the literature suffers from the lack of analyses that are focused on policies aimed at maximizing the efficiency of land use while reducing the environmental impact of the production of biofuels.

1.3 Theoretical Framework

A simple way to calculate the environmental benefit of a cooperative outcome is to simulate a voluntary program that aims to maximize the net energy produced from first generation biofuel in Alabama. Maximizing the net energy from a mix of energy crops consists essentially in an abatement of GHG associated with the production of biofuels. A key assumption is that landowners who participate in this hypothetical program will voluntarily seek an environmental improvement of their region. Farmers are also assumed to have knowledge of past climatic events as a result of consultation with agricultural extension personnel who advise them on how to be prepared for possible future weather scenarios. Furthermore they will share information on soil productivity, management practices and individual farms' characteristics with the experts. The extension personnel would use this information and give appropriate technical advice on the most suitable energy crop to grow under different climatic conditions and landowners' individual farms' characteristics. It is also assumed that the program will include the adoption of sustainable farming techniques resulting in the practice of appropriate crop rotations. Finally, participants will receive a premium from the government if they decide to participate in the program and follow the prescribed cropping recommended by the extension service specialists.

The government is represented by a Social Planner who seeks to maximize the social welfare $SWF = B(n \cdot a) + n\Pi(x,a) - TS(n \cdot a)$[3] that, in case of one pollutant (GHG), is the environmental benefit plus net returns for farmers less total social costs of the policy.

[3] B is the environmental benefit deriving from the GHG abatement (a) of n farms. $\Pi(x,a)$ is the net return of an individual farmer that depends on production level (x) and abatement (a). TS is the total social cost of the agricultural/environmental policy.

Baumol and Oates (1989)[14] suggest that when a tax mechanism cannot be used as a policy instrument, as in the current and similar studies where the GHG emissions derived from ILUC are difficult to measure, then a subsidy can produce the same first-best outcome.

The premium received by the farmer is twofold: it provides an incentive to maximize the net energy produced in the area and also creates an abatement of GHG emissions that will result in an environmental benefit shared by the entire community.

Because the objective of the social planner is to find the best crop pattern that would maximize net bioenergy produced in the state as a whole, considering different weather conditions, a classical general equilibrium framework[4] based on supply and demand for crops and biofuels, would not be the best tool for this purpose. Besides, the complexity of the vertical structure of the market for biofuels that includes an intermediate market between processors and fuel blenders would deserve a separate study specifically for the calibration of the model if the ultimate goal of the research is an accurate analysis as in the current case in Alabama.

Therefore, if the farmer has the ultimate decision on land use, even when this is affected by other exogenous factors such as crop market prices, agricultural policies, or weather conditions, it is plausible to study the problem using a partial equilibrium model, assuming that the crop price taken by the farmers, under the hypothesis of perfect competition, clears the market and that the price is the same as that paid by the biofuel processors.

In order to quantify the environmental value of the program it is convenient to compare its impact (social optimization problem) to a real baseline scenario (self-optimization)[5]. To isolate the value of the cooperative outcome, we assume that the social cost of the programs

[4] GTAP-BIO and MIRAGE are computable general equilibrium models and FASOM (Beach and McCarl, 2010)[15], a dynamic partial equilibrium model, are being currently used for land-use change analyses in biofuel production. Besides the different resolution of these models that lie on large agro-ecological zones, as far as I know, they do not explicitly maximize the net energy gain of biofuels simulating a cooperative outcome of the economic agents.

[5] In the real scenario it is assumed that farmers made rational choices and they maximized their net return excluding external environmental costs.

incentives (TS) is equal to the total agricultural subsidies provided by Direct and Counter-cyclical Payment (DCP) program of the USDA for the state of Alabama in 2009. The DCP program, a provision of the 2008 Farm Bill, provides payments from 2009 through the 2012 crop year (USDA, 2008)[16]. Consequently, we also assume that the voluntary program simulated in the current study has the same time horizon of three years as the DCP program.

A more sustainable land use can be achieved optimizing the land productivity of biofuel. Therefore, the social planner problem is that of choosing the optimal amount of agricultural subsidies (to be given to the energy crop farmers) in order to maximize the Net Energy Gain (NEG) of biofuel produced from energy crops. Under these circumstances, if ℓ is the amount of land to be allocated to energy crop (i), and j represents the counties, then the objective function to be maximized will be similar to a linear profit function $\sum_{ij}(EG_i\ell_{ij} - EL_i\ell_{ij})$. EG_i. EG_i[6] is revenue per unit of land expressed in terms of energy while EL_i[7] is energy expended to produce biofuels expressed in BTU per unit of land. The *optimum-optimorum* is reached when the objective function is maximized. In fact the optimal amount of land that maximizes the production of green energy, by symmetry, minimizes fossil fuel (EL) used to produce biofuels and the GHG emissions associated with the whole process.

A simple way to simulate this decision-making process that includes climate information is to use a recursive discrete stochastic programming (DSP) algorithm as formulated by Rae (1971a; 1971b)[17][18]. The advantages of using this technique are several. A general algorithm in a simple algebraic framework converges to the same solution obtainable as do more complex algorithms of dynamic programming. Moreover, using the DSP approach simplifies the econometric calibration of the mathematical model. Consequently, a holistic analysis (from a single county to the whole state) would produce results that are more

[6] $E_i^{biofuel} + E_i^{coproduct}$ is the energy content of the biofuel produced from crop i and from the crop residue (biomass) expressed in MMBtu/acre

[7] $E_i^{farm} + E_{ij}^{trip} + E_i^{process}$ is the total energy consumed during the different stages of production such as energy used for farming operations, energy used to transport the crop from the farm to the biofuel processor plant and the energy spent to convert the crop in ethanol or oil. All these energy expenditures are fossil fuel based and expressed in MMBtu/acre.

realistic and robust with respect to the outliers[8]. Furthermore, the multistage characteristic of models of the type proposed provides the analyst with knowledge of the transitional phases of the system in the sequential states of nature.

Formally, if we assume the existence of a probability space (Ω, Σ, Θ) and a random state variable $(\omega_t \in \Omega)$ that defines a climatic state of nature at time t, Σ is a σ-algebra[9] collection of all weather events and Θ is a likelihood function that measures the probability $\Theta(S) \in [0,1]$ of the occurrence of an element $s \in \Sigma$, the Social Planner's multistage stochastic problem for optimal land productivity can be formulated as

$$\max_{\ell_{ijt}\geq 0; s_{ijt}\geq 0} \sum_{i=1}^{n}\sum_{j=1}^{J} NEG_i \ell_{ij0} + \mathbb{E}_{\omega_t} \sum_{i=1}^{n}\sum_{j=1}^{J}\sum_{t=1}^{3} NEG_{it}(\omega_t)\ell_{ijt}(\omega_t) \tag{1.1}$$

subject to

$$\sum_{i=1}^{n} \ell_{ij0} \leq b_j \tag{1.2}$$

$$\ell_{ijt} - \ell_{ijt-1} \leq 0 \tag{1.3}$$

$$d_i \ell_{ij0} - \frac{1}{2}\sum_{i'=1}^{n} \ell_{ij0} q_{ii'} \ell_{i'j0} - s_{ij0} \leq p_i y_{ij0} \ell_{ij0} \tag{1.4}$$

$$\begin{aligned} &d_i(\beta\ell_{ijt} - \ell_{ijt-1}) - \frac{1}{2}\sum_{i'=1}^{n}(\beta\ell_{ijt}q_{ii'}\ell_{i'jt} - \ell_{ijt-1}q_{ii'}\ell_{i'jt-1}) - \beta s_{ijt} \leq \\ &p_i(y_{ijt}\beta\ell_{ijt} - y_{ijt-1}\ell_{ijt-1}) - s_{ijt-1} \end{aligned} \tag{1.5}$$

$$\sum_{i=1}^{n}\sum_{j=1}^{J} s_{ijt} \leq TS \tag{1.6}$$

with reference to the i major crops (biofuels), corn (ethanol), cotton (cottonseed oil), peanuts (peanut oil) and soybeans (soybean oil) grown in county j, NEG_i is the net energy gain of the biofuel produced from energy crop i, estimated as difference between the energy content of the biofuel (EG_i) and the energy loss (EL_i) during the stages of production (see

[8]Optimal land solutions will be produced for each county in the sample.

[9]Given a set $A = \{0,1,2\}$, a possible σ-algebra collection of A will be a set $B = \{\{0\},\{1\},\{2\},\{0,1\},\{0,2\},\{1,2\},\{1,0\},\{2,0\},\{2,1\},\{0,1,2\},\{0,2,1\},\{1,0,2\},\{1,2,0\}\}$ or any other similar combination of elements of A.

Appendix B for technical details). The state variable ω_t refers to the weather, ℓ_{ijt}[10] is the amount of land devoted to growing energy crop i in the state of nature ω_t expressed in acres, s_{ijt} is a policy variable, optimal subsidy (US$) given for energy crop i in the weather state ω_t for county j; y_{ijt} is the stochastic yield (lbs./acre) of crop i in county j in the weather state ω_t; b_j is a vector of cropland available in the county to be allocated to energy crops (acres); and d_i and $q_{ii'}$[11] are linear and quadratic calibration parameters, respectively, correspondent to the linear and the quadratic coefficient of a quadratic cost function that will be discussed in Section 1.5. The vector p_i consists of cash price for each crop i (US$/lbs.), β is a discount rate, TS is the total cost of the program and $\mathbb{E}_{\omega_t}$ is the mathematical expectation operator.

Constraints (2) and (3) are first period and intermediate constraints related to the land fixed resource. This inequality guarantees that the land used for biofuel production will not exceed the total cropland existing in each county, avoiding undesired ILUC emissions from conversion of forests and pastures to crop land. Constraint (4) is a behavioral constraint that implicitly assumes perfect competition and rational choices made by farmers who maximize their profit. In fact, if the total cost ($d_i \ell_{ij0} - \dfrac{1}{2} \sum_{i'=1}^{n} \ell_{ij0} q_{ii'} \ell_{i'j0}$ in US$)[12] is less than the revenue ($p_i y_{ij0} \ell_{ij0}$ in US$) then the farmer is making a profit. The contrary is true if the total cost exceeds the revenue so that a compensation s_{ij0} in US$ would be given to the farmer for his or her loss. Constraint (5) replicates constraint (4) in the transitional phases. It should be noticed that the compensation is a specific subsidy for crop i for the particular county j that maximizes the NEG_{it} in the state of nature (ω_t) resulting in a first-best agricultural policy. Because subsidy and land are endogenous variables, their simultaneous solution serves to quantify the cooperative outcome that is the purpose of this study.

[10]The land choice variable is function of the weather state, therefore, correctly should be written as $\ell_{ijt}(\omega_t)$, however the functionality relationship (ω_t) has been omitted for convenience. The same convention is made for the other endogenous variable s_{ijt} and for the stochastic yield y_{ijt}.

[11]$q_{ii'}$ is a (4 x 4) positive semidefinite matrix where i' is the index i transposed. This matrix will have the crops as rows and columns.

[12]This is a cost function that is quadratic in ℓ. In a scalar notation with respect to only one crop it would have been written as $d\ell - \frac{1}{2} q \ell^2$ where d and q are linear and quadratic coefficient of the cost function, respectively.

The objective function (1) is a sequential probability model that can be represented as the tree diagram in Figure 1, where the expected value of the net energy gain after 3 years, assuming, for example, the sequence of states of nature 1—2—1,[13] would be $\theta_1 NEG_1 + \theta_1\theta_2 NEG_2 + \theta_1\theta_2\theta_1$[14]$NEG_1$. The θ parameters are the probabilities of the occurrence of each single state of nature. Halter and Dean (1971)[19] specify six different weather conditions and index them from "poor" to "very good". The probability of occurrence of each of these conditions may be subjectively assessed by the decision maker (Rae, 1971b)[18].

A scientific approach for computation of probabilities based on history, that would avoid ad-hoc assessments, can be done under the assumption that climatic states of nature occur as a sequence of martingales and that the weather can be separated into categories that comprise a finite Markov chain. Under this assumption, the climatic state variable is a member of a discrete set $K(1, 2, ..., k_t)$ and the stationary probabilities are determined by $\theta_{ij} = Pr(\omega_{t+1} = j|\omega_t = i)$.

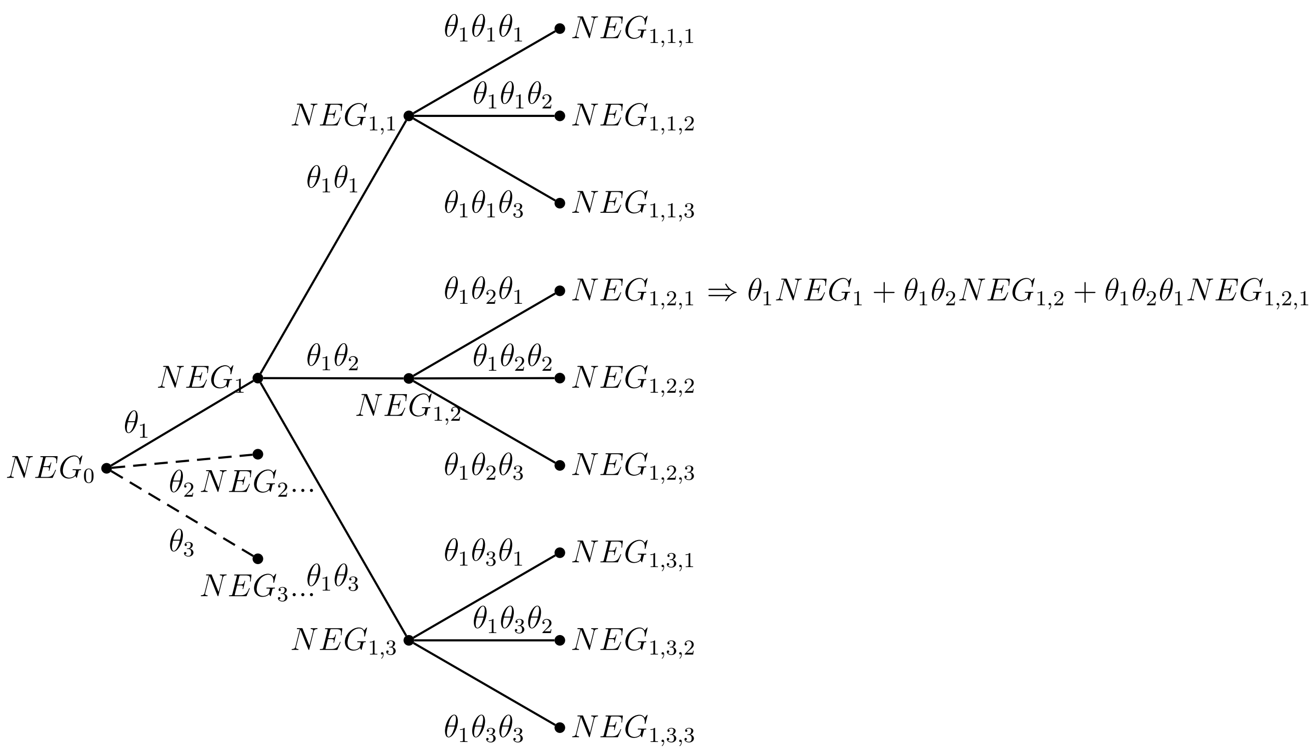

Figure 1.1: Probability Model

[13]This sequence would be an element of the σ-algebra set Σ.

[14]$\theta_1\theta_2$ and $\theta_1\theta_2\theta_1$ are joint probailities.

Alabama's weather patterns are affected by El Niño Southern Oscillation Phases (ENSO), and thus are very suitable for a scientific assessment of the probabilities. In fact, the National Oceanic and Atmospheric Administration (NOAA) labels a particular year "El Niño" or "La Niña" if the Oceanic Niño Index 3.4 hits or exceeds the bounds of +0.5 C or -0.5 C, respectively, for five consecutive overlapping seasons, and "Neutral" otherwise. In this study, there is no distinction between weak and strong ENSO events.

Under this assumption ENSO events from 1950 to 2009 represent an observed first order Markov chain that is also the simplest case for the estimation of the transitional probabilities. Prof. James D. Hamilton (2010)[20], in a personal communication, suggested that if the weather state vector ω_t can take values "El Niño", "La Niña", or "Neutral", respectively, in a given year t, then when the transitional probabilities are stationary[15] the likelihood function of the transition matrix is given by

$$\mathcal{L}(\theta_{ij}) = \prod_{t=1}^{50} \prod_{i,j=1}^{3} \theta_{ij}^{n_{ij}(t)} = \prod_{i,j=1}^{3} \theta_{ij}^{n_{ij}} \tag{1.7}$$

where n_{ij} is the number of times that an ENSO event in state i was followed by an ENSO event in state j. Taking the log of function (1.7) and maximizing the log-likelihood function with respect to the probabilities under the adding-up restriction $\sum_{j=1}^{3} \theta_{ij} = 1$, leads to the maximum likelihood estimates of the matrix $\hat{\theta}_{ij} = \frac{n_{ij}}{\sum_{j=1}^{3} n_{ij}}$.

Anderson and Goodman (1957)[22] show the consistency of this result in addition to providing a log-likelihood ratio test for homogeneity. In fact, since a second order Markov chain is always reducible to a first order chain, the authors suggest testing the null hypothesis that the chain is first order against the alternative that it is second order by calculating the log-likelihood ratio as $LL = \sum_{j=1}^{m} -2\lambda_j = 2\sum_{i=1}^{3}\sum_{j,k=1}^{3} n_{ijk}(log\hat{\theta}_{ijk} - log\hat{\theta}_{jk})$.[16]

[15] For an introduction to finite Markov Chains and their properties see Häggström (2002)[21].

[16] See Anderson and Goodman (1957)[22], p. 101. The asymptotic distribution of $-2\lambda_j$ is χ^2 with $(m-1)^2$ degrees of freedom where m is the number of states. Consequently, $\sum_{j=1}^{m} -2\lambda_j \sim \chi^2[m(m-1)^2]$ where in the current study $m = 3$ states and the degrees of freedom become 12.

In the current study, the test provided the result of $LL = 0.663 < 21.026\chi^2(12)$ at 5% level of significance failing to reject the null that the ENSO phases are a first order Markov chain. The chain converges to the steady state after the fourth year and the stationary transition probabilities of having El Niño, La Niña, or a Neutral event are 0.33, 0.30 and 0.37, respectively. According to these figures, the deterministic equivalent of the probability model (1) becomes: $\max \sum_{i=1}^{4} \sum_{j=1}^{J} (NEG_i\ell_{ij0} + 0.33NEG_i\ell_{ij1} + 0.30NEG_i\ell_{ij1} + 0.37NEG_i\ell_{ij1} + 0.09NEG_i\ell_{ij2} + 0.099NEG_i\ell_{ij2} + 0.111NEG_i\ell_{ij2} + ... + 0.050653NEG_i\ell_{ij3})$.

1.4 Data Sources

Economic data used in this study for the year 2009 are available at the Economic Research Service of the United States Department of Agriculture (ERS-USDA). The total agricultural subsidies are based on a projection for the year 2009 made by the Environmental Working Group (EWG, 2011)[23] and the USDA Census of Agriculture for the state of Alabama in 2007 (United States Department of Agriculture). A discount rate of 3.29% is the average return on assets from US agricultural income as suggested by the Agricultural and Applied Economics Association (AAEA, 2000)[24]. The observed land allocations in the base year are part of the National Agricultural Statistics Service (NASS) database of the USDA 2009 as well as the historical yields of the four major crops modeled. To capture the yield response to the ENSO phases, the crop yields time series, from 1950 to 2009, have been detrended using autoregressive linear techniques and brought to the 2009 level for all the 38 counties considered in this study. This is a common procedure that was implemented in a previous study that analyzed the irrigation profitability of corn in Northern Alabama under different ENSO scenarios (Novak *et al.*, 2008)[25] . Detrending the yields serves essentially as a mitigation of market and agricultural policies effects (as, for instance, the peanut quota system) that would confound the estimation of crop supply responses to climate and soil variability. Therefore, the average yields used under the three different states of nature can be plausibly considered as historical yields that were achieved as a response to pedological characteristics of each county. Because data on biomass crop residue are not available, simulated data obtained by the Soil and Water Assessment Tool (SWAT) supported by the Agricultural Research Service of the USDA have been employed. Details on the simulation are available in Appendix C.

Table 1.1 reports the economic data and the estimated Fossil Fuel Energy Ratio (FER)[17], that is the net return in terms of bioenergy of one unit of fossil fuel energy spent.

Table 1.1: Economic Data and Estimated Fossil Fuel Energy Ratio

	cash price[a]	accounting costs[b]	Total Subsidies[c]	FER[d]
corn	4.15	294.43	10,418,808	1.18±0.03
cotton	0.538	521.14	91,407,357	1.36±0.03
peanuts	0.222	513.67	12,471,234	1.78±0.05
soybeans	10.4	155.38	8,873,174	2.76±0.06

[a]Corn and soybeans are expressed in US$/bu. [b]Accounting costs are expressed in US$/acres. [c] Projection in 2009 of the total subsidies are in US$ and refers to the all state of Alabama. Source: Environmental Working Group. [d]FER has been estimated by the author according to the guidelines reported in Appendix C and refers to average values ± the standard deviation of the ENSO response.

1.5 Econometric Calibration of the Model

The reason for using a discrete mathematical program to solve for optimal land allocation lies in the normative nature of this study. However, a normative linear mathematical programming procedure can produce solutions that would be far from reality if it does not allow for spatial variation[18] of crop yields. Such solutions may show some counties to be overspecialized[19] in energy crops that would easily maximize the objective function and satisfy the constraints imposed to the model. A possible solution from linear models, produced by design, is to have the whole cropland of the state of Alabama allocated to soybeans. This

[17] $FER_i = \frac{EG_i}{EL_i}$

[18]Spatial variation would be a consequence of soil heterogeneity that is unobserved. This would produce different yields for the same crops across the counties.

[19]Overspecialization is a term used by agricultural economists to refer to an economic solution commonly called the corner solution.

will be the result of soybeans being the energy crop with the best fossil fuel energy ratio among the first generation biofuel produced in Alabama.

To overcome the problem of overspecialization, Howitt (1995)[26] and Paris and Howitt (1998)[27] introduced positive econometric modeling characteristics into the mathematical programming framework. The positive mathematical programming approach is a procedure that consists of three steps. First, the dual variable λ, marginal profit of land, is calculated from a linear program of profit maximization where the production level of the farm is forced to favor the observed production level in the base year. Next, the variable λ that is, by symmetry, the opportunity cost of land, is then added to the total observed costs of the firm to estimate the linear and non-linear parameters of a cost or supply function[20] that serves to capture unobserved farm characteristics; these characteristics can be heterogeneous land quality or the adoption of non-linear technologies that are unknown to the analyst and determine the observed land allocation in the base year (Howitt, 1995)[26]. The final step of PMP is to write a calibrated model for agricultural policy analyses that includes the recovered cost or supply function and would reproduce the base year land allocation as its baseline.

Heckelei and Wolff (2003)[28] extend positive mathematical programming to the case of a cross sectional study and examine the methodology from the point of view of an econometrician proposing a calibration procedure that avoids the first step of PMP. I refer now to this procedure as Econometric Mathematical Programming (EMP); that is the procedure that has been used to calibrate the decision model of this study.

Let us consider the following profit maximization problem for farmers in matrix notation

$$\begin{gathered}\max_{\mathbf{x}\geq 0} \mathbf{p}'\tilde{\mathbf{x}} - \mathbf{c}'\tilde{\mathbf{x}} + \mathbf{s}'\tilde{\mathbf{x}} - \mathbf{d}'\tilde{\mathbf{x}} - \frac{\mathbf{1}}{\mathbf{2}}\tilde{\mathbf{x}}'\mathbf{Q}\tilde{\mathbf{x}} \\ \text{subject to } \tilde{\mathbf{A}}\tilde{\mathbf{x}} \leq \mathbf{b}\end{gathered} \tag{1.8}$$

[20]Generally a quadratic cost function.

Considering only the land as the sole limiting resource, the expected level of energy crop production is $\tilde{\mathbf{x}} = \tilde{\mathbf{y}}\tilde{\ell}$[21] where $\mathbf{p}$ is the cash price of the energy crop, $\mathbf{c}$ is a vector of variable accounting cost that excludes the rent of land, $\mathbf{s}$ represents direct payments received by the government, $\mathbf{d}$ and $\mathbf{Q}$ are the linear and non-linear coefficient of a quadratic cost function[22], and $\tilde{\mathbf{A}}$ is the expected matrix of technical coefficients, which in this case would be equal to $\widetilde{\mathbf{y^{-1}}}$ and have the dimension of acres/lb[23]. $\mathbf{Q}$ is a (n x n) positive-semidefinite matrix given the quadratic functional form and its symmetry can be imposed through a Cholesky factorization in order to ensure the right curvature of the cost function; as a consequence, the number of parameters in the matrix to be estimated is n(n+1)/2.

From (1.8), the Lagrangean function, will be

$$\mathcal{L}(\tilde{\mathbf{x}}, \tilde{\lambda}) = \mathbf{p}'\tilde{\mathbf{x}} - \mathbf{c}'\tilde{\mathbf{x}} + \mathbf{s}'\tilde{\mathbf{x}} - \mathbf{d}'\tilde{\mathbf{x}} - \frac{\mathbf{1}}{\mathbf{2}}\tilde{\mathbf{x}}'\mathbf{Q}\tilde{\mathbf{x}} + \tilde{\lambda}[\mathbf{b} - \tilde{\mathbf{A}}\tilde{\mathbf{x}}] \tag{1.9}$$

ignoring slackness conditions for simplicity. From the first order conditions it follows that

$$\begin{gathered} \frac{\partial \mathcal{L}(\tilde{\mathbf{x}}, \tilde{\lambda})}{\partial \tilde{\mathbf{x}}} = \mathbf{p} - \mathbf{c} + \mathbf{s} - \mathbf{d} - \mathbf{Q}\tilde{\mathbf{x}} - \tilde{\mathbf{A}}'\tilde{\lambda} = \mathbf{0} \\ \therefore\ \tilde{\mathbf{x}} = \mathbf{Q^{-1}}(\mathbf{p} - \mathbf{c} + \mathbf{s} - \mathbf{d} - \tilde{\mathbf{A}}'\tilde{\lambda}) \end{gathered} \tag{1.10}$$

$$\frac{\partial \mathcal{L}(\tilde{\mathbf{x}}, \tilde{\lambda})}{\partial \tilde{\lambda}} = \mathbf{b} - \tilde{\mathbf{A}}\tilde{\mathbf{x}} = \mathbf{0} \tag{1.11}$$

Substituting the right-hand side of (1.10) into (1.11) and solving for $\tilde{\lambda}$ yields

$$\tilde{\lambda} = (\tilde{\mathbf{A}}\mathbf{Q^{-1}}\tilde{\mathbf{A}}')^{-\mathbf{1}}[\tilde{\mathbf{A}}\mathbf{Q^{-1}}(\mathbf{p} - \mathbf{c} + \mathbf{s} - \mathbf{d}) - \mathbf{b}] \tag{1.12}$$

[21] $\tilde{\mathbf{y}}$ is the yield expressed in lb/acres and $\tilde{\ell}$ is the land expressed in acres. The tilde sign indicates the expected value. As always the deterministic equivalent of $\tilde{\mathbf{y}} = 0.33y^{ElNiño} + 0.30y^{LaNiña} + 0.37y^{Neutral}$. The same convention is valid for the expected values of $\tilde{\mathbf{x}}$, $\tilde{\lambda}$ and $\tilde{\mathbf{A}}$.

[22] Heckelei and Wolff (2003, p. 32)[28] replace $\mathbf{p} - \mathbf{c}$ with a vector of gross margin $\mathbf{gm}$, in this case because I want to include also subsidies $\mathbf{s}$ in the calibration procedure I did not use the gross margin specification leaving the model transparent for the sake of clarity.

[23] This simplification is a consequence of having only the land as a limiting factor, see also Paris (2011)[30] p. 401

Plugging (1.12) into (1.10) will lead to the expected optimal value of energy crop activity level $\tilde{\mathbf{x}}$ as a function of the exogenous parameters of the model

$$\tilde{\mathbf{x}} = \mathbf{Q^{-1}}(\mathbf{p} - \mathbf{c} + \mathbf{s} - \mathbf{d}) - \mathbf{Q^{-1}}\tilde{\mathbf{A}}'(\tilde{\mathbf{A}}\mathbf{Q^{-1}}\tilde{\mathbf{A}}')^{-1}[\tilde{\mathbf{A}}\mathbf{Q^{-1}}(\mathbf{p} - \mathbf{c} + \mathbf{s} - \mathbf{d}) - \mathbf{b}] \tag{1.13}$$

In case of a change in crop price, the response of the expected optimal supply level will depend on the full information of the $\mathbf{Q}$ matrix that encompasses the full set of crops.

$$\frac{\partial \tilde{\mathbf{x}}}{\partial \mathbf{p}} = \mathbf{Q^{-1}} - \mathbf{Q^{-1}}\tilde{\mathbf{A}}'(\tilde{\mathbf{A}}\mathbf{Q^{-1}}\tilde{\mathbf{A}}')^{-1}\tilde{\mathbf{A}}\mathbf{Q^{-1}} \tag{1.14}$$

For ill–posed[24] problems, the entropy econometrics criterion (Golan *et al.*, 1996)[31] can result in a solution for estimating the unknown parameters that calibrate the decision model. Maximum entropy estimation is a statistical inference that allows to derive probability distributions on the basis of partial information. This technique provides the best unbiased estimator possible on available information (Jaynes, 1957)[32].

Another factor that would favor the entropy criterion over other estimation techniques is the stochastic nature of the model and prior information of the ENSO transition probabilities, which is the ideal case for the implementation of the generalized maximum entropy — cross entropy econometric formulation (GME–GCE).

The idea behind the entropy estimation is to find a set of posterior distributions of support points of the topological space of parameters[25] that satisfies the sample observations and have the least distance to a prior distribution of the supports. Such support points can be identified with the moments of the population of parameters. Although there is no limit on the number of supports that can be employed, choosing two support points is equivalent

[24]A problem is ill-posed if it has negative degrees of freedom, that is when the number of parameters to be estimated exceeds the number of observations available.

[25]In case of well–posed problems support points can be defined also for the unknown disturbances. For further details see Golan *et al.* (1996)[31] chap. 6, and for an application to well–posed problems in Mathematical Programming see Paris (2001)[33] p. 1052 and Heckelei and Wolff (2003)[28] p. 33.

to specify the mean and variance of the sample of parameters that are going to be estimated and the results can be quite satisfactory[26].

To avoid subjective specifications of the support points, Heckelei and Wolff (2003)[28] suggest using out of sample land elasticities of the gross margin. However, such prior information is not always available. Therefore, in this case an alternative method would be to use the prior price elasticities of supply. In fact, multiplying both sides of (1.14) by the ratio of the average crop price to the average state production will yield

$$\frac{\partial \tilde{\mathbf{x}}}{\partial \mathbf{p}} \odot \left[\frac{\bar{\mathbf{p}}}{\bar{\bar{\mathbf{x}}}^{\mathbf{o}}}\right]' = \left[\mathbf{Q}^{-1} - \mathbf{Q}^{-1}\tilde{\mathbf{A}}'(\tilde{\mathbf{A}}\mathbf{Q}^{-1}\tilde{\mathbf{A}}')^{-1}\tilde{\mathbf{A}}\mathbf{Q}^{-1}\right] \odot \left[\frac{\bar{\mathbf{p}}}{\bar{\bar{\mathbf{x}}}^{\mathbf{o}}}\right]'^{27} \tag{1.15}$$

Expression (1.15) is the matrix of own and cross price elasticities of supply. The range of these elasticities, previously estimated by Shumway (1986; see Appendix A)[29], can replace uninformative priors of the support points. The simultaneous estimation of (1.15) and (1.10) allows recovery of missing information of the parameters of the quadratic cost function and the dual variable λ. The recovered vectors $\tilde{\lambda}$, $\mathbf{d}$ and $\mathbf{Q}$, that calibrate the social planner model, capture individual farm characteristics and the opportunity cost of land that the program's participants share with the extension specialists during the program's participatory activities to obtain the advice on best farming practices[28]. Details on the entropy formulation are available in Appendix A.

The base year land allocations and the estimated expected opportunity costs of land for each county are reported in Table 1.2, while the parameters of the cost function estimated with the entropy criterion are reported in Table 1.3.

[26] See Golan *et al.* (1996)[31] p. 139 for an extensive explanation on the number of supports.

[27] '$\odot$' is the Hadamard entrywise product: given two matrices $\mathbf{A}, \mathbf{B} \in \mathbb{R}^{(m \times n)}$ then $\mathbf{A} \odot \mathbf{B} = A_{ij} \cdot B_{ij}$.

[28] $\mathbf{d}$, $\mathbf{Q}$ and the expected opportunity cost of land that is affected by the climate (ENSO) capture information such as farmers risk aversion, machinery failure, plant disease and non linear technologies that are unknown to the analysts (see Howitt, 2005)[26].

Table 1.2: Observed Land Allocation and land opportunity costs (Base Year 2009)

County	Crop Area (acres)				Land Opp. Cost
	corn	cotton	peanuts	soybeans	$\tilde{\lambda}^a$ (US$/acre)
Autauga		5,100		1,900	5,000.17
Baldwin	4,600	8,350	16,200	23,600	618.81
Barbour	2,800		3,280		3,797.00
Blount	800				12,917.13
Calhoun	1,100	1,700		4,200	2,484.80
Cherokee	2,200	5,910		23,700	617.84
Coffee	5,600	12,700	7,800	6,800	1,477.99
Colbert	16,400	2,700		22,900	448.75
Conecuh	900	3,300		2,700	3,711.08
Covington	2,500	12,600	6,400	2,200	2,563.82
Cullman	2,400			5,300	2,136.71
Dale	2,800	9,400	9,300		1,835.92
Dallas	4,050	4,450	3,800	9,100	1,308.92
DeKalb	10,900			10,800	878.40
Elmore		9,110		2,200	4,273.24
Escambia	4,700	12,100	9,600	11,900	1,018.05
Etowah	1,800			5,500	2,058.72
Fayette	1,600				6,371.88
Geneva	6,200	22,600	16,300	6,600	1,063.94
Henry	6,000	14,200	18,700		1,175.21
Houston	2,600	19,400	33,500	7,600	945.54
Jackson	18,600			31,800	289.58
Lamar	1,200				8,528.53
Lauderdale	20,200	10,800		21,900	266.23
Lawrence	34,700	4,300		23,900	77.39
Limestone	23,100	11,000		63,900	0.00
Macon	2,300			2,300	4,240.89
Madison	18,500	18,800		45,800	41.83
Marshall	3,000			6,000	1,886.71
Mobile		6,900		2,300	4,191.83
Monroe	1,800	16,000	5,780	4,200	2,326.27
Morgan	3,700			6,900	1,669.59
Pike	4,900	4,100	3,200	1,500	2,048.03
Shelby	700	2,500			14,854.04
Sumter				800	11,328.46
Talladega	7,250	2,810		10,000	1,205.51
Tuscaloosa	2,650			5,000	2,210.37
Washington	600		2,250		5,527.41

The opportunity cost of land is solution of the entropy econometric model and the value reported refers to the expected value and is calculated as $\lambda\theta$.

Table 1.3: Estimated **Q** and **d** matrices

Q	corn	cotton	peanuts	soybeans
corn	**0.0034**	0.0137	-0.0018	0.0041
cotton	0.0137	**0.0549**	-0.0074	0.0166
peanuts	-0.0018	-0.0074	**0.0010**	-0.0022
soybeans	0.0041	0.0166	-0.0022	**0.0050**
d	48.80	1,562.87	-184.36	-181.03

Notes: Quadratic and linear coefficients of the cost function estimated with the entropy criterion.

1.6 Results and Discussion

Before revealing the results, it would be convenient to summarize the sequential steps that were followed to conduct hypothesis tests. First, calibration of the social planner model was conducted using the econometric entropy criterion with respect to the observed land allocation of the 4 major crops grown in 38 Alabama counties in 2009. Secondly, the calibration allows recovery of the expected opportunity cost of land and provides a quadratic cost function that captures unobservable farm information that explain the land allocation chosen by the landowners in the base year. Lastly, the recovered function is used with a linear revenue function as a constraint in the stochastic model that maximizes the net energy produced in the state. The reason for the behavioral constraint was to include the program's incentives and impose the assumption of a perfectly competitive market.

The central hypothesis is that the voluntary program would indeed increase the production efficiency of biofuels while reducing carbon emissions. The impact evaluation of the program can be performed by calculating the Value of Stochastic Solution (VSS).

Birge (1982)[34] defines VSS as the benefit of considering uncertainty during the decision process. This value can be calculated as the difference between the long run solution of the stochastic recursive problem (1.1) and the expected value solution (EVS) of a deterministic problem. In the latter case, the optimal decision on land allocation is made individually and it is based on average value of yields ignoring advice provided by the climate experts of the Extension Service. In mathematical notation

$$VSS = \max_{x,s}\{\mathbb{E}_{y(\omega)}[NEG(\ell(y(\omega)), y(\omega)\} - \mathbb{E}_y\left[NEG(\ell^o(\bar{y}), y)\right] \tag{1.16}$$

Let us make this point clear and demonstrate how this concept can be exploited to support the central hypothesis test of this study. The first term of (1.16) is the long run solution[29] of (1.1) and represents the impact of the program. This is calculated as the sum over the all modeled counties of the product of the net energy value of each single energy crop (NEG_i) by the optimal land allocations as reported in Table 1.4. The second term in (1.16) can be calculated as the sum of the product of NEG_i by the observed land allocations in 2009 as reported in Table 2 that assumes farmers do not participate in the program and make individual decisions on land use. As a result, if all farmers were to participate in the program, a total net energy gain of 7.05 Trillion BTU obtained from the optimal mix of biofuels produced in Alabama would occur. This value in percentage terms corresponds to an increase of 208% in net energy compared to the baseline. This result is not surprising considering that soybeans biodiesel has a net energy value of almost 300%. Figure 1.2 provides a graphical illustration of the response of (1.16) to climate phases in terms of net energy and carbon emissions.

For example, Figure 1 illustrates 27[30] possible ENSO sequences in 3 years. If we assume the possible sequence El Niño - La Niña - Neutral, then the Blue curve in figure 1.2 is the recursive problem solution (RPS) of (1.1). The solution depicts the net energy gain (carbon emissions) from the biofuel produced in the entire state if farmers participated in the voluntary program. The red curve by contrast, represents the net energy produced (carbon emissions released) in the baseline. The green curve is the difference between the previous curves and represents the impact of the program expressed in terms of net energy

[29] The long run solution is calculated as the sum of the expected land allocation over the time horizon modeled divided by the number of years, see Birge and Louveaux (1997)[35], p. 9 and pp. 137-152.

[30] 27 possible sequences are determined as 3 states of nature raised to 3 years.

Table 1.4: Long Run Expected Optimal Land Use and Subsidies

County	Crop Area (acres)				Direct Payment[a]
	corn	cotton	peanuts	soybeans	$\tilde{\mathbf{s}}$ (US$/acre)
Autauga			7,000		626,118.71
Baldwin	38,508		14,242		12,330,250.00
Barbour			6,080		455,189.28
Blount		17	6	777	34,181.71
Calhoun	7,000				2,014,072.00
Cherokee	22,267	8,875	668		13,775,560.00
Coffee	402	495	32,003		7,986,210.00
Colbert		1,760	6,087	33,802	3,850,806.00
Conecuh			6,900		40,153.62
Covington	4,601		15,607	3,492	1,422,224.00
Cullman	5,390	2,234	76		5,290,972.00
Dale	8,907	1,209	11,399		5,080,161.00
Dallas	14,719	1,229	5,453		7,894,680.00
DeKalb		735	1,470	19,495	1,663,674.00
Elmore		693	1,111	9,506	1,301,411.00
Escambia	24,512		13,788		9,051,999.00
Etowah	5,110	2,118	72		4,885,541.00
Fayette		133	41	1,426	270,041.54
Geneva	12,208		39,492		3,792,075.00
Henry	10,160	1,866	26,247		6,635,935.00
Houston	28,561		30,387	4,230	6,059,995.00
Jackson		686	490	49,224	1,098,576.00
Lamar				1,200	0.00
Lauderdale		1,216	1,918	49,213	2,342,874.00
Lawrence		822	159	61,919	1,280,461.00
Limestone		11,490	1,914	83,914	637,598.30
Macon	3,031	791	778		2,545,430.00
Madison		2,355	3,935	76,811	1,383,760.00
Marshall	4,525			4,475	1,664,700.00
Mobile			9,200		63,161.29
Monroe	10,279		17,501		4,141,769.00
Morgan	7,420	223	2,957		3,327,253.00
Pike			13,700		3,254,491.00
Shelby		194		3,006	361,894.47
Sumter			11	788	4,442.25
Talladega				20,060	7,044.39
Tuscaloosa	5,583	1,991	76		4,927,116.00
Washington	482			2,368	106,948.61

[a] $\tilde{\mathbf{s}}$ is the expected value of the optimal direct payment in each ENSO scenario and is calculated as $\sum_{\mathbf{i}} \mathbf{s_i}\theta$, where $\mathbf{s}$ is the $(4 \times 38 \times 3)$ vector of optimal subsidies and θ is the (3×1) vector of Markovian ENSO probabilities.

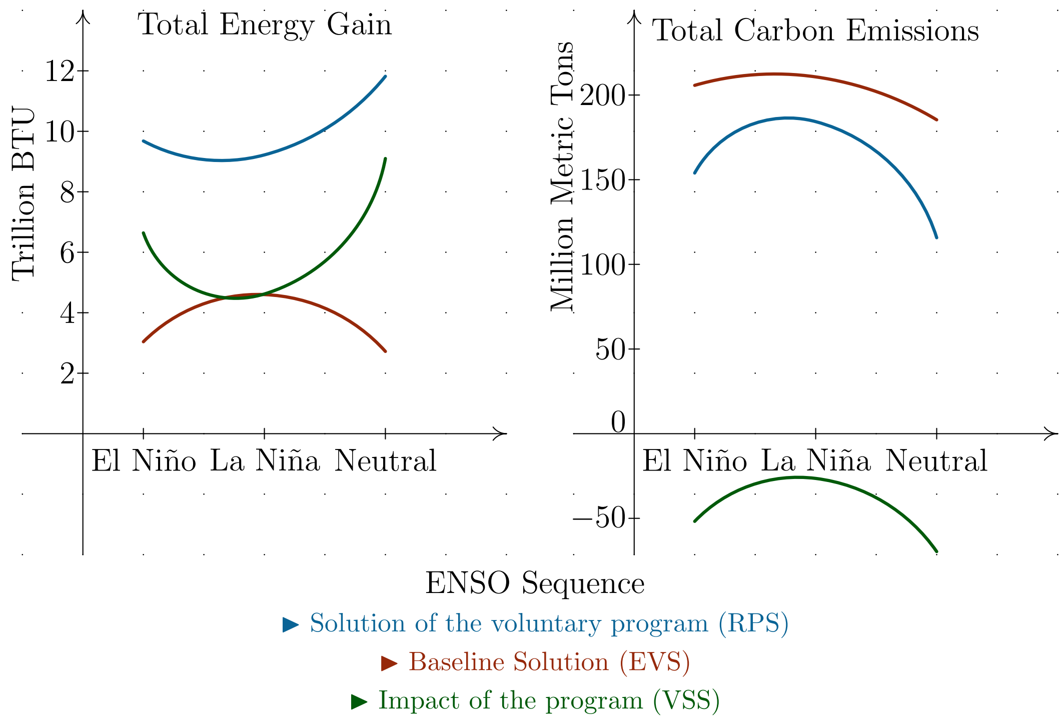

Figure 1.2: NEG and CO_2 emissions in the transitional phases

and green house gas emissions. The chart on the right presents negative values of the VSS related to total carbon emissions. This result indicates that such a program would reduce emissions in each ENSO scenario.

The model, however, does not consider the complete life cycle of biofuels because further reductions that occur when biofuel is substituted for fossil-fuel in the transportation sector depend strongly on the degree of blending. The optimal degree of blending of alternative fuels is beyond the scope of this research. However, Sheehan *et al.* (1998)[36] argue that if the Chicago metropolitan area school transportation system were to use biodiesel B20[31] to fuel bus engines, then a further 15.66% emissions reduction would be achievable.

The program, in terms of reduction of GHG emissions, could result in 51.84 million metric tons of CO_2 in the long run. This figure in percentage terms would consist of a 26% GHG reduction compared to the baseline scenario. As illustrated in Figure 1.3, the majority of energy gains can be attributed to a hypothetical increase in acreage of soybeans and

[31] B20 is a mixture of 20% seeds crop oil and 80% petrol-diesel that is commonly used in the U.S.

peanuts, which are crops with a high percentage of oil content assuming that the average value of peanut yields achievable in Alabama produce an oil yield that is more than twice the oil yield from soybeans. However, the use of large quantities of pesticides in production stages lowers the fossil-fuel energy ratio of this crop, in this case making peanuts the second best choice after soybeans. Because peanuts could be the crop with the strongest response to the program (the total acreage in the state could almost double) future research in genetics can aim to design an engineered crop that needs less chemical inputs, increasing the FER. In this case, peanuts may become the best choice, and further reduction in carbon emissions may be achievable.

Cellulosic ethanol would be certainly the optimal solution in terms of FER, but given the economic limitations of production of second generation biofuels (Khanna, 2008)[37], at the moment biodiesel seems to be the best alternative option in Alabama. This option should not be discarded if we take into account the fact that in 2008, total consumption of petrol-diesel in the state was 26.8 million barrels, making diesel the second most used commercial fuel. Considering that diesel is also the first fuel used for farming activities, production expansion of biodiesel can be viewed as an opportunity for development of the rural areas of the state. Positive macroeconomics effects of the expansion of biodiesel have been examined by Van Dyne *et al.* (1996)[38] in agricultural areas of Missouri that are similar to the areas studied in this research.

To capture the effect of the technical support provided by extension personnel to farmers, the analysis is conducted considering only the effect of climate and soil, *ceteris paribus*. Because crop price and average farming costs are held constant for the three years' time horizon, and the policy variable is tied to the estimated federal direct payments received by farmers in 2009, there is no change in welfare for landowners. In other words, the social planner makes a redistribution of the 2009 total level of subsidies towards the most efficient energy crops, reducing the opportunity cost of land that is borne by the participants. In this setting the incentives given to the farmers would represent a first-best agricultural policy.

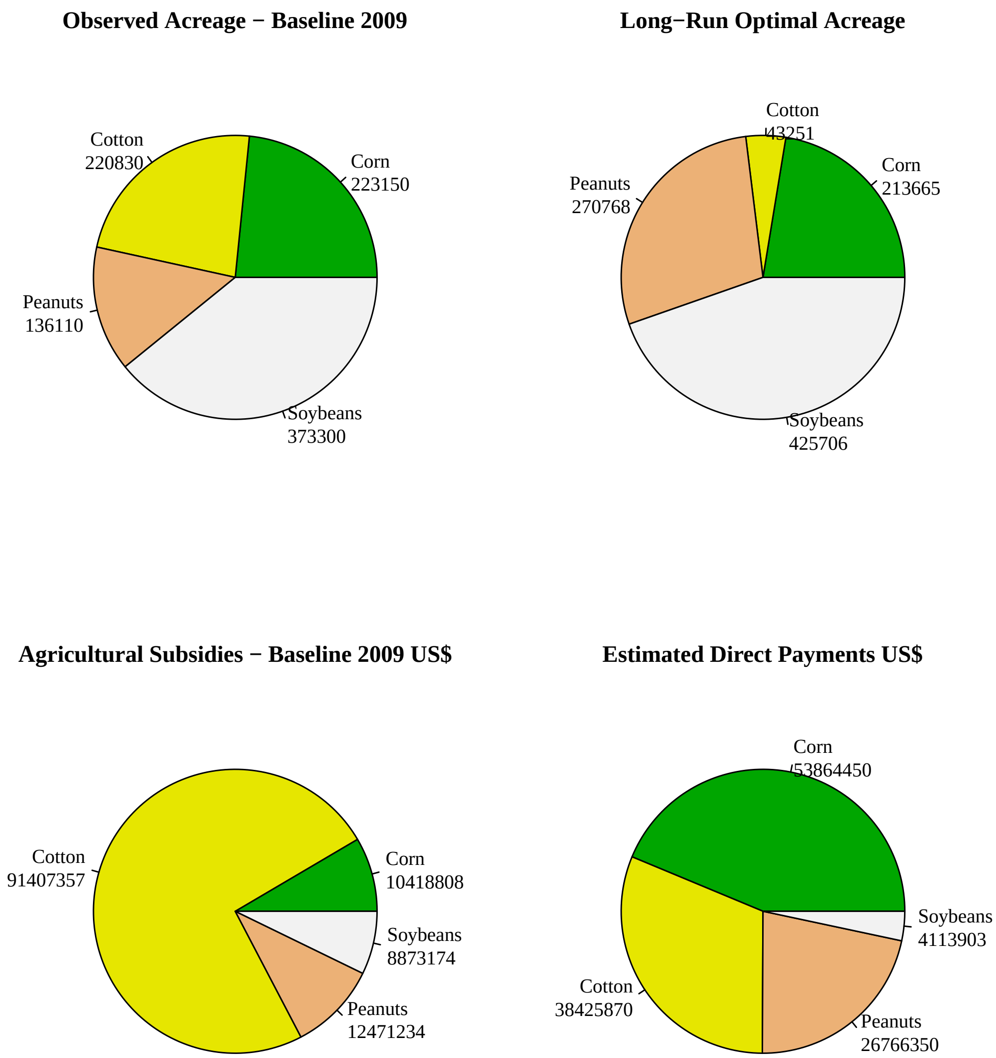

Figure 1.3: Land and Agricultural subsidies in the baseline and optimal scenarios

A natural question would be to ask how a new policy that incentivizes the farmers towards more sustainable land use affects the crop price in the next period? To answer this question, further assumptions that would increase the complexity of the model should be considered. For example, if one assumes that crop prices are not Markovian[32] then direct payments can create pecuniary externalities, resulting in an increase in food prices that will impact economic welfare. However, questioning the ethics of producing biofuels in place of food crops as well as the actual federal system of the agricultural subsidies is not the main objective of this research. The economic welfare implications of participatory programs of optimal land management may be the objective of future studies.

On the other hand, results achieved through this research seem clear. Integrated and participatory decisions made by landowners and the government that create incentives towards more efficient use of land can potentially create an environmental benefit, resulting in a consistent reduction of carbon emissions. Carbon reductions, besides contributing to the goal of the current state energy program and the RFS, would increase social welfare by improving environmental quality. In addition, expansion of the biodiesel industry in Alabama may have macroeconomic implications not accounted for the current paper and needs to be explored in future research.

1.7 Conclusions

The Renewable Fuel Standard, a key provision of the Energy and Independent Security Act (2007), aims to expand the production of biofuels to improve energy efficiency and decrease the greenhouse gas emissions in the US. The effectiveness of this regulation is being hotly debated by the scientific community, which has some concerns about carbon emissions from direct and indirect land-use change (ILUC). Given the uncertainty associated with

[32]Under the non-Markovian assumption, direct payments do have an impact on crop prices in the next period. In contrast, under the Markovian assumption of two price regimes (low and high) the cause of switching between the two regimes is unknown. In this case, the state variables of the model respond to 24 states of nature (4 crops $\times$ 2 price regimes $\times$ 3 weather states). The probability model (1.1) would consist of 3^{24} possible states at the end of the modeling period.

estimation of ILUC factors, some authors are also skeptical about the effectiveness of carbon tax and cap-and-trade policies when these factors are considered in designing regulations. A valid alternative may be to design policies that can create incentives for sustainable land use in biofuel production.

In this article a mathematical model was developed that simulates a voluntary agricultural program to increase land use efficiency in the production of first generation biofuels in Alabama. Under the common goal to reduce the carbon emissions in the state, landowners who participate in this hypothetical program can follow advice given by extension specialists on land use best practices under climate uncertainty. Participants would receive a direct payment from the government if they agree to follow the recommendations and plant the energy crop that provides the best energy gain given the soil and climate conditions of the farm. Participatory decisions were simulated through an original dynamic partial equilibrium model based on a discrete stochastic programming algorithm where land allocations and agricultural policy variables are endogenized to maximize net energy returns from biofuels that can be produced in Alabama. The model was calibrated using econometric mathematical programming techniques that involve the entropy criterion in order to recover the behavior of the farmers in Alabama.

Although the analysis is based on first generation biofuels and is restricted to the agricultural crop land area, given the current economic limitations of production of second generation biofuels, simulation results show an increase of 208% in the net energy gain from a mix of biofuels produced in the state that correspond to a carbon emission abatement of 26% if all farmers were to participate in the program. Environmental quality improvements derived from the implementation of this program may provide external benefits that further increase the social welfare, and produce a contribution to meet the goal of the current state energy programs. Specifically, at the current level of agricultural subsidies ($123.2 M) in the form of incentives to farmers to participate in the hypothetical voluntary program, it can be concluded that a more efficient use of crop land use would result in a more cost-effective subsidy program.

Given the flexibility of the model, future high resolution studies can extend the analysis to all the counties in the United States to simulate the economic welfare implications of participatory decisions that induce a more sustainable use of land in biofuel production.

Chapter 2

A Stochastic Frontier Analysis to Examine Research Priorities for Genetically Engineered Peanuts

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2.1 Introduction

Peanuts (*Arachis Hypogaea L*) are the seeds of a legume that has high nutritional energetic values and represents one of the major commodities produced worldwide. In 2009 the United States, with a production of 1.67 million metric tons, was the fourth largest world producer after China, India and Nigeria (FAO, 2011)[46].

The highest acreage of peanut planting in US was reached in 1943 with 3.5 million acres. From the end of World War II until 1981, the land devoted to peanut production had been restricted by acreage allotments to a limit of 1.5 million acres annually. After that period, poundage quotas replaced the acreage allotments reaching a new peak of 2.04 million acres in 1991, and subsequently, peanut acreage steadily declined to an average of 1.49 million acres (Dohlman *et al.*, 2004)[47]. Despite the decline in production in several southeastern counties of the United States, peanuts, for several of these counties, still represent from 50% to 70% of the total agricultural income (Fletcher, 2002)[48].

Given the high oil content of peanuts (Duke, 1983)[43], this crop may be an attractive choice for alternative fuels in a bio-based economy. Therefore, the recent decline in domestic peanut production may be offset if the demand for peanut oil increases to meet the rapid growth of biodiesel consumption (Davis, 2010)[1]. Therefore, peanuts are a commodity crop that deserves particular attention.

An important issue that threatens the productivity of peanuts is the susceptibility of this cultivar to several types of fungal pathogens. In particular, *Aspergillus* (*flavus*, *fumigatus*, *parasiticus*), a group of fungi responsible for producing mycotoxins and aflatoxins which have serious consequences in food safety. Specifically, *A. flavus*, the most dangerous hepatocarcinogen known to man, has been associated with an increased risk of liver cancer and is commonly found in peanuts (Hedayati, *et al.*, 2007)[49]. Although the rates of primary liver cancer are highest in places where peanuts are a mainstay in the diet (e.g. Asia and Africa), each year more than 15,000 men and 6,000 women are found to have primary liver cancer in the US (Wu and Khlangwiset, 2010; NCI, 2011)[50][51]. In 2011, the number of new cases of liver cancer is projected to reach over 26,000 persons along with approximately 20,000 deaths (NCI, 2011)[51]. To reduce the level of aflatoxin exposure and the risk of liver cancer, the FDA maintains a tightly controlled screening program of the food supply including peanut products (FDA, 2011)[52]. To mitigate the presence of the *A.flavus* mold, peanut producers use large amounts of chemicals to prevent fungal growth.

Therefore, the use of chemical factors has a positive effect on social welfare by reducing the risk exposure to human carcinogenic that may be present in edible peanuts; on the other hand, the excessive use of pesticides may also have a negative effect on the social welfare by degrading the quality of the ecosystems surrounding the peanuts farms. For example Carsel *et al.* (1987)[53] simulate the level of mass fluxes of *aldicarb*, an insecticide commonly used by peanut growers in North Carolina, to the groundwater, and they assessed a concentration level between 0.01 and 0.1 Kg ha^{-1} within a radius of 120 m downgradient[1] from the application point. Pesticides residual can be transported and be a serious threat for public health when they reach water bodies that are source of drinkable water.

In the past decade, genetic engineering has offered a potential remedy to help peanut producers successfully defeat the problem of fungal pathogens. For example Jonnala *et al.* (2005)[54] analyze the differences between three transgenic peanut lines (resistant to fungal

[1]Downgradient is a term used in water sciences that indicates the direction of groundwater flows.

pathogens) in the southwestern United States. From the comparison with the parent line, they found that genetic modification did not cause substantial unintentional changes in the nutritional value of peanuts.

Price *et al.* (2003)[55] argue that, the adoption of agricultural biotechnologies for cotton, soybean and corn, has increased the US total welfare by US$ 750 million. The world benefit, from adopting herbicide tolerant cotton, is shared by the consumers (57%), US farmers (4.1%), biotech firms (4.6%), seed firms (1.6%) and other producers from the rest of the world (32.6%). The use of genetically engineered (GE) crops in agriculture may have environmental benefits such as improved water use efficiency, for crops that are modified to be adapted to arid climates, or abatement of non-source point pollutants. This is the case with GE crops that have a high resistance to pests and reduce the need of pesticides. GE peanuts, still in the developing stage, may represent a promising alternative that may reduce the costs of inputs and increase crop yield and productivity (Fernandez-Cornejo and Caswell, 2006)[56].

In the current study, microdata of U.S. peanut production are used to make an economic analysis on technical and allocative inefficiency of chemical factors related to the stochastic production of the peanuts sector. From the analysis we intend to capture the needs of peanut producers, related to the use of inorganic inputs, and address research priorities in agricultural biotechnology. To my knowledge this is the first study that addresses this question in the peanuts sector.

The essay is organized as follows: section two reviews previous research, section three offers theoretical considerations, section four presents the econometric model, section five describes the data used in this research and further details on the applied econometric model; section six discusses the results. Section seven concludes.

2.2 Literature Review

Holbrook and Stalker (2010)[57] provide a review of the hybridization efforts that the agronomic science has done with the *Arachis Hypogaea*. The authors cite several studies that addressed the issue of breeding peanuts with resistance to root-knot nematode, fungal pathogens and drought. Although there is a large qualitative and quantitative variation[2] of the U.S. domesticated peanut, the genetic traits has been studied only for few traits (Wynne and Coffelt, 1982; Murthy and Reddy, 1993; Knauft and Wynne 1995)[58][59][60].

Few studies reported the economic losses of peanut producers due to fungal pathogens or soil born diseases that could be mitigated if a GE cultivar was available to the farmers. For example, Lamb and Sternitzke (2001)[61] argue that the average annual cost of aflatoxin borne by all segments of the southeast peanut industry is approximately US$ 25.8 million. Isleib *et al.* (2001)[62] report that the breeding program, which improved the resistance of domesticated peanuts to Sclerotinia blight, root-knot nematodes, and tomato spotted, had increased producer welfare by more than $200 million over a twenty year period.

While the first study is an accounting estimation of the costs of plant disease based on four years period (1993-1996) only in one region, the second study calculates the farmer benefits by comparing the advantage of the increased yield obtained from the resistant cultivar to the old yield. The authors also accounted for the reduction costs of pesticides. Both studies do not use a neo-classical economic framework for estimating the potential benefit deriving from the improved genetic traits, and they both ignore climatic variable that may also affect the crop yield of both traditional and new cultivars. The current literature is missing a large-scale positive economic analysis of the potential benefits deriving from the use of GE peanuts.

A positive economic study that examined the potential benefit of biotechnology has been done by Hanson, Hite and Bosworth (2001)[63] in the fishery sector. The authors conducted an economic analysis of the value of various forms of farm-raised catfish in the attempt to help geneticists determine on which inherited traits breeders should focus their research. The methodology used is based on an economic framework consisting of a complete demand system derived from an indirect translog utility function. The estimation of these

[2] The authors refer to discontinuous and continuous genotypic variations of the cultivar.

simultaneous equations allows calculating a substitution matrix of different product forms while the change in welfare is measured by the change in compensation variation. This highly flexible model is used to simulate different welfare scenarios deriving from the potential genetic manipulations which may increase the quantity and cut of catfish available in the market.

Replicating this methodology to estimate a complete demand system of inorganic factors used by peanut farmers may be economically sound but it would not be supported by a scientific rationale in this study. For example, one would expect no substitution between nitrogen and fungicide because these two factors serve two different tasks. To mirror the example in multi-budget consumer theory, this would consist of assuming that economic agents would not substitute house appliances with clothing because those commodities would belong to different branches of the purchasing decision tree.

The hypothesis of no substitution among chemical factors in agricultural economics is supported by several authors (Paris and Knapp, 1989; Frank *et al.* 1990; Ackello-Ogutu, *et al.*, 1985; Grimm *et al.*, 1987)[64][65][66][67]. Those authors propose crop response functions to chemical factors that exhibit a plateau effect.

2.3 Theoretical Consideration

Paris (1992)[68] tested the von Liebig hypothesis which consists of a linear response model with plateau. The author argues that such a functional form is superior to any other response function that exhibits a plateau. This formulation is based on the von Liebig's law of the minimum that can be expressed as

$$y = min\{f_{(x_j)}(x_j, u_{(x_j)})\} \tag{2.1}$$

where x_j is the j^{th} chemical input and u_{x_j} is an experimental error associated with that input. Although f in (2.1) can be a linear function of inputs x_j, such a functional form presents few shortcomings: Mitscherlich switching-regimes should be included to make this function differentiable. In general, the function does not allow substitution between factors;

> "[...]it is not possible to separate issues of plateau growth and factor substitution"

as pointed out by Frank *et al.* (1990, p. 597)[65]. A plausible alternative may be the Mitscherlich-Baule (MB) response function, which can be expressed by

$$y = \beta_0 \prod_{j=1}^{J} \{1 - exp[-\beta_{2j-1}(\beta_{2j} + x_j)]\} \tag{2.2}$$

where β_0 is the yield plateau and β_{2j-1} and β_{2j} are nonlinear coefficients of the MB response function. An indirect profit function based on (2.2) can be obtained by substituting the peanut yield — right-hand side of (2.2) — in a profit function and solve a simple optimization problem. From the first order necessary condition and the implicit function theorem, the profit maximizing value of the endogenous variable x_j^*, as function of input and output prices can be substituted into the profit function to derive an indirect profit function. The indirect specification may be used to derive the elasticities of substitution that are expected to be of small magnitude.

This exercise in mathematical economics was performed for this study but the result was inconclusive because the indirect profit function does not have a closed form. Although, a second-order Taylor approximation reduces the production function to a quadratic form, the approximation consistently misspecifies the original MB form. The approximation error is relevant considering that, in economics, we stop the approximation at the second order as we are often interested in finding elasticities — in the current problem the elasticities of substitution. Therefore, estimating the inorganic factor demand system, based on misspecified functional forms, would not be the appropriate strategy to make policy recommendations.

2.3.1 An Alternative Approach

Since directly estimating the substitution elasticities of inputs (nutrients and pesticides) used in peanut production is flawed, an alternative approach to study the input use of peanut farmers is to assess inefficient use of these inputs. For example, producers may overuse an herbicide with respect to labor.[3] In other words, peanut farmers may systematically overuse a particular chemical input, say herbicide, because they believe that using large quantities of this factor can help them to defeat unwanted weeds.

The overuse of an input is an example of allocative inefficiency. Schmidt and Lovell (1979)[71] define allocative inefficiency as a failure to allocate inputs in the right proportions given the input prices. In a production process that has an allocative inefficiency, the product of the marginal revenue of an input is not be equal to its marginal cost. Technically inefficient producers fail to maximize the output given a bundle of inputs. In reference to allocative efficiency, Kumbhakar and Lovell (2000, p. 152)[69] state that

> "Another example is provided by agriculture, in which evidence suggests that in a wide variety of environments farmers use excessive amounts of fertilizers and pesticides relative to other inputs."

Kumbhakar and Wang (2006)[72] extend the primal system approach of Schmidt and Lovell (1979)[71] by using the more flexible transcendental logarithmic functional form of the stochastic frontier. The authors argue that if the input endogeneity is considered during the implementation of the econometric problem, then the output-oriented or input-oriented technical inefficiencies are the same.

The primal system technique consists of estimating simultaneously a parametric self-dual production function

[3] Labor and nutrients, in general, are complementary factors. However, different nutrients' application techniques may have different labor costs associated. For example, it is logical that there is no substitution between water and labor; farmers can select an irrigation technique which requires less labor (see Neswiadomy, 1988)[70].

$$\ln y = \ln f(x) + v - u \tag{2.3}$$

and the first-order conditions of a cost minimization problem that can be implicitly formulated as

$$\frac{f_j}{f_1} = \frac{w_j}{w_1} e^{\eta_j} \quad \forall j = 2, ..., J \tag{2.4}$$

where y is the level of production; x is a vector of inputs; v is a vector of unobserved farmers' heterogeneities; u is the vector of technical inefficiencies; f_j and f_1 are the marginal products of input j and input 1, respectively; w_j and w_1 are prices of input j and input 1, respectively and η_j is a vector of allocative inefficiencies.

The cost minimizing condition for a profitable producer is that the marginal rate of technical substitution of input j with respect to input 1 should equal the price ratio w_j and w_1. This condition occurs if the allocative inefficiency term equals zero $\eta_j = 0$. However, this condition is violated if $\eta_j \neq 0$. Assuming a small substitution between chemical factors, if the allocative inefficiency for the input pair $(j, 1)$ is $\eta_j < 0$ then $w_j e^{\eta_j} < w_j$ that consists of an overuse of input j with respect to input 1. In other words, the farmer will reduce the use of input 1 in favor of input j. This problem can be graphically illustrated by figure 2.1a. Point B is the observed combination of input 1 and input j that produces the peanut quantity y. However if the farmer optimally allocates a bundle of input 1 and input j to produce y then the expected allocative inefficiency of input j would be $\eta_j = 0$, i.e. the optimal bundle of input 1 and input j would lie on the tangency point A. Point B violates the optimal condition given the input price ratio. The difference in slopes between the dotted and continuous isocost is the measure of the allocative inefficiency of input j with respect to input 1.

If the peanut producer is also technically inefficient then the isoquant would shift from y to $y \cdot e^u$ further increasing the costs of producing peanuts (fig 2.1b). A cost analysis in a

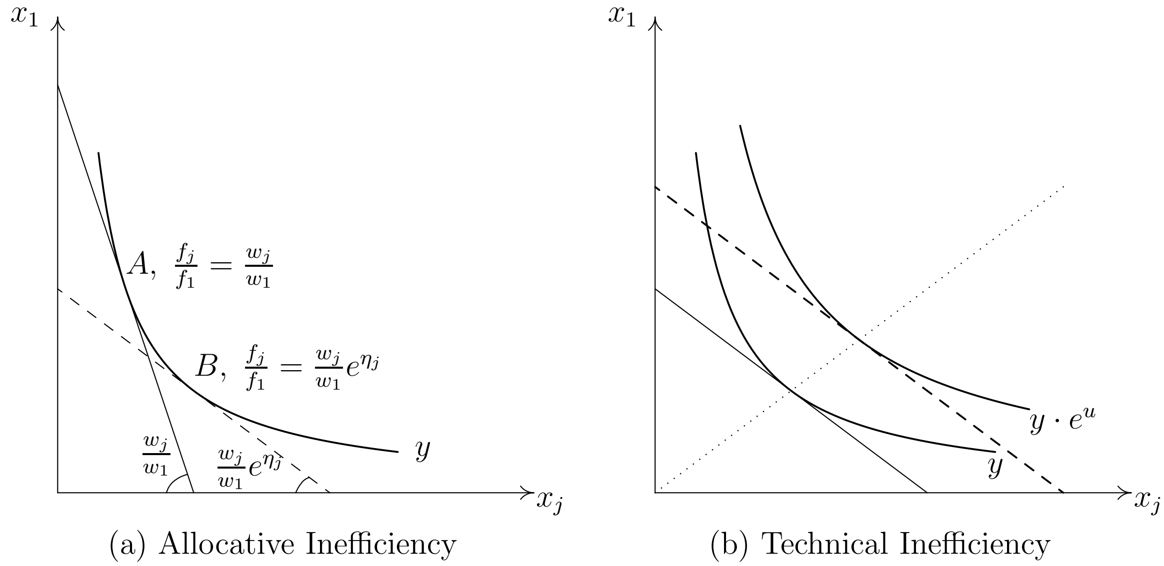

Figure 2.1: Technical and Allocative Inefficiencies

stochastic frontier framework would provide results which are less biased by including the inefficiency terms that raise the costs of production. Furthermore, the knowledge of the overuse of a particular chemical input should be exploited as precious information to address research priority in genetic manipulations of inherited traits. For example, if farmers overuse herbicides then the adoption of a new cultivar with enhanced traits that are more resistant to weeds, thus reducing the need of the herbicide, will increase the welfare of the farmers by lowering the cost of this chemical factor in addition to reducing the induced cost increase due to the allocative inefficient use of herbicides

2.4 Econometric Model

The analytical expression that allows the econometric estimation of technical and allocative inefficiency using the primal approach is formulated assuming a cost function$c(w, y)$ and using Shephard's lemma to derive the conditional demand of factor $x_j(w_j, y)$. In logarithmic form it follows that

$$\frac{\partial \ln c(w_j, y)}{\partial \ln w_j} = \frac{\partial c(w_j, y)}{\partial w_j}\frac{w_j}{c(w_j, y)} = \frac{w_j x_j}{c(w_j, y)} = s_j \Rightarrow w_j = \frac{s_j c(w_j, y)}{x_j} \tag{2.5}$$

This result is used to substitute the new expression of w_j in (2.4) to obtain

$$\frac{f_j}{f_1} = \frac{w_j}{w_1}e^{\eta_j} = \frac{s_j c(w_j,y)}{x_j}\frac{x_1}{s_1 c(w_j,y)}e^{\eta_j} \Rightarrow \frac{s_j x_1}{s_1 x_j} = \frac{w_j}{w_1}e^{\eta_j}$$
$$\Rightarrow \frac{s_j}{s_1} = \frac{w_j x_j}{w_1 x_1}e^{\eta_j} \quad \forall j = 2, ..., J \tag{2.6}$$

Taking the logarithm of (2.6) we get

$$\eta_j = \ln s_j - \ln s_1 - \ln(w_j x_j) + \ln(w_1 x_1) \quad \forall j = 2, ..., J \tag{2.7}$$

Where s_j are cost shares of the input x_j given the input price w_j.

The econometric estimation of the primal system described by (2.3) and (2.7) can be performed under the assumption that the error components have the following distributions as suggested by Kumbhakar and Lovell (2000)[69]

$v \sim N(0, \sigma_v^2)$, is a vector of normally distributed random noises that capture specific heterogeneities of peanut farmers;

$u \sim N^+(0, \sigma_u^2)$, is the vector of technical inefficiencies half-normally distributed;

$\eta = (\eta_{2i}, \eta_{3i}, ..., \eta_{Ji})' \sim N(0, \Sigma)$ is the vector of allocative inefficiencies for the i^{th} peanut farmer; η_j are assumed to be independent of v and u for simplicity.

The joint density function of the three error components can be simply calculated by multiplying their probability density functions. Consequently, the log-likelihood function for the i^{th} peanut farmer will be

$$\ln L_i = \ln 2\pi - \frac{1}{2}\ln\sigma^2 + \ln\phi(\frac{\varepsilon_i}{\sigma}) + \ln\Phi(-\frac{\varepsilon_i\lambda}{\sigma}) - \frac{1}{2}\ln|\Sigma| - \frac{1}{2}\eta_i'\Sigma^{-1}\eta_i + \ln|J_i| \tag{2.8}$$

where the error components u and v and the related standard deviations are reparameterized as $\varepsilon = v - u$, $\sigma = \sigma_u^2 + \sigma_v^2$ $\lambda = \frac{\sigma_u}{\sigma_v}$, $\phi(\cdot)$ and $\Phi(\cdot)$ are probability density and cumulative density functions of a standard normal variable, respectively. Note that the $|J|$ is the determinant of the Jacobian matrix of the transformation from (ε, η) to $(\ln x_1, \ln x_2, ..., \ln x_j)$ that serves to capture endogeneity of input x under the cost minimizing assumption (farmers choose the inputs x's). In other words, the determinant of the Jacobian is the degree of homogeneity or the return to scale that may lower the production costs if the producers adopt economies of scale.

The number of parameters to be estimated can be reduced if (2.8) is concentrated with respect to Σ. Schimdt and Lovell (1979)[71] show that the element σ_{jk} of Σ, when (2.8) reaches its maximum, can be expressed as

$$\sigma_{jk} = \frac{1}{N}\sum_{i=1}^{N} \eta_{ji}\eta_{ki} \quad \forall j, k = 2, ..., J; viz, \tag{2.9}$$

$$\Sigma = \frac{1}{N}\sum_{i=1}^{N} \eta_{\mathbf{i}}\eta_{\mathbf{i}}' \tag{2.10}$$

Substituting (2.10) into (2.8) leads to the concentrated log-likelihood function $LL_i(y_i|x_{ji}, \beta_j, \sigma, \lambda)$ as a function of the technical parameters β_j and the parameters σ and λ that allow the recovery of the vector of inefficiencies. In particular, the technical efficiency can be calculated using the formula suggested by Jondrow *et al.* (1982)[73] that is

$$\mathbb{E}\{u(v-u)\} = \mu^* + \sigma^* \frac{\phi(\frac{\mu^*}{\sigma^*})}{\Phi(\frac{\mu^*}{\sigma^*})} \tag{2.11}$$

Where $\mu^* = (-v-u)\frac{\sigma_u^2}{\sigma^2}$ and $\sigma^* = \sigma_u \frac{\sigma_v}{\sigma}$, while the allocative inefficiencies η_j for the input bundle $(j, 1)$ can be calculated from the residuals of the FOC in (2.7).

Knowing the allocative inefficiency would be enough to address research priority in biotechnology to produce a crop that has resistant traits that would reduce the (over)use of the chemical input that is applied inefficiently. However, to quantify the economic and environmental impact of the allocative inefficiency Kumbhakar and Wang (2006)[72] suggest placing the estimated η into the input demand equation. The authors derive the demand equation that for the Cobb-Douglas case will be

$$\ln x_j = b_j + \frac{1}{r}\sum_{k=1}^{J}\beta_k \ln w_k - \ln w_j + \frac{1}{r}\ln y + \frac{1}{r}\sum_{k=2}^{J}\beta_k\eta_k - \eta_j - \frac{1}{r}(v-u) \tag{2.12}$$

$$\ln x_1 = b_1 + \frac{1}{r}\sum_{k=1}^{J}\beta_k \ln w_k - \ln w_1 + \frac{1}{r}\ln y + \frac{1}{r}\sum_{k=2}^{J}\beta_k\eta_k - \frac{1}{r}(v-u) \tag{2.13}$$

where $r = \sum_{k=1}^{J}\beta_k$ (return to scale) and $\beta_j = \ln\beta_j - \frac{1}{r}[\beta_0\sum_{k=1}^{J}\beta_k\ln\beta_k]$; j=1,2,...,J.

Note that in the above demand equations, components due to allocative (η) and technical inefficiency (v) are added to the neoclassical demand for input (first part of 2.12 and 2.13 that does not include η, v and u). Furthermore, a higher r (return to scale) would imply lower values of all the other components, *ceteris paribus*. Those equations can be used to make a simulation to capture the actual input demand increase due to the allocative inefficiencies that would be: $[\ln x_j|\eta=\hat{\eta}] - [\ln x_j|\eta=0] = \frac{1}{r}\sum_{k=2}^{J}\beta_k\eta_k - \hat{\eta}_j$ percent increase for input x_j and $\frac{1}{r}\sum_{k=2}^{J}\beta_k\eta_k$ percent for input x_1. That information can be used to calculate the potential welfare change for the farmers who adopt genetically modified peanuts. The welfare change is the result of the abolishment of the use of the inefficiently used chemical factor. Additional welfare change derives from a re-adjustment in the use of the other inputs once the inefficient input is not used (as shown in equation 2.12 and 2.13).

Overuse of chemical factors can occur systematically and such systematic inefficient farming behavior can be modeled by assuming the following multivariate normal distribution of the allocative inefficiencies: $\eta \sim N(\rho,\Sigma)$ where $\rho_j = \bar{\eta}_j = \frac{1}{N}\sum_{i=1}^{N}\eta_{ji} \quad \forall j = 2,...,J \quad \text{and} \quad i=1,...,n$.

2.5 Data and Empirical Model

Peanut production data are part of the USDA Agricultural Resource Management Survey (ARMS) on cost and returns sponsored by the Economic Research Service (ERS) and the National Agricultural Statistical Service (NASS). In 2004 ARMS collected data regarding peanut farming operations in three phases. A screening phase (Phase I) conducted in the summer of 2004 served to identify peanut farmers who were operative. In Phase II (fall 2004 and winter 2004-2005), NASS randomly selected a sample of peanut farmers from Phase I and interviewed them concerning their production practices and chemical use. Finally, in Phase III (spring 2005) a national representative sample of peanut farmers provided information on costs and returns during the crop year 2004. Components of Phase II and Phase III surveys are related.

Additional climatic data such as average temperature, average precipitation and average dew point temperature (air moisture - humidity) of each farm in the 2004 growing period were calculated through a geospatial analysis conducted on gridded data from the National Oceanic and Atmospheric Administration (NOAA), USDA and PRISM Oregon State University. Such variables were merged with the ARMS dataset and used as exogenous frontier shifters in the following model

$$\begin{aligned}\ln y_i &= \beta_0 + \beta_1 \ln x_{1i} + \beta_2 \ln x_{2i} + \beta_3 \ln x_{3i} + \beta_4 \ln x_{4i} \\ &+ \beta_5 \ln x_{5i} + \beta_6 \ln x_{6i} + \beta_7 \ln x_{7i} + \delta_1 \ln z_{1i} + \delta_2 \ln z_{2i} + \delta_3 \ln z_{3i} + v_i - u_i\end{aligned} \tag{2.14}$$

Where y is the total physical production of peanuts expressed in pounds, x_1 is hired labor expressed in hours, x_2, x_3, x_4, x_5, x_6, x_7 are Nitrogen, Phosphate, Potash, Insecticide, Herbicide, Fungicide expressed in pounds, respectively; z_1, z_2, z_3 are rainfall, temperature and relative humidity (dew point) expressed in millimeters and Celsius degrees, respectively.

The most parsimonious first order approximation (Cobb-Douglas) is used for convenience. Although the quadratic translog specification would be more economically appealing, in this case it would imply the estimation of 68 parameters[4] considering all the interaction terms. These parameters would be part of the entries of the Jacobian matrix in (2.8) and such elements would also be non-linear. In the attempt to calculate the symbolic determinant of such a matrix on a new generation UNIX[5] workstation, the computer system was not able to allocate all its resources to accomplish the task.

Using Labor (x_1) as the numeraire, the first order condition of cost minimization would produce the column vector of allocative inefficiencies with w_j $(j = 1, 2, ..., 7)$ as prices of production factors expressed in US$/lbs.

$$\eta = \begin{bmatrix} \eta_2 \\ \eta_3 \\ \eta_4 \\ \eta_5 \\ \eta_6 \\ \eta_7 \end{bmatrix} = \begin{bmatrix} \ln \beta_2 - \ln \beta_1 - \ln(w_2 x_2) + \ln(w_1 x_1) \\ \ln \beta_3 - \ln \beta_1 - \ln(w_3 x_3) + \ln(w_1 x_1) \\ \ln \beta_4 - \ln \beta_1 - \ln(w_4 x_4) + \ln(w_1 x_1) \\ \ln \beta_5 - \ln \beta_1 - \ln(w_5 x_5) + \ln(w_1 x_1) \\ \ln \beta_6 - \ln \beta_1 - \ln(w_6 x_6) + \ln(w_1 x_1) \\ \ln \beta_7 - \ln \beta_1 - \ln(w_7 x_7) + \ln(w_1 x_1) \end{bmatrix} \tag{2.15}$$

while the determinant of the Jacobian matrix of the transformation from $(v - u, \eta)$ to $(\ln x_1, \ln x_2, ..., \ln x_7)$ will be

[4]The number of parameters including intercept, λ and σ is $2 + (n^2 + 3n + 2)/2$

[5]Unix/Debian 6.0 Dual Core workstation with 2.8Ghz CPU and 4Gb RAM software: Maxima Computer Algebra System

$$
|J| = \begin{bmatrix} -\beta_1 & -\beta_2 & -\beta_3 & -\beta_4 & -\beta_5 & -\beta_6 & -\beta_7 \\ 1 & -1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & -1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & -1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & -1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & -1 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & -1 \end{bmatrix} = \beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta_5 + \beta_6 + \beta_7 \tag{2.16}
$$

The NASS survey design is a stratified sample frame according to farms' characteristics (ERS, 2011)[74]. For each observation, the dataset includes sampling weights or expansion factors ($Q_i = 1/\pi_i$) that are based on the probability of the farmers being selected within a stratum. Therefore, in order to provide unbiased estimators, (2.8) must be weighted using the weighted exogenous sampling estimator (WESML) suggested by Manski and Lerman (1977)[75]. According to the authors, with reference to this study, the quasi-loglikelihood function will be

$$
\begin{aligned} Q_{WML}(\beta, \delta, \sigma, \lambda) = & Q_i\{\ln L_i = \ln 2\pi - \frac{1}{2}\ln\sigma^2 + \ln\phi(\frac{\varepsilon_i}{\sigma}) + \ln\Phi(-\frac{\varepsilon_i\lambda}{\sigma}) - \frac{1}{2}\ln|\Sigma| \\ & - \frac{1}{2}\eta_i'\Sigma^{-1}\eta_i + \ln|J_i|\} \end{aligned} \tag{2.17}
$$

Cameron and Trivedi (2005)[76] show that even if the sampling process is affected by endogeneities, WESML[6] estimator is still consistent. Since the information matrix does not hold for the quasi-maximum likelihood estimator (Q_{WML}), the asymptotic variance-covariance matrix can be calculated using the sandwich estimator $n^{-1}\sum_{i=1}^{n}(\mathbf{Q}_i \odot \mathbf{H}_i)^{-1}(\mathbf{Q}_i^2 \odot \mathbf{G}_i\mathbf{G}_i')(\mathbf{Q}_i \odot \mathbf{H}_i)^{-1}$ where n is the sample size, $\mathbf{G}$ and $\mathbf{H}$ are the gradient and the Hessian of

[6]WESML is also called sometimes Weighted Endogenous Sampling Estimator

(2.17), respectively, Q_i is the sampling weight associated with each observation and $\odot$ is the element by element Hadamard product (Cameron and Trivedi, 2005, p. 828)[76].

Table 2.1: Descriptive Statistics

Variable	Unit	Mean	Std Dev
Production	Lbs.	839,158.580	1,180,553.940
Hired Labor	Hr	32.460	86.149
Nitrogen	Lbs.	2,447.960	5,382.990
Phosphate	Lbs.	2,164.480	3,012.960
Potash	Lbs.	2,471.720	3,149.980
Insecticide	Lbs.	138.460	297.241
Herbicide	Lbs.	175.458	257.082
Fungicide	Lbs.	195.972	304.414
Price Labor	US$/Hr	7.708	1.517
Price Nitrogen	US$/Lbs.	2.779	1.959
Price Phosphate	US$/Lbs.	1.274	1.991
Price Potash	US$/Lbs.	1.299	2.120
Price Insecticide	US$/Lbs.	10.208	3.373
Price Herbicide	US$/Lbs.	38.150	17.502
Price Fungicide	US$/Lbs.	60.396	27.727
Precipitation	mm	120.985	24.124
Dew Point	$^{\circ}C$	16.148	2.735
Temperature	$^{\circ}C$	22.126	1.310
Sample Size	389		

Notes: Nutrients and pesticides refer to the actual weight of the active chemical component. The actual active component of the commercial pesticides has been calculated using the specific gravity of each chemical component as reported by the "EPA Pesticides Standard Reference Guide". Prices of Nitrogen, Phosphate and Potash have been simulated through an OLS model.

The ARMS survey does not report the price of single nutrients applied by the respondents; therefore, it was necessary to derive these data on the basis of available information provided by the survey. The sample of peanut farmers was asked to report: (i) total cost of all commercial fertilizer products applied in their field[7], (ii) total acres treated with these products, (iii) quantity applied per acre, (iv) percentage analysis of plant nutrients applied

[7]This cost refers only to the cost of materials (N-P-K nitrogen-phosphorus-potash) and it excludes lime, gypsum, manure and application costs.

per acre. Consequently, the prices of nutrients have been calculated using an ordinary least square model where the fertilizer expenditure (E)[8] per unit of land (US$/acre) was regressed on the actual acreage treated [9] with the chemical components producing the estimates as reported in table 2.2[10].

Table 2.2: Estimated Nutrients Expenditures

Dependent Variable: Expenditure per unit of land (E)	
Intercept	41.014***
	(2.092)
Acres treated with Nitrogen (A_N)	0.045**
	(0.017)
Acres treated with Phosporus (A_P)	-0.085**
	(0.042)
Acres treated with Potash (A_K)	0.077**
	(0.038)
F-statistics	6.22***
Observations	389

Notes: ***99%, **95%, *90% Confidence Interval. Standard Errors in parentheses.

The single nutrient's expenditure per acre (US$/acre) has been calculated by simulation setting equal to zero the mutually exclusive components' acreages (A_N, A_P or A_K). For example, the phosphorus' expenditure per unit of land is $E_P = 41.014 - 0.085A_P$. Finally the nutrients' price for each farmer is calculated by the ratio of the total nutrient expenditure (US$) to the total pounds of nutrient applied; for example the price of phosphorus (US$/Lbs.) for each farmer is calculated as $P_P = (E \cdot A_P)/P$ where P are total Lbs. of phosphorus.

[8]is calculated as the ratio of the total expenditure on fertilizer to the total acres treated.

[9]The actual acreage treated with a specific nutrient is calculated by the product of the total acres treated and the percentage of plant nutrient applied per acre.

[10]$E_i = \alpha_0 + \alpha_1 A_{Ni} + \alpha_2 A_{Pi} + \alpha_3 A_{Ki} + \xi_i \quad i = 1, ..., n$ where where A_N, A_P and A_K are acreages treated with nitrogen, phosphorus and potash, respectively.

2.6 Results

The quasi-loglikelihood function (2.17) is optimized using the Broyden–Fletcher–Goldfarb–Shanno (BFGS) method for non-linear optimization available in the optimization library of the Ox Matrix language (Doornik, 2006)[77]. The BFGS algorithm is widely used to numerically solve very complex unconstrained problems such as the optimization of equation (2.17) using a limited amount of computer memory. Furthermore, this algorithm numerically approximates the Hessian matrix of (2.17) with a positive–semidefinite matrix that is updated at each step by an iterative procedure based on gradients evaluation. As a consequence, it could be avoided to provide the analytical Hessian of (2.17) that can be cumbersome while ensuring a convergent solution of the numerical optimization problem.

Table 2.3 presents the parameter estimates of the production function with and without systematic errors in allocation. The parameter λ is statistically different from zero at the 10% confidence level; therefore, the peanuts production frontier is stochastic as also previously found by Nadolnyak *et al.* (2006)[11][78].

In terms of the magnitude of the parameters, no substantial differences exist between the model that includes systematic error in allocation and the model that disregards them. However, given the lower Akaike Information Criteria (AIC), the model representing the production function that accounts for systematic errors better fits the data. Additionally, given the hypothesis that agricultural producers systematically overuse chemical inputs, the model with systematic errors is a better choice.

Table 2.4 reports the model statistics also in case of systematic error in allocation. On average peanut farmers have a technical efficiency that is 65.3%. The hypothesis of overuse of chemical production factors is confirmed by the negative sign of all the allocative inefficiency terms η's. In particular fungicides, by the magnitude of their mean allocative inefficiency, appear to be the chemical factor that is used in the least efficient way. In fact, with reference

[11]The authors conducted a stochastic cost frontier analysis in the peanut sector.

Table 2.3: Stochastic Frontier Analysis

Parameter	Estimates	Estimates with systematic error in allocation
Constant	8.134***	8.134***
	(0.022)	(0.022)
Hired Labor	0.455***	0.453***
	(0.003)	(0.003)
Nitrogen	0.243***	0.242***
	(0.115)	(0.114)
Phosphate	0.284**	0.284**
	(0.134)	(0.133)
Potash	0.260*	0.259*
	(0.136)	(0.135)
Insecticides	0.275***	0.274***
	(0.043)	(0.042)
Herbicides	0.268***	0.267***
	(0.077)	(0.077)
Fungicides	0.234***	0.234***
	(0.077)	(0.077)
Precipitation	-0.241**	-0.240**
	(0.105)	(0.104)
Temperature	3.832***	3.833***
	(0.068)	(0.068)
Dew Point	-1.666***	-1.666***
	(0.061)	(0.061)
σ	1.242***	1.237***
	(0.178)	(0.177)
λ	0.208*	0.205*
	(0.087)	(0.087)
Log-Likelihood	-206,763	-191,445
AIC	413,529	382,893
Observations	389	389

Notes: ***99%, **95%, *90% Confidence Interval. Standard Errors in parentheses. AIC = Akaike Information Criteria.

to figure 2.1a at the mean value it results in $w_F \cdot exp(\eta_F) = 0.38 < w_F = 60.39$, and the labor/fungicide ratio is lower than the cost minimizing condition.

Table 2.4: Model Statistics

	Model		Model with systematic error in allocation	
	mean	St. Dev.	mean	St. Dev.
Technical Efficiency	0.645	0.056	0.653	0.055
η_N	-3.764	1.052	-3.763	1.052
η_P	-3.602	0.754	-3.600	0.753
η_K	-3.624	0.915	-3.623	0.915
η_I	-1.910	0.929	-1.911	0.929
η_H	-4.790	1.918	-4.790	1.918
η_F	-5.058	1.012	-5.056	1.011
	Cost increase		Cost increase with systematic error in allocation	
	Technical Inefficiency	Allocative Inefficiency	Technical Inefficiency	Allocative Inefficiency
Mean	0.219	0.847	0.214	0.849
1^{st} Quartile	0.186	0.612	0.182	0.614
2^{nd} Quartile	0.218	0.701	0.213	0.703
3^{rd} Quartile	0.249	1.101	0.243	1.103

Notes: 389 observations. Technical Efficiency and Cost increases are expressed in percentage.

The over-use of fungicide with respect to all the other inputs is also confirmed by the fact that $(w_F/w_i) \cdot exp(\eta_F/\eta_i) < w_F/w_i$ $(i = N, P, K, I, H)$ and $(w_F/w_L) \cdot exp(\eta_F) < w_F/w_L$. Table 2.5 reports these inequalities evaluated at mean values.

A comparison of the results in table 2.5 indicates that the price ratio of fungicide to other inputs price is on average always lower than the cost minimizing ratios. The derivation of the cost increase due to both technical and allocative inefficiency is the percentage cost increase of allocative inefficiency

$$\frac{1}{r}\sum_{j=2}^{7}\beta_j\eta_j + \ln[\beta_1 + \sum_{j=2}^{7}\beta_j e^{-\eta_j}] - 2\ln r \tag{2.18}$$

Table 2.5: Overuse of Fungicide with respect to other inputs

	$(w_F/w_i) \cdot exp(\eta_F/\eta_i)$	w_F/w_i
Nitrogen	0.274	21.737
Phosphorus	0.233	47.406
Potash	0.239	46.508
Insecticides	0.043	5.917
Herbicides	0.766	1.583
	$(w_F/w_L) \cdot exp(\eta_F)$	w_F/w_L
Labor	0.001	7.836

Notes: Input price ratios are evaluated at the mean value of the variables.

while the percentage cost increase of technical inefficiency is $100 \cdot (u/r)\%$ (Kumbhakar and Wang 2006, pp. 435-436)[72].

In the current study, peanut farmers face a cost increase of 21.4% due to technical inefficiency on average, while 50% of farmers see their costs augmented by 70.3% due to allocative inefficiency. Those cost increases could be reduced if peanut farmers appropriately reduced chemical input use. For example, Nadolnyak *et al.* (2006)[78] found that the experience and managerial skill (proxied by education) of the peanut farmer increase technical efficiency and reduce the associated costs.

Isolating the effect of fungicides, if peanut farmers could cultivate an engineered crop that would avoid the use of this factor then they would have potentially reduced the total cost of chemical inputs up to 36.2%.

2.6.1 Environmental Implications

Climate variables have a significant impact on the productivity of peanuts. In particular the temperature appears to be an important growth factor as also confirmed by field experiments conducted by Cox (1979)[79]. Farmers who have their farm located in areas which had on average a temperature of 2° Celsius higher could expand their production by 250,000 lbs. in the 2004 growing period, *ceteris paribus*. Farms located in wet areas appear to be less productive. A 10% increase in rainfall would decrease the production of peanuts by 2.4%. A similar negative impact of water was found by Wright and Ross (1986)[80] in Virginia. These authors attributed the decrease in peanut's yield to the excess of water that may increase the proliferation of soil borne disease. In line with the previous result, but to different extent, this research also finds a negative impact of an increase in relative humidity (Dew Point). Cotty and Jaime Garcia (2007)[81] found evidence that warm and humid climates are particularly favorable for *Aspergillus*' infections and aflatoxin contamination that may explain the decline in productivity of those areas.

The results of this research are clear: peanut farmers in the United States overuse fungicides. The impact of allocative inefficiency of fungicide on the demand for other inputs can be derived easily from equations (2.12) and (2.13)[12]. This analysis shows that the inefficient use of fungicides would also increase the demand for other chemical factors in the extent of 2.43% per farmer. The overuse of all chemical factors can be seen as an environmental externality connected to the inefficient use of fungicides. The magnitude of this finding is not extremely severe for the case of non-point source pollution deriving by the induced over-use of fertilizer; however, considering the cumulative effect of some pesticides released in the environment over time and the aggregate contribution of all peanut farmers in the U.S., the inefficient use of fungicides can have a significant negative impact on the quality of the ecosystems. Between 1992 and 2001 pesticides and their degradates were found in 4,380 water samples derived from agricultural, urban and mixed-use land streams across the nation (Gilliom *et al.*, 2007)[82].

Agricultural biotechnological research should pay attention to genetic traits of peanuts to make this cultivar resistant to fungal pathogens. However, the current study considers the entire aggregated class of fungicides. Peanuts are known to be affected by more than forty fungal diseases (Gnanamanickam, 2002)[83]; therefore, a future analysis should be even more disaggregated and restricted only to the chemical class of fungicides to study the over use of a particular fungicide with respect to the others. Such an analysis will allow understanding

[12] Demand increase for input x_j due to allocative inefficiency of fungicide is $\frac{1}{r}\sum_{k=2}^{J}\beta_k\eta_k - \hat{\eta_F}$.

of precisely the particular class of fungal pathogen that should be the research focus of geneticists.

In addition to the farmers' welfare improving by cutting the cost of fungicide, an increase in social welfare would be derived by reducing the usage of other chemicals that may affect soil and water quality of those areas in proximity of peanuts farms. A cultivar that is genetically manipulated to be resistant to fungal pathogens would also induce the farmers to reduce the usage of other chemicals decreasing the environmental contamination. The ecotoxicological impact deriving from the overuse of pesticides in the peanut sector can be a future research avenue that can be explored in an interdisciplinary effort.

2.7 Conclusions

A consistent amount of agricultural output is known to be lost every year to insects, weeds and other plant pathogens. The use of pesticides is a common agricultural practice that, combined with other inorganic factors such as nutrients, produce environmental externalities. Genetic engineering may mitigate these problems. Additionally, it may also increase the agricultural productivity and reduce the associated costs of production. While there is evidence in agricultural sectors such as cotton, corn and soybean, that biotechnology indeed increased the economic welfare of producers and consumers (Falk-Zepeda, Traxler and Nelson, 2000)[84], in the peanut sector biotechnological research is still at the developing stage.

This study addressed the issue of the economic and environmental benefits that may potentially derive from using genetically manipulated peanuts. In particular this research used a cross-sectional sample of U.S. peanut farmers to test the hypothesis of overuse of chemical factors with respect to labor and to address research priorities in biotechnology towards the chemical input that has been mostly misused. A primal system approach of a stochastic frontier analysis, consisting of a self-dual production function and the first order condition of cost minimization, revealed that U.S. peanut farmers overused fungicides more than any other input. The overuse of fungicide could be a particular need of peanut farmers to defeat crop infections from fungi that produces mycotoxins. Although this research does not explain the overuse of this particular factor, that can be a future research direction to be investigated, the positive analysis shows that misusing fungicide induced also an increase in demand for other chemical factors.

If peanut farmers could adopt an engineered cultivar that could be resistant to fungal pathogens, they could potentially reduce on average the total cost of chemicals up to 36.2% and the demand for all other factors by 2.43%. Considering the cumulative effect of pesticides in the environment, reducing the use of these factors can be a further contribution towards the increase in social welfare by improving the quality of the ecosystems in proximity of the farming areas.

Chapter 3

Rotation of Peanuts and Cotton for Optimal Nitrogen Applications

⋆⋆⋆

3.1 Introduction

Webster *et al.* (2000)[85] argues that diminishing carrying capacity of the land was one of the reasons for the demise of the Mayan civilization. This society was mainly dependent on maize, the single crop locally grown. Monocultural practices adopted by the Mayan population diminished and eventually destroyed the productivity of land. If there is environmental historical evidence supporting the thesis that monoculture leads to an unsustainable land use, the agronomic science provides a systematic proof of this thesis. Spatiotemporal continuous crop systems may become susceptible to pests and plant disease because of a lack of crop diversification.

Tilman *et al.* (2002)[86] provide an exhaustive review of the benefits derived from multiple cropping systems and the practice of crop rotation. Such practices induce an increase in economic and social welfare derived from a natural increase in soil fertility. Consequently, farming activities would benefit from increased agricultural yields and reduce the need for chemical inputs. For example, the authors cite a study of Zhu *et al.* (2000)[87] where the adoption of multiple cropping systems consisting of two different rice varieties increased the profitability of Chinese farmers partly through reduction of use of powerful pesticides. Rotation practices can complement breeding and genetic programs to meet the future demand for food of the growing world population. While these practices can promote the sustainability of agroecological systems, they can also increase the welfare of those who live in agricultural areas.

There is also evidence that including legume species into crop rotation schemes can reduce the need for nitrogen fertilizers with a consistent positive impact on the cost reduction of agricultural productions (Yusuf *et al.*, 2009; Umrit, *et al.*, 2009; Farthofer *et al.*, 2004; Balkcom and Reeves, 2005; Becker and Johnson, 1999)[85][86][87][88][89][90][91][92]. Legumes can fix a considerable amount of atmospheric nitrogen and they can be cultivated without the need of supplemental fertilization (Giller, 2001)[93].

A rotation practice that is common worldwide is that of cotton (*Gossypum hirsitum L.*) and legumes. Kumbhar *et al.* (2008)[95] conducted a series of experiments in Pakistan and found a substantial improvement in yield and nitrogen uptake of cotton subsequent to legumes. This practice is also common among Australian cotton farmers. Rochester *et al.* (2001)[94] observed a nitrogen rate reduction up to 52 Kg/Ha in cotton systems following green-manured legumes versus 179 Kg/Ha in continuous cotton.

In the Southeastern United States, a cotton and peanuts (*Arachis hypogea L.*) rotation is common (Johnson, 2001)[96]. Scientific evidence support the complementary role of peanuts and cotton in multiple cropping systems. For example, Rodriguez-Kabana and Backman (1987)[97] suggested that the rotation of these two crops would be the optimal choice to manage the pathogenic nematode *Meloidogyne arenaria*. From a 2 years field study in southeast Alabama, the authors found that the occurrence for *juvenile M. arenaria* was 98% lower in the peanut plots where the previous year cotton was planted. They concluded that such a practice would increase peanut yield without using nematicides.

On the other hand, the peanut is a legume that has N_2-fixation properties and can transfer the nitrogen to the next cultivar in intercropping systems (Chu, *et al.* 2004)[98]. The nitrogen transfer from peanut to cotton can reduce the application of nitrogen fertilizer the year that cotton is cultivated, thus lowering the costs of producing cotton.

The purpose of the current research is to develop a bioeconomic model that can be used to design an optimal decision rule for the application of nitrogen that maximizes the net return of farmers who practice a two-crop agricultural system. Such a decision will be used to compare the economic and environmental implications of a scenario where *(a)* cotton (*Gossypum hirsitum L.*) farmers practice crop rotation using the peanut (*Arachis hypogea L.*) as a complementary crop versus *(b)* a scenario of cotton monoculture in an agricultural area of Alabama.

Previous studies on the nitrogen contribution of peanuts to cotton are mainly agronomic in nature. These studies do not use economic data neglecting potential long run environmental and economic benefits derived from this cropping system. To my knowledge only two studies exist that examine the economic implications of a cotton–peanut rotation to manage soil-borne diseases from the perspective of peanut farmers. A welfare analysis of cotton farmers adopting peanuts as a complementary crop needs to be addressed.

This article unfolds as follows: section two reviews previous research, section three presents the bioeconomic model, section four is dedicated to the data used in this study, section five presents the econometric part of the bioeconomic model, section six discusses the results and finally section seven offers some concluding remarks.

3.2 Review of Previous Research

Taylor and Rodriguez-Kabana (1999a)[99] quantified the positive impact of *microbivore nematodes* on peanuts and cotton production as being approximately US$ 0.11 and US$ 0.13 per 100 cm^3 of soil. Subsequently Taylor and Rodriguez-Kabana (1999b)[100] designed a bioeconomic model to study the optimal decision rule for peanut–cotton crop rotation to manage soil–borne organisms. They found that the expected return per acre for peanuts and cotton monocultures would be potentially $133.95 and $10.14 less than what could be achieved using an optimal rotation scheme. Therefore, these economic studies provide evidenced that peanut farmers attain higher yields and lowers the pesticide costs if they use cotton as a complementary crop.

Adams *et al.* (1998)[101] points out that continuous monocultural production have been very popular in Alabama for 150 years. For example over the years continuous cotton production induced over–fertilization of soil that may not need more supplemental nutrients. After a series of chemical tests conducted on the soil of the state of Alabama, the authors recommend nitrogen applications of approximately 90 Kg/Ha for cotton and no fertilization for peanuts. These recommendations should be followed especially in those areas where the nitrogen supplying capacity of soil is low. When cotton is produced subsequent to peanuts, Adams *et al.* (1998)[101] recommended nitrogen rate up to 56 Kg/Ha. The reason of the reduced nitrogen application rate is consistent with nitrogen credits derived from the previous land use.

Smith and Sharpley (1990)[102] found evidence of nitrogen mineralization of indigenous and fertilized soils when peanut residues are retained in the soil. In contrast, Meso *et al.* (2007)[103] conducted field experiments at Headland, Alabama during the growing seasons 2003 and 2005 testing the nitrogen contribution of peanut residues to cotton. These experiments occurred in several subplots within Dothan sandy loam soil with and without peanuts residues. In the experiment, the researchers applied nitrogen to subplots at the rate of 0, 34, 67 and 101 Kg/Ha. Although peanuts residues had total soil nitrogen accumulation of 46 Kg/Ha (for the entire time of the experiment, i.e. 15.3 Kg/Ha·year), these authors argue that nitrogen transfers from peanut to cotton do not have a significant contribution and therefore peanuts should not be promoted as a nitrogen supplier to following crops in rotation schemes. However, the authors found evidence of an improvement in the physical and chemical properties of the soil when the crop residues were not removed.

Previous research has not attempted to examine whether previous peanut land use has a potential economic impact (positive or negative) on cotton farming activities and, moreover, ignored the potential environmental effects in terms of non-point source nitrogen pollution that may be reduced in the peanut-cotton rotation system.

3.3 Bioeconomic Model

Bioeconomic models have become a common tool to design optimal policies that simultaneously maximize human welfare and environmental quality of agro–ecological areas. An advantage of these models consists of having a more comprehensive view of the interactions between human activities and natural resources (Holden, 2005).[104].

Stochastic Dynamic Programming (SDP) is the dominant strategy for the bioeconomic modeling of the current research. This is a necessary choice if the scope of the research is to design an optimal decision rule for nitrogen applications in a rotation system over a long time horizon. There are two approaches to solve SDP problems. The first is a recursive model based on a Lagrangean framework such as the one used in Chapter 1. A second method, which is more suitable for long time horizons, is a recursive model with Bellman's Equation. In both cases an objective function, state, and decision variables need to be specified. In the current study it would be more suitable to use the second approach based on Bellman's Principle of Optimality. Bellman (1957, p. 83)[105] postulated:

> "An optimal policy has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision."

The Bellman's DP approach is a computer based numerical optimization technique to solve dynamic models. Before proceeding to the introduction of the formal bioeconomic model used in this research a simple deterministic numerical example is provided to see the economic structure behind the Bellman recursive solution. The example is based on a introductory problem available in Zietz (2007)[106].

For simplicity let us consider a simple linear production function where a generic crop yield (y) is equal to the amount of nitrogen applied (N) with a quadratic cost function of $0.4N^2$. Over a two year time horizon, the is to maximize the net return $\sum_{t=0}^{2} \beta^t (pN_t - 0.4N_t^2$ subject to the linear transition equation $x_{(t+1)} = x_t - N_t$ where N_t is the nitrogen application at time t and x_t is the nitrogen present in the soil that describes the state of the system at period t. Let us also assume that the nitrogen available in the soil is depleted completely at period 2; therefore, the terminal condition is $x_2 = 0$ and the price of the farmed crop is p. The problem is to find the optimal application rule that maximizes the net return of the farmer over the time horizon.

The problem can be rewritten using the Bellman equation introducing the value function V_t assuming a discount factor $\beta = 0.9$.

$$V_t = \max_{N_t}(pN_t - 0.4N_t^2) + 0.9V_{t+1}, \quad t = 0, 1.$$

The solution starts recursively backward from the boundary condition $x_2 = 0 = x_1 - N_1$. Therefore the transition equation at period 1 is $x_1 = N_1$ and the value function for this period is $V_1 = px_1 - 0.4x_1^2$ that can be plugged back into the Bellman equation for period 0.

$$V_0 = \max_{N_0}[(pN_0 - 0.4N_0^2) + 0.9V_1] = \max_{N_0}[(pN_0 - 0.4N_0^2) + 0.9(px_1 - 0.4x_1^2)].$$

At period 0 the transitional equation will be $x_1 = x_0 N_0$ that can be substituted back in the above equation to obtain $V_0 = \max_{N_0}[(pN_0 - 0.4N_0^2) + 0.9[p(x_0 - N_0) - 0.4(x_0 - N_0)^2]$ that can be maximized with respect to N_0 to find the optimal nitrogen application rule $N_0 = 0.4p - 0.32x_0$. This policy rule maximizes the net return of the farmer over two years. This procedure is particularly convenient for solving problems over a long time horizon by simply repeating these recursive steps n times.

However, the degree of complexity of the modeling design increases with the number of state and decision variables, functional forms of the production and cost functions, and whether stochastic processes affect the states of the system. Therefore, to find the best decision rule for optimal nitrogen application in a peanut-cotton rotation system, the recursive Bellman equation can be formulated as

$$V_t = \max_{LU_t, N_t} \{\mathbb{E}[R_t(N_t, NP_t, PCOT_t, PPNT_t, LU_{t-1}, LU_{t-2})] + \beta V_{t+1}\} \tag{3.1}$$

where the net return R_t at time t is a function of decision and state variables of the model. In particular, N_t is a decision variable that is the nitrogen application expressed in Kg/Ha; NP_t is a deterministic state variable related to the nitrogen contribution at time t deriving from previous peanuts land use; $PCOT_t$ and $PPNT_t$ are stochastic state variables of cotton and peanut prices at time t expressed in US$/lbs.; LU_t is a binary choice variable that refers to the land use at stage t and takes value one if cotton is planted and zero otherwise; $\mathbb{E}$ is the mathematical expectation; and β is a discount factor.

Equation (3.1) is maximized subject to the following transition equations

$$N_{t+1} = N_t + f(NP_t) \tag{3.2}$$

$$PCOT_{t+1} = \alpha_0^{COT} PCOT_t e^{\varepsilon_{t+1}^{COT}} \tag{3.3}$$

$$PPNT_{t+1} = \alpha_0^{PNT} PPNT_t e^{\varepsilon_{t+1}^{PNT}} \tag{3.4}$$

Equation (3.2) describes the nitrogen rate that depends on the previous rate plus the peanut contribution, derived from the previous period, which can be absorbed by the cotton root system according to a biophysical functional form. Equations (3.3) and (3.4) describe the price movements of cotton and peanuts disturbed by white noise ε_{t+1}^{COT} and ε_{t+1}^{PNT}. The stochastic prices serve essentially to simulate the uncertainty that is common in agricultural decision problems (Novak *et al.*, 1994; Danielson, 1993; Duffy, 1993)[107][108][109].

The next two subsections present in some details the net revenue function and the crop response functions to nitrogen and previous land-use. The reason to specify these biophysical response functions is strictly connected to the nature of the bioeconomic model.

Consequently, the objective value function (1) will be expressed in terms of choice (N_t, LU_t) and state variables (NP_t, $PCOT_t$, $PPNT_t$, LU_{t-1}).

3.3.1 Net Revenue Function

The net revenue function that appears in (3.1) has the following structure

$$\begin{aligned} R_t = & [(PCOT_t \cdot YCOT_t) - VCCOT_t - FCCOT_t - P_N N_t]LU_t \\ & + [(PPNT_t \cdot YPNT_t) - VCPNT_t - FCPNT_t](1 - LU_t) \end{aligned} \tag{3.5}$$

where $YCOT_t$ and $YPNT_t$ are crop yields in lbs./acres of cotton and peanut at time t, respectively; $VCCOT_t$ and $VCPNT_t$ are variable costs in US\$/acres that exclude the cost of nitrogen and the opportunity cost of land for cotton and peanut, respectively; $FCCOT_t$ and $FCPNT_t$ are fixed costs in US\$/acre for cotton and peanuts; PN is the price of nitrogen expressed in US\$/Kg; the other variable have been defined in the previous section 3.3.

3.3.2 Crop yields

In order to determine the optimal nitrogen applications, cotton yield is expressed as a function of nitrogen. For this purpose it is assumed that the cotton response to nitrogen is determined by the Mitscerlich-Baule (MB) functional form which exhibits a plateau at the maximum of the function as in Frank *et al.* (1990)[65]. In the current study the cotton response to nitrogen is conditional on previous land use. This condition is necessary to account for the nitrogen carryover derived from previous crop.

$$YCOT_t = \beta_0\{1 - exp[-\beta_{1t}(\beta_{2t} + N_t)]\} \tag{3.6}$$

Because peanuts do not require supplemental nitrogen, the yield will be the only function of the previous land use LU_{t-1} as follows

$$YPNT_t = \beta_4 + \beta_5 LU_{t-1} \tag{3.7}$$

3.4 Data

The model is parameterized to forecast 25 years of agricultural activities among the growers of peanuts and cotton in Monroe County in southwest Alabama. This county is a natural case study candidate because the soil characteristics favor the cultivation of both peanuts and cotton; however, cotton seems to be the first choice made by the farmers from this area. In fact, in 2010 the total acres devoted to cotton production were 17,500 versus 8,900 of peanuts (NASS, 2011). These crops represent the main agricultural activities of the county.

Economic data used in this study for the year 2010 are available at the Economic Research Service (ERS) of the United States Department of Agriculture (USDA) and are reported in Table 3.1. Time series data of peanut and cotton prices from 1913 to 2010 have been used to calibrate the price transition equations and are available at the National Agricultural Statistical Service (NASS) of the USDA. A discount rate of 3.29% is the average return on assets from US agricultural income as suggested by the Agricultural and Applied Economics Association (AAEA, 2000)[24].

Table 3.1: Economic Data

	cash price[a]	variable costs[b]	fixed costs[b]	Nitrogen price[c]
cotton	0.711	371.90	134.78	0.51
peanuts	0.215	541.25	181.63	—

[a]Cotton and peanuts are expressed in US$/lbs. [b]variable and fixed costs are expressed in US$/acre and they exclude the cost of nitrogen and the opportunity cost of land. [c]price of nitrogen is expressed in US$/lb.

Agronomic and environmental data were obtained from a biophysical simulation performed at the watershed level using the Soil and Water Assessment Tool (SWAT) supported by the Agricultural Research Service (ARS) at the Grassland Laboratory to estimate the potential nitrogen savings for a peanut-cotton rotation. The analysis has been conducted using 53 sub–basins in Monroe County which are subdivided into 199 independent hydrological response units (HRUs) as illustrated in Fig. 3.1. Each HRU is unique for geomorphology, pedological and phonological characteristics. Data on soil came from the *Soil Survey Geographic* (SSURGO2.2) *Database for Monroe County* from the Natural Resource Conservation Service (NRCS) of the USDA while land use has been modeled using the 2010 Cropland Data Layer from NASS (2011). Climate has been modeled using data on precipitation and minimum and maximum temperatures. Collected at a daily frequency from 01/01/1950 to 10/30/2009, these data, come from rain gauge-climatic stations located at (LAT 31.71667, LON -87.21666) , (LAT 31.71667, LON -87.26666), (LAT 31.61667, LON -87.55), (LAT 31.58333, LON -87.26666), and (LAT 31.38333, LON -87.41666) and available at ARS[110].

The nitrogen applications in each HRU have been simulated by selecting the auto-fertilization option of SWAT. The advantage of using this option consists of applying an optimal rate of nitrogen that is a function of the phonological characteristics of the HRU and the nitrogen stress threshold. This threshold is a function of the potential plant growth. If the plant goes intonitrogen stress then the SWAT model will apply an optimal amount of nitrogen in the HRU in order to ensure functional plant growth (Neitsch *et al.*, 2010)[111]. Table 3.2 shows the scheduled annual operations of management.

Table 3.2: Management Operations

Date	Operation	Cotton	Peanuts
1 May	Plant	—	×
10 May	Plant	×	—
10 June	N_2 Fertilization	×	—
10 October	Harvest	×	×

× indicates the event's occurrence; — is the non-occurrence of the event.

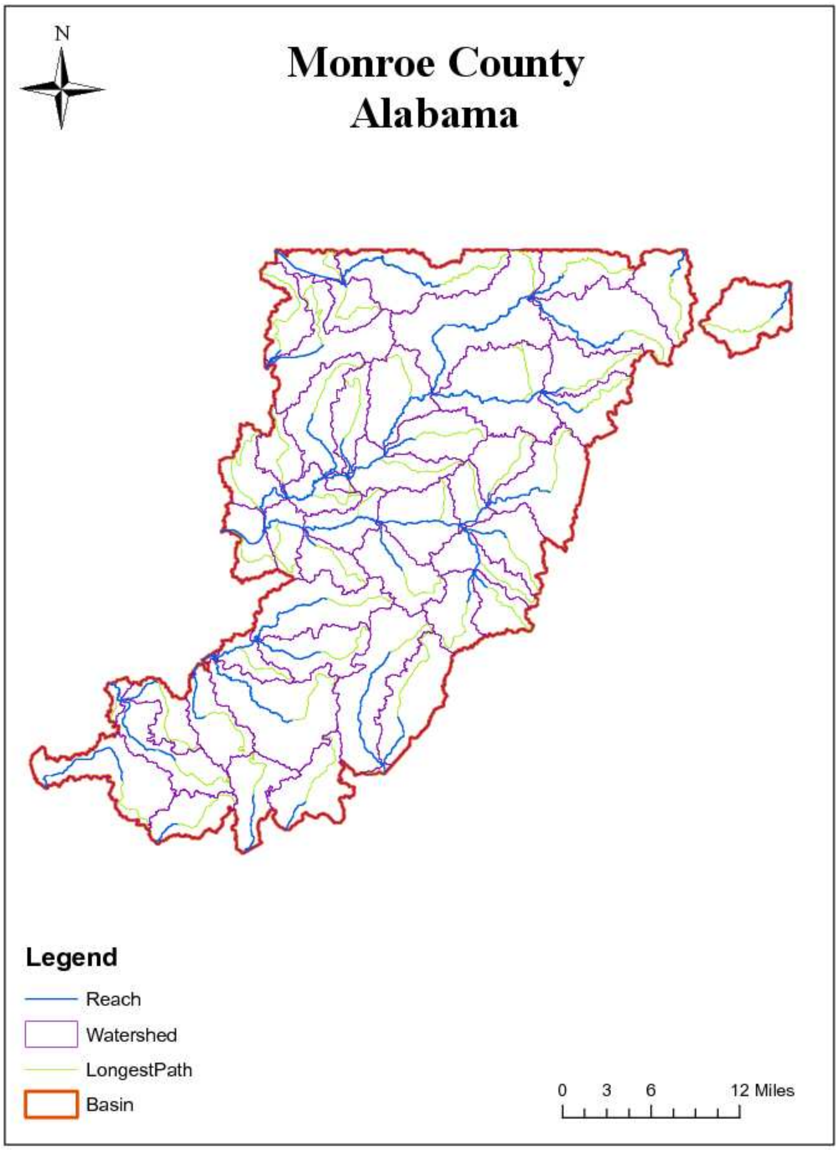

Figure 3.1: The Study Area

3.5 Econometric Calibration

Parameters of the bioeconomic model are econometrically estimated using data for Monroe County as described in the previous section. The econometric estimation of the parameters allows us to calibrate the model to perform simulations that provide realistic scenarios. The econometric procedure used for the calibration varies according to the mathematical relationship used in the SDP model and the data availability. The next subsections present in detail those econometric techniques used to estimate the equations that have been defined in the previous sections. In particular it will be shown the estimation of: *(i)* cotton and peanut response function to nitrogen and previous land–use, *(ii)* nitrogen elasticity of cotton supply that is used as prior data to calibrate the cotton response function, *(iii)* the deterministic transitional equation of nitrogen carryover, and *(iv)* the Markov switching models used to predict the transitional equations of cotton and peanut prices.

3.5.1 Cotton Response and Peanut Yield

Equation (3.6) can be estimated following the same econometric procedure proposed by Heckelei and Wolff (2003)[28] that has been used in Chapter 1, with the difference in this case that the limiting resource is nitrogen. The problem is to estimate the non-linear parameters of the MB response function β_{0t}, β_{1t} and β_{2t}. Therefore, the solution of the econometric problem starts with the profit maximization problem of the cotton grower that can be written in Lagrangean form as follows

$$\mathcal{L}_t = \{PCOT \cdot YCOT_t(N_t) - OCCOT - P_N N_t + \lambda_t[b_t - N_t]\}|LU_{t-1} \tag{3.8}$$

where b_t[1] is the nitrogen application at time t; λ_t is the opportunity cost of nitrogen; OCCOT are operative costs in US$/acre for the year 2010, which is the sum of variable and fixed costs as reported in table 3.1; the remaining variables have been previously defined.

[1] The nitrogen rate is the optimal amount of nitrogen applied by the biophysical simulator. The average values are between 71.83 Kg/Ha and 135.18 Kg/Ha depending on the previous land use.

From (3.8) the first order necessary condition can be written, $\forall t | LU_{t-1}$, as

$$\begin{aligned} \frac{\partial \mathcal{L}_t}{\partial N_t} &= PCOT \cdot \frac{\partial YCOT_t(N_t)}{\partial N_t} - P_N - \lambda_t = 0 \\ \Rightarrow \lambda_t &= PCOT \cdot \beta_{0t}\{\beta_{1t} exp[-\beta_{1t}(\beta_{2t} + N_t)]\} - P_N \end{aligned} \tag{3.9}$$

$$\frac{\partial \mathcal{L}_t}{\partial \lambda_t} = b_t - N_t = 0 \quad \text{(trivial)} \tag{3.10}$$

It can be observed from (3.9) that the crop response to a change of nitrogen application is

$$\frac{\partial YCOT_t(N_t)}{\partial N_t} = \beta_{0t}\{\beta_{1t} exp[-\beta_{1t}(\beta_{2t} + N_t)]\} \tag{3.11}$$

By multiplying both sides of (11) by the ratio of the nitrogen to the crop supply observed in a base year, it follows that

$$\frac{\partial YCOT_t(N_t)}{\partial N_t} \frac{N^o}{YCOT^o} = \beta_{0t}\{\beta_{1t} exp[-\beta_{1t}(\beta_{2t} + N_t)]\} \frac{N^o}{YCOT^o} \tag{3.12}$$

where the superscript '^{o}' refers to observed quantities. Equation (3.12) represents the nitrogen elasticity of supply that can be used as prior information to estimate the unknown parameters of (3.10). The problem is ill–posed because the number of observations (=1 nitrogen applications) is less than the number of parameters that need to be estimated (=3 β's). Therefore the only econometric technique that allows the estimation of ill–posed problems is the entropy criterion as suggested by Golan, *et al.* (1996)[31]. The problem consists of estimating simultaneously the equations (3.9), (3.10) and (3.12). The extreme points of the interval (variance) of the U.S. nitrogen elasticity of supply can be used as supports to recover the missing parameters. Therefore the estimated cotton response to nitrogen, although based on simulated nitrogen applications, carries real economic information derived from prior data.

The Generalized Maximum Entropy problem is formulated as

$$\max_{w_{mt},\beta_{0t},\beta_{1t},\beta_{2t},\lambda_t} H(w_m) = -\sum_{m=1}^{2} w_{mt} \ln w_{mt} \tag{3.13}$$

Subject to

$$\lambda_t = PCOT \cdot \beta_{0t}\{\beta_{1t} exp[-\beta_{1t}(\beta_{2t} + N_t)]\} - P_N \tag{3.14}$$

$$N_t = b_t \tag{3.15}$$

$$\sum_{m=1}^{2} v_m w_{mt} = \beta_{0t}\{\beta_{1t} exp[-\beta_{1t}(\beta_{2t} + N_t)]\} \frac{N^o}{YCOT^o} \tag{3.16}$$

$$\sum_{m=1}^{2} w_{mt} = 1 \tag{3.17}$$

where v_m are the support points centered in the midpoint of the elasticities' interval and w_{mt} is the posterior probabilities of the support points that maximize the entropy (3.13). Constraint (3.17) is the adding-up condition from the posterior supports' probabilities.

3.5.2 Nitrogen Elasticity of Supply

The prior information on elasticity of supply have been estimated using time series data from 1964 to 2009 of production and nitrogen use among the cotton farmers in the United States. These data are available at NASS and ERS. The ADF test (Dickey and Fuller, 1981)[112] detected a unit root in the log–linear stochastic processes[2]. However, the logarithmic form of total cotton production and nitrogen use are I(1) processes as confirmed by the ADF test[3]. The Box-Ljung test detected serial autocorrelation on the first lag of

[2] ln(Cotton): $\tau = |-3.10| < \tau^* = |-4.15|$ and $\phi = |4.94| < \phi^* = |9.31|$; ln(Nitrogen): $\tau = |-1.85| < \tau^* = |-4.15|$ and $\phi = |1.82| < \phi^* = |9.31|$. The test failed to reject the null hypothesis of non-stationarity.

[3] ln(Cotton): $\tau = |-5.03| > \tau^* = |-4.15|$ and $\phi = |13.73| > \phi^* = |9.31|$; ln(Nitrogen): $\tau = |-5.28| > \tau^* = |-4.15|$ and $\phi = |14.63| > \phi^* = |9.31|$. The test rejected the null hypothesis of non-stationarity.

the residuals obtained from the regression $\Delta \ln(Cotton)_t = -0.002 + 0.798 \Delta \ln(Nitrogen)_t$[4]. Therefore, the Cochrane-Orcutt (1949)[113] procedure can be implemented to correct this issue and provide a robust estimator of the elasticity that will be

$$\begin{aligned} \Delta \ln(Cotton)_t = \quad & 0.001 \quad +0.988^{***} \Delta \ln(Nitrogen)_t \\ & (0.015) \quad (0.019) \\ & \sigma = 0.15 \text{ Adj. } R^2{=}0.417 \\ & 45 \text{ observations} \end{aligned} \tag{3.18}$$

with standard errors in parentheses. Consequently, the two support points used in the entropy model to recover the missing parameters of the MB function are 0.869 and 1.107. These data[5] are used to numerically optimize the entropy problem to provide the estimated cotton response to nitrogen conditional on the previous land use (3.19; 3.20), while figure 3.2 illustrates the response curves conditional on previous land uses.

$$1276.001 - exp[-0.091(12.29 + N_t)] | LU_{t-1} = \text{cotton} \tag{3.19}$$

$$1320.541 - exp[-0.056(18.89 + N_t)] | LU_{t-1} = \text{peanut} \tag{3.20}$$

The estimated peanut yield based on the simulated data of the biophysical model conditioned on previous land use has a linear functional form given by

$$YPNT_t = 2558.6 + 796.5 LU_{t-1} \tag{3.21}$$

3.5.3 Transitional equations

The carryover function $f(NP_t)$ in equation 3.2, that relates the nitrogen contribution of peanuts, can be replaced by the nitrogen uptake function estimated by Meso *et*

[4]Although the parameters are still unbiased in presence of autocorrelation, the estimated variance of the parameters is downward biased; consequently, the standard errors are not reported.

[5]The support points [0.869; 1.107] which are the range of the nitrogen elasticity of cotton supply are obtained in the following way 0.988-0.119 = 0.869 and 0.988+0.119=1.107.

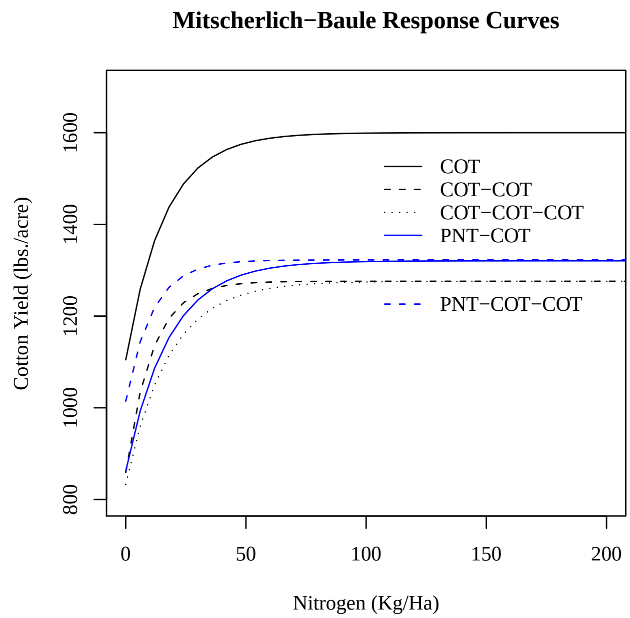

Figure 3.2: Mitscherlich-Baule cotton response to nitrogen

al. (2007)[103]. Using this biophysical relationship consists of the assumption that only a fraction of the nitrogen transferred from peanuts is absorbed by cotton in the soil root zone. Therefore, equation (3.2) can be rewritten as

$$N_{t+1} = N_t + 17 + 0.27(NP_t) \tag{3.22}$$

3.6 Markovian prices

A common assumption made in stochastic dynamic programming applied to agricultural economic problems is to consider the price as a result of a hidden Markov chain. Thus, equations (3.3) and (3.4) can be rewritten in log-linear form as

$$\ln(PCOT)_{t+1} = \phi_0^{COT} + \phi_1^{COT} \ln(PCOT)_t + \varepsilon_{t+1}^{COT} \tag{3.23}$$

$$\ln(PPNT)_{t+1} = \phi_0^{PNT} + \phi_1^{PNT} \ln(PPNT)_t + \varepsilon_{t+1}^{PNT} \tag{3.24}$$

Such log–linear Markovian processes may be subject to structural breaks that may determine different price regimes. Consequently, Markov switching regime models would be appropriate to assess the transitional probabilities between two different price regimes. For example, with reference to cotton (the same applies to peanuts) high and low price regimes labeled H and L can be assumed. Therefore the following process can be posited

$$\begin{aligned} \ln(PCOT)_{t+1} &= \mu_H^{COT} + \phi_1^{COT}\ln(PCOT)_t + \varepsilon_{t+1}^{COT} \text{ where } \varepsilon_{t+1}^{COT} \sim N(0,\sigma_H^2) \\ \ln(PCOT)_{t+1} &= \mu_L^{COT} + \phi_1^{COT}\ln(PCOT)_t + \varepsilon_{t+1}^{COT} \text{ where } \varepsilon_{t+1}^{COT} \sim N(0,\sigma_L^2) \end{aligned} \tag{3.25}$$

where the interecepts μ_H and μ_L represent the expectations of the cotton price in both regimes and σ_H^2 and σ_L^2 are price volatilities for the two regimes. Because the Markov chain is not visible, the transition from a high to a low price state is stochastic; therefore, equation (3.25) can be rewritten as

$$\ln(PCOT)_{t+1} = \mu_{s_t}^{COT} + \phi_1^{COT}\ln(PCOT)_t + \varepsilon_{t+1}^{COT} \text{ where } \varepsilon_{t+1}^{COT} \sim N(0,\sigma^2) \tag{3.26}$$

where the intercept $\mu_{s_t}^{COT}$ is a function of a latent random variable s_t that would assume value one if the price of cotton is high (μ_H) and zero otherwise (μ_L). In this case s_t is a two–state Markov chain where $Pr(s_t = j|s_{t-1} = i) = \pi_{ij}$ (Hamilton, 1994)[114]. The value of s_t can be assessed by observing the behavior of the price $\ln(PCOT)_t$, ϕ_1^{COT}, σ_2, μ_H, μ_L and the probabilities π_{HH} and π_{LL} of the price when those are on the same regime. To infer the value of s_t, Hamilton (1989)[115] implemented an iterative maximum likelihood algorithm where at each iteration the inferred probability of being in a regime (say j) will be $\xi_{jt} = Pr[s_t = j|\Omega_t; (\sigma, \phi_1^{COT}, \mu_H, \mu_L, \pi_{HH}, \pi_{LL})']$ with $\Omega_{t-1} = \{PCOT_{t-1}, PCOT_{t-2}, ..., PCOT_0\}$ and $j = H, L$.

If the probability density function for the two regimes is

$$
\begin{aligned}
\eta_{jt} &= f[\ln(PCOT)_t | s_t = j, \Omega_{t-1}; (\sigma, \phi_1^{COT}, \mu_H, \mu_L, \pi_{HH}, \pi_{LL})'] \\
&= \frac{1}{\sqrt{2\pi}\sigma} exp[-\frac{(\ln(PCOT)_t - \mu_j - \phi_1^{COT} \ln(PCOT)_{t-1})^2}{2\sigma^2}] \quad \text{with } j = H, L
\end{aligned} \tag{3.27}
$$

then the transitional probabilities will be filtered in the following step by the Hamilton filter that is

$$
\xi_{jt} = \frac{\sum_{i=H,L} \pi_{ij} \xi_{j,t-1} \eta_{jt}}{\sum_{i=H,L} \sum_{j=H,L} \pi_{ij} \xi_{j,t-1} \eta_{jt}} \tag{3.28}
$$

Results of the numerical analysis used to estimate the Markov switching autoregressive processes are reported in Table 3.3 while Figure 3.2 offers a graphical illustration of the stochastic processes, the smoothed[6], and the filtered switching regime probabilities.

For simplicity's sake, it has been assumed that cotton and peanut prices are not correlated and the price volatility does not switch. There is evidence from the analysis that the second order lagged dependent variable is statistically equal to zero; as a consequence, both cotton and peanut price are first order Markov chains.

3.7 Results

All the variables of the model have been discretized to simplify the numerical solution. The model consists of two states for each price variable and two and 250 levels for land use and nitrogen variables, respectively. There are a total of 2,000 states for the model and the dynamic program has been written and compiled using the computer language `ANSI C` (Kernighan and Ritchie, 1988)[116] to produce the optimal decision rule reported in table 3.4.

[6]The smooth probability refers to the regime probability based on the available information (up to time t)

Table 3.3: Markov Switching Model

	Cotton		Peanut	
	Low Regime	High Regime	Low Regime	High Regime
Intercept	-0.481***	0.481***	-0.532***	0.532***
	(0.041)	(0.057)	(0.041)	(0.049)
$\ln(Price)_{t-1}$	0.799***	0.799***	0.782***	0.782***
	(0.195)	(0.195)	(0.202)	(0.202)
$\ln(Price)_{t-2}$	0.074	0.074	0.172	0.172
	(0.191)	(0.191)	(0.209)	(0.209)
σ^2	0.240***	0.240***	0.158***	0.158***
	(0.060)	(0.060)	(0.018)	(0.018)
π_{HH}	0.9		0.9	
π_{HL}	0.1		0.1	
π_{LH}	0.1		0.1	
π_{LL}	0.9		0.9	
Ergodic Probability π_H	0.5		0.5	
Ergodic Probability π_L	0.5		0.5	
Log-Likelihood	-64.57		-73.29	
AIC	146.152		160.58	
Observations	97		97	

Notes: Standard error in parentheses, ***99%. **95%,*90% confidence interval. AIC=Akaike Information Criteria.

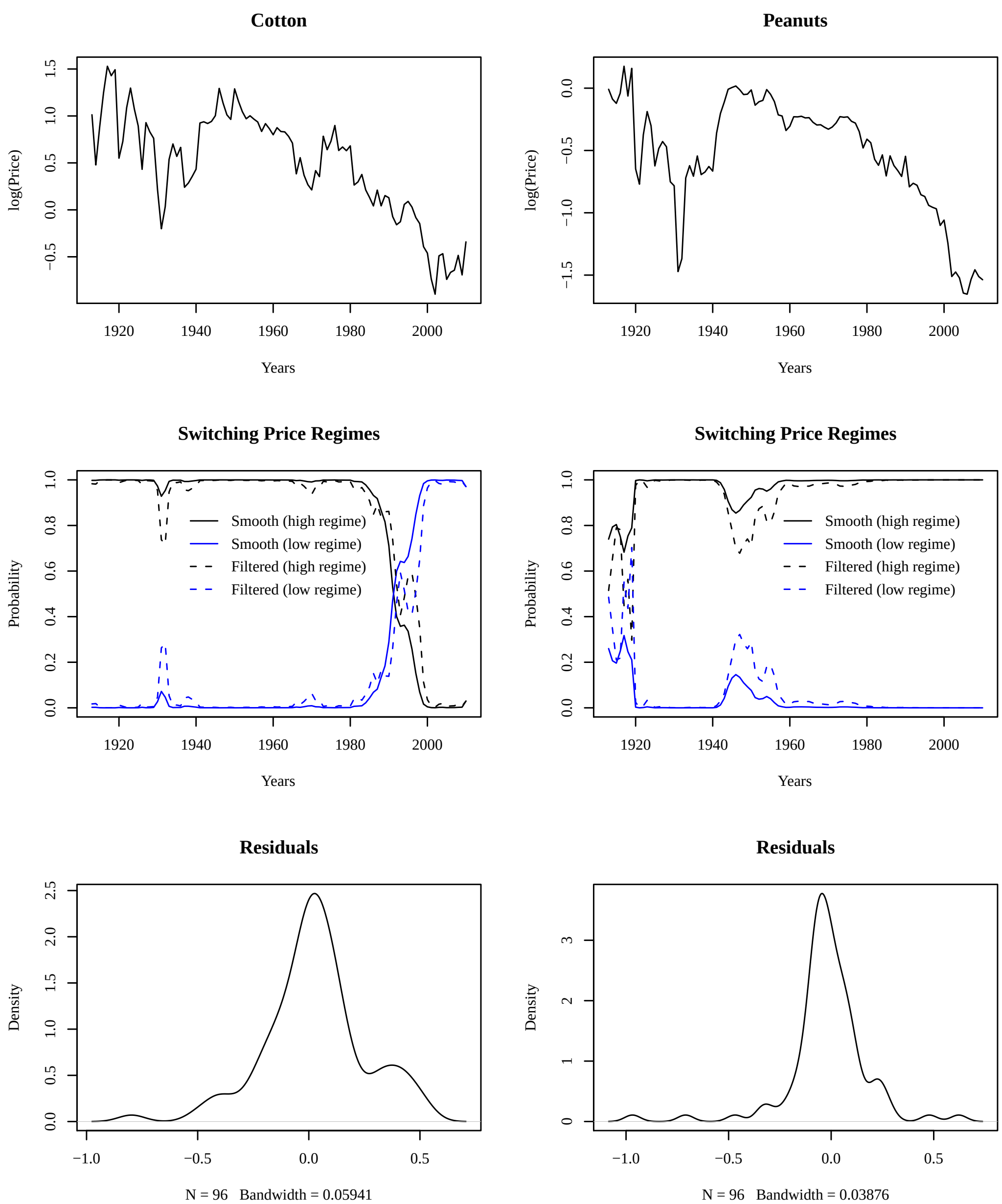

Figure 3.3: Markow Switching Autoregressive Model

Table 3.4: Time path - optimal decision rule for nitrogen applications

	Scenario (a)		Scenario (b)	
Year	Land Use	N_2 Rate (Kg/Ha)	Land Use	N_2 Rate (Kg/Ha)
2011	Cotton	123.460	Cotton	204.750
2012	Peanut	0.000	Cotton	95.000
2013	Cotton	79.826	Cotton	71.750
2014	Peanut	0.000	Cotton	71.750
2015	Cotton	80.151	Cotton	100.860
2016	Peanut	0.000	Cotton	100.860
2017	Cotton	80.482	Cotton	101.514
2018	Peanut	0.000	Cotton	101.514
2019	Cotton	80.820	Cotton	102.173
2020	Peanut	0.000	Cotton	102.173
2021	Cotton	81.163	Cotton	102.838
2022	Peanut	0.000	Cotton	102.838
2023	Cotton	81.513	Cotton	103.509
2024	Peanut	0.000	Cotton	103.509
2025	Cotton	81.868	Cotton	104.187
2026	Peanut	0.000	Cotton	104.187
2027	Cotton	82.229	Cotton	104.870
2028	Peanut	0.000	Cotton	104.870
2029	Cotton	82.596	Cotton	105.559
2030	Peanut	0.000	Cotton	105.559
2031	Cotton	82.970	Cotton	106.254
2032	Peanut	0.000	Cotton	106.254
2033	Cotton	83.349	Cotton	106.956
2034	Peanut	0.000	Cotton	106.956
2035	Cotton	51.234	Cotton	107.663
Expected Net Return	\$4,128,160.93		\$3,540,777.71	
Nitrogen in Runoff (Kg/acres)	2.450		2.610	

Scenario (a) is the peanut cotton agricultural system. Scenario (b) is continuous cotton. The expected net return is the expected return in the long of the cotton farmers in Monroe county for the two different scenarios.

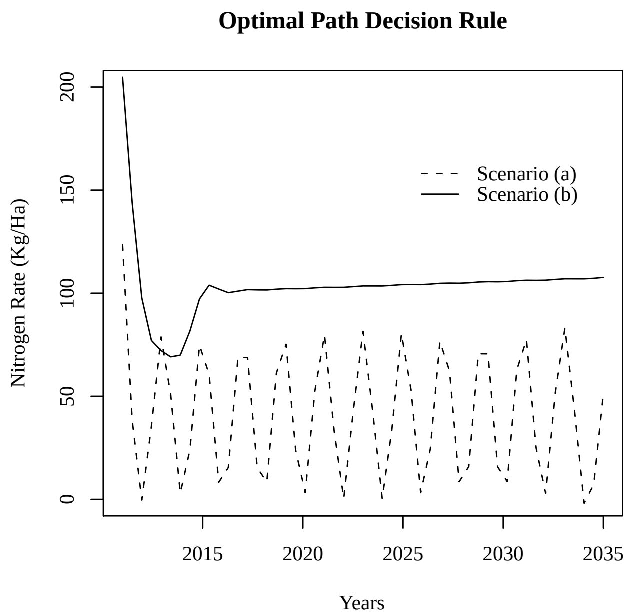

Figure 3.4: Time Path – Nitrogen Decision Rule

According to the model, cotton farmers should apply less nitrogen the year that cotton follows peanuts (scenario a) compared to cotton monocolture (scenario b). Figure 3.4 shows the dynamic rule of nitrogen applications for both scenarios.

The average nitrogen contribution of peanut is estimated at an average of 23 Kg/Ha per year. This figure is 33% smaller than the 34 Kg/Ha that are recommended by Adams *et al.* (1994)[101]. However, the model estimated nitrogen transfers from peanut to cotton that are not equal to zero and this result contrasts with the finding of Meso *et al.* (2007)[103] who estimated 46 Kg/Ha in 3 year period. The reason for the differences may be attributable to the different climatic and geographic location and the different source of data used. We should remember that the authors used experimental data while the model of the current research adopts data derived from a biophysical simulation.

We should also remember that the objective of this analysis is an economic assessment of potential benefits resulting from the inclusion of peanuts in a continuous cotton system. Because the objective function of the model is of an economic nature the output and input prices play a crucial role on the amount of nitrogen that is applied. While previous studies

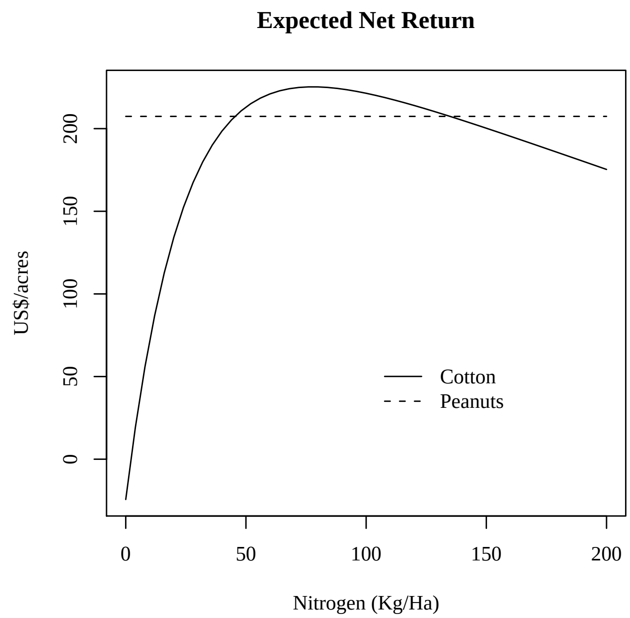

Figure 3.5: Expected Net Return in 2019

attempted to measure with a short period of time the optimal amount of nitrogen that maximizes the cotton yield in both scenarios, the current study is more concerned with a nitrogen decision rule that maximizes the net return of farmers to reach an economic optimum. For example Figure 5 is a graphical illustration of the objective function of the model in the year 2019. The expected net return is a function of nitrogen application and the maximum return would occur at a lower application rate (80.82 Kg/Ha) compared to scenario (b). This condition happens to be a consequence of having nitrogen credits from the previous land use that would lower the nitrogen costs in the cotton year.

If all cotton farmers from Monroe County would adopt peanuts in a rotation scheme and if they followed the strategy depicted in scenario (a) then their net return would potentially increase by approximately 14% which aggregates up to a US$ 587,383.21 increase in economic welfare for the entire area.

A secondary research question was to investigate whether the crop rotation scenario would also lead to an improvement in the water quality of the watershed by reducing the non-source nitrogen pollution. Because the nitrogen runoff does not directly affect the choice variables of the model (N_2 rate and land use), this state variable was calculated after the model was solved (post DP). With this state variable, analysis of the environmental consequences of the rational economic behavior of farmers in both scenarios is possible.

The analysis shows that rotation scenario (a) would reduce the long run nitrogen in runoff by 160 grams/acres corresponding to a reduction of approximately 6.13%. This figure may seem negligible; however, if the amount of nitrogen reduction is aggregated over the entire group of farmers (17,500 acres) then the total nitrogen released in the watershed as non–point source pollution would decrease by 2.8 metric tons per year. Considering a potential cumulative effect over the years, this result demonstrates a contribution in reducing the phenomenon of eutrophication of water bodies.

The environmental and agronomic data used in this research are simulated, and the biophysical model was not calibrated against experimental data from the case study area. If these data become available in the future, then an extension of this work may consists of a biophysical calibration and validation of the bioeconomic model to produce results that are more accurate in agronomic terms. However, despite these agronomical numerical improvements, results suggest that if cotton farmers adopt peanuts as a complementary crop in a two crop rotation system they would increase their economic benefit and improve the sustainability of their agroecological area.

3.8 Concluding Remarks

Rotation of cotton and legumes is an agricultural practice that is common in many rural areas of the world. Legumes have the property to fix atmospheric nitrogen and grow in soil with extremely low nitrogen content. In the Southeast of the United States, cotton–peanut rotation is quite popular. In particular, peanut growers alternate this crop with cotton to manage nematode and soil-borne diseases. Evidence in the literature suggests that cotton-peanut rotation can increase the economic returns of peanut farmers by increasing peanut yields and reducing the use of pesticides (Sholar *et al.*, 1995; Taylor and Rodriguez-Kabana, 1999)[117][100].

The peanut as a legume also has a potential benefit for cotton farmers. Peanuts can provide a nitrogen contribution to the soil in the year subsequent to when the cotton is planted. As a result, cotton growers may reduce the use of nitrogen fertilizer and benefit from higher returns the year that cotton is planted. This research tested this hypothesis and developed a bioeconomic model that compared economic returns in a peanut-cotton rotation scenario and a cotton monoculture one. As a byproduct of the research, environmental implications consisting of nitrogen levels in runoff were also estimated for both scenarios as an indicator of non-point source pollution.

The bioeconomic model consists of a *couplage* of two models: a biophysical model that simulates cotton and peanut cultivation at the watershed level and a stochastic dynamic model that simulates economic decisions made by the farmers at the farm level such that the comprehensive model can provide important information on the interaction between farmers, natural resources, and the environmental quality of the watershed. The model was parameterized to test the hypothesis of the study and forecast the optimal nitrogen rates that maximize the net returns of cotton farmers in both scenarios for 25 years in an agroecological area in Monroe County in Alabama.

There is evidence from the analysis that if cotton growers alternate cotton with peanuts then their net return would increase approximately by 14% in the long run in addition to a reduction of 6% of nitrogen released into the watershed, thereby improving the social welfare of the entire area. Future studies may estimate the long run social welfare improvement as a result of the synergic joint action of this rotation system. Such gains may consist of nitrogen and pesticides savings in the cotton and peanut year, respectively.

Bibliography

[1] Davis, Stacy C., S. W. Diegel and R. G. Boundy. 2010. *Transportation Energy Data Book*. Washington, DC: U.S. Department of Energy, Edition 29.

[2] Renewable Fuel Association, Available at: `http://www.afdc.energy.gov/afdc/ethanol/production.html` (Accessed May 30, 2011).

[3] Searchinger, T., Heimlich, R., Houghton, R. A., Dong, F., Elobeid, A., Fabiosa, J., Tokgoz, S., Hayes, D. and Yu, T. 2008. "Use of U.S. Croplands for Biofuels Increases Greenhouse Gases Through Emissions from Land-Use Change" *Science*, 319(5867): 1238-1240.

[4] Fargione, J., Hill, J., Tilman, D., Polasky, S. and Hawthorne, P. 2008."Land Clearing and the Biofuel Carbon Debt." *Science*, 319(5867): 1235-1238.

[5] Baker, J. S., McCarl, B. A., B. C. Murray, S. K. Rose, R. J. Alig, D. Adams, G. Latta, R. Beach, A. Daigneault. 2010. "Net farm income and land use under a U.S. greenhouse gas cap and trade." *Policy Issues*, 7:1-5.

[6] Khanna, M., C. L. Crago, and M. J. Black. 2011. "Can Biofuels be a Solution to Climate Change? The Implications of Land Use Change Related Emissions for Policy" *Interface Focus*, 1:233-247.

[7] Khanna, M., and L. A., Damon. 1999. "EPA's Voluntary 33/50 Program: Impact on Toxic Releases and Economic Performance of Firms", *Journal of Environmental Economics and Management*, 37:1-25.

[8] Krarup, S. and S. Ramesohl. 2002. "Voluntary agreements on energy efficiency in industry not a golden key, but another contribution to improve climate policy mixes." *Journal of Cleaner Production*, (10):109-120.

[9] Auld, G., S. Bernstein and B. Cashore. 2008. "The new corporate social responsibility." *Annual Review of Environment and Resources*, 33:187-211.

[10] Ali, S. H. 2002. "Environmental Planning and Cooperative Behavior: Catalyzing Sustainable Consensus". *Journal of Planning Education and Research*, (23):165-176.

[11] Shapouri, H., Duffield, J. A., and Wang, M., 2002, *The energy balance of corn ethanol: an update*. Washington, DC/Office of Energy Policy and New Uses, Agricultural Economics, Rept. No. 813:14

[12] Pimentel, D. and T. W. Patzek. 2005. “Ethanol Production Using Corn, Switchgrass, and Wood, Biodiesel Production Using Soybean and Sunflower”, *Natural Resources Research*, 14(1):65-76.

[13] Persson, T., A. Garcia y Garcia, J. O. Paz, J. W. Jones and G. Hoogenboom. 2009. “Net energy value of maize ethanol as a response to different climate and soil conditions in the southeastern USA ”, *Biomass and Bioenergy*, 33(8):1055-1064.

[14] Baumol, W. J, and W. E. Oates. *The theory of environmental policy*. New York: Cambridge University Press, 1989.

[15] Beach, R. H. and B. A. McCarl. 2010. U.S. Agricultural and forestry impacts of the energy independence and security act: FASOM results and model description. Research Triangle Park, NC: RTI International.

[16] United States Department of Agriculture Farm Service Agency: Direct and Counter-cyclical Payment (DCP) Program 2008. Available at: `http://www.fsa.usda.gov/Internet/FSA\File/dcp2008.pdf` (Accessed May 30, 2011).

[17] Rae, A. N. 1971. “Stochastic Programming, Utility, and Sequential Decision Problems in Farm Management”, *Am. J. Agr. Econ.*, 53 (3): 448-460.

[18] Rae, A. N. 1971. “An Empirical Application and Evaluation of Discrete Stochastic Programming in Farm Management”, *Am. J. Agr. Econ.*, 53 (4): 625-638.

[19] Halter, A. N., and G. W. Dean. 1971. *Decision Under Uncertainty with Research Applications*. Cincinnati: Southwestern Publishing Co.

[20] Hamilton, J. D. 2010. Personal Communication. University of South California San Diego, May.

[21] Häggström, O. 2002. *Finite Markov Chains and Algorithmic Applications*. London: Cambridge University Press.

[22] Anderson, T. W. and L. A. Goodman. 1957. “Statistical inference about Markov chains”. *The Annals of Mathematical Statistics*, 28(1):89110.

[23] Environmental Working Group Available at `http://farm.ewg.org/region.php?fips=01000&progcode=total&yr=2009` (Accessed January 25, 2011).

[24] Agricultural and Applied Economics Association. 2000. *Commodity Costs and Returns Estimation Handbook*. Report of the AAEA Task Force on Commodity Costs and Returns.

[25] Novak, J. L., D. Nadolnyak and R. McNyder. 2008. Analysis of Irrigated Corn Production Adoption Decisions in Alabama. Paper presented at the annual meeting of Southern Agricultural Economic Association, Dallas, Texas, February 2-6.

[26] Howitt, R. E. 1995. “Positive Mathematical Programming.”, *Amer. J. Agr. Econ.*, (77):329-342.

[27] Paris, Q., and R. E. Howitt. 1998. "An Analysis of Ill–Posed Production Problems Using Maximum Entropy", *Am. J. Agr. Econ.*, 80 (1): 124-138.

[28] Heckelei, T. and H. Wolff. 2003. "Estimation of constrained optimisation models for agricultural supply analysis based on generalised maximum entropy", *Eur. Rev. of Agr. Econ.*, 30(3):27-50.

[29] Shumway, R. C. 1986. "Supply relationships in the South What we have learned?", *Southern Journal of Agr. Econ.*, 18(1):11-19.

[30] Paris, Q. *Economic foundations of symmetric programming*. New York: Cambridge University Press, 2011.

[31] Golan, A., G. Judge, and D. Miller. 1996. *Maximum Entropy Econometrics: Robust Estimation with Limited Data*. New York: John Wiley Sons.

[32] Jaynes, E. T. 1957. "Information Theory and Statistical Mechanics", *The Physical Review*, 106(4):620-630.

[33] Paris, Q. 2001. "Symmetric Positive Equilibrium Problem: A Framework for Rationalizing Economic Behavior with Limited Information", *Am. J. Agr. Econ.* 83(4): 1049-1061.

[34] Birge, J. R. 1982. The value of stochastic solution in stochastic linear programs with fixed recourse, *Mathematical Programming*, 24:314-325.

[35] Birge, J. R., and Louveaux, F. *Introduction to stochastic programming*. New York: Springer, 1997.

[36] Sheehan, J., V. Camobreco, J. Duffield, M. Graboski, and H. Shapouri. 1998. *An overview of biodiesel and petroleum diesel life cycles*. Washington, DC: U.S. Department of Energy/National Renewable Energy Laboratory, Pub. No. 580-24772.

[37] Khanna, M. 2008. "Cellulosic biofuels: Are they economically viable and environmentally sustainable?", *Choices*, 23:16-21.

[38] Van Dyne, D. L., J. A. Weber and C. H. Braschler. 1996. "Macroeconomic effects of a community-based biodiesel production system.", *Bioresource Technology*, 56:1-6.

[39] Lau, L.J. 1978. "Testing and Imposing Monotonicity, Convexity, and Quasi-Convexity Constraints." Appendix A4 in *Production Economics: A Dual Approach to Theory and Applications*. Edited by M. Fuss and D. McFadden. Amsterdam: North Holland.

[40] Jenkins, B. M., L. L. Baxter, T. R. Miles Jr., and T.R. Miles. 1998. "Combustion properties of biomass", *Fuel Processing Technology*, 54:1746.

[41] United States Environmental Protection Agency. 2010. *Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2008*, Washington D.C.: U.S. EPA 430-R-10-006, chap. 7 and Annex 2.

[42] Collins, H., S. Frantzen, A. Alva, R. Boydston, A. Hang and S. Fransen. 2005. "Biofuel Variety Trials", Working Paper, Center for Sustaining Agriculture and Natural Resources, Washington State University. Available at `http://cff.wsu.edu/publications/posters/FieldDAY\2005\BioFuels.pdf` (Accessed January 25, 2011).

[43] Duke, J.A,.1983. Handbook of Energy Crops. Unpublished book, Purdue University.

[44] U.S. Department of Energy - Oak Ridge National Laboratory. Available at: `http://bioenergy.ornl.gov/papers/misc/energy\_conv.html` (Accessed January 30, 2011).

[45] United States Department of Agriculture. 2009. *Alabama, State and County Data*, 2007 Census of Agriculture, Volume 1, Geographic Area Series, Part 1, AC-07-A1.

[46] Food And Agriculture Organization. 2011. `http://faostat.fao.org/site/339/default.aspx` (Accessed October, 24 2011).

[47] Dohlman, E., Hoffman, L., Young, E. McBride W. 2004. "Peanut Policy Change and Adjustment Under the 2002 Farm Act", OCS-04G-01, *Economic Research Service*/United States Department of Agriculture

[48] Fletcher, S.M. 2002. *Peanuts: Responding to Opportunities and Challenges from an Intertwined Trade and Domestic Policies*. The University of Georgia, National Center for Peanut Competitiveness. Athens, GA.

[49] Hedayati, M. T., A. C. Pasqualotto, P. A. Warn, P. Bowyer, and D. W. Denning. 2007. "Aspergillus flavus: human pathogen, allergen and mycotoxin producer", *Microbiology*, 153:16771692.

[50] Wu F. and P. Khlangwiset. 2010. "Health economic impacts and cost–effectiveness of aflatoxin reduction strategies in Africa: Case studies in biocontrol and postharvest interventions.", *Food Additives Contaminants*, 27:496-509.

[51] National Cancer Institute. 2011. Available at: `http://www.cancer.gov/cancertopics/types/liver` (Accessed August, 29 2011).

[52] Food and Drug Administration. 2011. Available at: `http://www.fda.gov/ICECI/ComplianceManuals/CompliancePolicyGuidanceManual/ucm074703.htm` (Accessed August, 29 2011).

[53] Carsel, R. F., R.L. Jones, J.L. Hansen and R.L. Lamb. 1988. "Simulation Procedure for Groundwater Quality Assessments of Pesticides", *Journal of Contaminant Hydrology*, (2):125-138

[54] Jonnala, R. S., N. T. Dunford and K. Chenault. 2005. "Nutritional Composition of Genetically Modified Peanut Varieties.", *Journal of Food Science*, 70:4.

[55] Price, G.K., J. B. Lin, W. Falck-Zepeda, and J. Fernandez-Cornejo. 2003. "The Size and Distribution of Market Benefits from Adopting Agricultural Biotechnology.", *U.S. Department of Agriculture, Economic Research Service*, Technical Bulletin No. 1906.

[56] Fernandez-Cornejo, J. and M. Caswell. 2006. "The First Decade of Genetically Engineered Crops in the United States", U.S. *Department of Agriculture, Economic Research Service*, Technical Bulletin No. 11.

[57] Holbrook, C. Corley, and H. Thomas Stalker. "Peanut Breeding and Genetic Resources." In *Plant Breeding Reviews*, edited by Jules Janick, 297-356. Oxford, UK: John Wiley Sons, Inc., 2010.

[58] Wynne, J. C., and T. A. Coffelt. 1982. Genetics of Arachis hypogaea L. p. 5094. In: H. E. Pattee and C. T. Young (eds.), *Peanut science and technology.* Am. Peanut Res. Educ. Soc., Yoakum, TX.

[59] Murthy, T. G. K., and P. S. Reddy. 1993. *Cytogenetics and genetics of groundnut.* Intercept Ltd. Andover, England.

[60] Knauft, D. A., and J. C. Wynne. 1995. "Peanut breeding and genetics.", *Advances in Agron.*, 55:393445.

[61] Lamb, M. C., and D. A. Sternitzke. 2001. "Cost of aflatoxin to the farmer, buying point, and sheller segments of the Southeast United States peanut industry.", *Peanut Sci.*, 28:5963.

[62] Isleib, T. G., C. C. Holbrook, and D. W. Gorbet. 2001. "Use of plant introductions in peanut cultivar development.", *Peanut Sci.*, 28: 96113.

[63] Hanson, T., D. Hite and B. Bosworth. 2001. "A Translog Demand System for Inherited Traits in Aquacultured Catfish.", *Aquaculture Economics and Management*, 5(1/2):1-11.

[64] Paris, Q and K. Knapp. 1989. "Estimation of von Liebig Response Functions.", *Amer. J. of Agric. Econ.*, 71(1):178-186.

[65] Frank, M. D., B. D. Beattie and M. E. Embleton. 1990. "A Comparison Of Alternative Crop Response Models.", *Amer. J. of Agric. Econ.*, 72(3), 597-603.

[66] Ackello-Ogutu, C., Q. Paris and W. A. Williams. 1985. "Testing A Von Liebig Crop Response Function Against Polynomial Specifications.", *Amer. J. of Agric. Econ.*, 67(4), 873-880.

[67] Grimm, S,S., Q. Paris and W.A. Williams. 1987. "A Von Liebig Model For Water And Nitrogen Crop Response.", *Western J of Agr Econ*, 12:02.

[68] Paris, Q. 1992. "The von Liebig Hypothesis.", *Amer. J. of Agric. Econ.*, 74(4):1019-1028

[69] Kumbhakar, S. and C. A. K. Lovell, *Stochastic Frontier Analysis*, New York: Cambridge University Press, 2000.

[70] Neswiadomy, M. L. 1988. "Input Substitution in Irrigated Agriculture in the High Plains of Texas, 1970-80", *Western J of Agr Econ*, 13(1): 63-70

[71] Schmidt, P and C. A. Knox Lovell. 1979. "Estimating technical and allocative inefficiency relative to stochastic production and cost frontiers.", *Journal of Econometrics*, 9(3):343-366.

[72] Kumbhakar, Subal C. and H. Wang. 2006. "Estimation of technical and allocative inefficiency: A primal system approach.", *Journal of Econometrics*, 134(2):419-440.

[73] Jondrow, J., C. A. Knox Lovell, I. S. Materov and P. Schmidt. 1982. "On The Estimation Of Technical Inefficiency In The Stochastic Frontier Production Function Model.", *Journal of Econometrics*, 19(2-3):233-238.

[74] Economic Research Service USDA ARMS Farm Financial and Crop Production Practices: Documentation. Available at: `http://www.ers.usda.gov/Data/arms/GlobalDocumentation.htm` (Accessed November 8, 2011).

[75] Manski, C. F. and S. R. Lerman. 1977. "The Estimation of Choice Probabilities from Choice-Based Samples.", *Econometrica*, 45:1977-1988.

[76] Cameron, A. Colin and Pravin K., Trivedi. *Microeconometrics, Methods and Applications.* New York: Cambridge University Press, 2005.

[77] Doornik, J.A. 2006. *An Introduction to OxMetrics 4*. London: Timberlake Consultants Press.

[78] Nadolnyak, D. A., S. M. Fletcher and V. M. Hartarska. 2006. "Southeastern Peanut-Production Cost Efficiency Under the Quota System: Implications for the Farm-Level Impacts of the 2002 Farm Act.", *Journal of Agricultural and Applied Economics*, 38(1):213-224.

[79] Cox, F. R. 1979. "Effect of Temperature in Peanut Vegetative and Fruit Growth.", *Peanut Science*, 6:14-17.

[80] Wright, F. S., D. M. Porter, N. L. Powell, and B. B. Ross. 1986. "Irrigation and Tillage Effects on Peanut Yield in Virginia.", *Peanut Science*, 13(2):89-92.

[81] Cotty, P. J. and R. Jaime-Garcia. 2007. "Influences of climate on aflatoxin producing fungi and aflatoxin contamination", *International Journal of Food Microbiology*, 119:109115.

[82] Gilliom, R, J, J. E. Barbash, C. G. Crawford, P. A. Hamilton, J. D. Martin, N. Nakagaki, L. H. Nowell, J. C. Scott, P. E. Stackelberg, G. P. Thelin, and D. M. Wolock. 2007. *Pesticides in the Nations Streams and Ground Water, 19922001.* Reston, VA: U.S. Department of the Interior U. S. Geological Survey.

[83] Gnanamanickam, S. *Biological control of crop diseases.* New York: Marcel Dekker Inc., 2002.

[84] Falck-Zepeda, J.B., G. Traxler and R. G. Nelson. 2000. "Surplus Distribution from the Introduction of a Biotechnology Innovation.", *Amer. J. of Agric. Econ.*, 82:360-369.

[85] Webster, D., A. Freter, and N. Golin. *Copán: The Rise and Fall of an Ancient Maya Kingdom*. Forth Worth: Harcourt Brace Publishers, 2000.

[86] Tilman, D., K. G. Cassman, P. A. Matson, R. Naylor and S. Polasky. 2002. "Agricultural Sustainability and intensive production practices.", *Nature*, (418)671-677.

[87] Zhu, y., H. Chen, J. Fan, Y. Wang, Y. Li, J. Chen, J. Fan, S. Yang, L. Hu, H. Leung, T.W. Mew, P.S. Teng, Z. Wang. and C.C. Mundt. 2000. "Genetic diversity and disease control in rice.", *Nature* (406)718722.

[88] Yusuf, A.A., E.N.O. Iwuafor, R.C. Abaidoo, O.O. Olufajo and N. Sanginga, 2009. "Effect of crop rotation and nitrogen fertilization on yield and nitrogen efficiency in maize in the northern Guinea savanna of Nigeria.", *Afr. J. Agric. Res.*, 4(10): 913-921.

[89] Umrit, G., M.A. Bholah and K.F.N.K. Kwong, 2009. "Nitrogen benefits of legume green manuring in sugarcane farming systems in Mauritius". *Sugar Tech.*, 11(1): 12-16.

[90] Farthofer, R., J.K. Friedel, G. Pietsch, T. Rinnofner, W. Loiskandl and B. Freyer, 2004. Plant biomass nitrogen and effects on the risk of nitrate leaching of intercrops under organic farming in Eastern Austria. Proceedings of the EUROSOIL, Sept. 4-12, Freiburg, Germany, pp: 67-69.

[91] Balkcom, K.S. and D.W. Reeves, 2005. "Sunn-hemp, utilized as a legume cover crop for corn production.", *Agron. J.*, 97: 26-31.

[92] Becker, M. and D.E. Johnson, 1999. "The role of legume fallows in intensified upland rice-based systems of West Africa.", *Nutr. Cycl. Agroecosyst.*, 53: 71-81.

[93] Giller, K.E. 2001. *Nitrogen Fixation in Tropical Cropping Systems*. Oxon, UK: CAB International, Wallingford.

[94] Rochester, I., M.B Peoples, N.R Hulugalle, R.R Gault, G.A Constable. 2001. "Using legumes to enhance nitrogen fertility and improve soil condition in cotton cropping systems.", *Field Crops Research*, 70(1):27-41.

[95] Kumbhar, A. M., U. A. Burriro, S. Junejo, F. C. Oad, G.H. Jamro. B. A. Kumbhar and S. A. Kumbhar. 2008. "Impact of different nitrogen levels on cotton growth, yield and N-uptake planted in legume rotation.", *Pak. J. Bot.*, 40(2):767-778.

[96] Johnson,W. C., III, T. B. Brenneman, S. H. Baker, A.W. Johnson, D. R. Sumner, and B. G. Mullinix, Jr. 2001. "Tillage and pest management considerations in a peanut–cotton rotation in the southeastern Coastal Plain.", *Agronomy Journal*, 93:570576.

[97] Rodrguez-Kbana, R., H. Ivey, and P. A. Backman. 1987. "peanut–cotton Rotations for the Management of Meloidogyne arenaria.", *J Nematol.*,19(4): 484486.

[98] Chu, G.X., Q.R. Shen, and J.L. Cao. 2004. "Nitrogen fixation and N transfer from peanut to rice cultivated in aerobic soil in an intercropping system and its effect on soil N fertility.", *Plant and Soil*, 263(1):17-27.

[99] Taylor, C. and R. Rodriguez-Kabana. 1999. "Population dynamics and crop yield effects of nematodes and white mold in peanuts, cotton and velvet beans.", *Agricultural Systems*, 59(2): 177-191.

[100] Taylor, C. and R. Rodriguez-Kabana. 1999. "Optimal rotation of peanuts and cotton to manage soil-borne organisms.", *Agricultural Systems*, 61(1): 57-68.

[101] Adams, J. F., C. C. Mitchell, and H. H. Bryant. 1994. Soil test fertilizer recommendations for Alabama crops. Alabama Agriculture Experiment Station, Agronomy and Soils Department Series. No. 178.

[102] Smith, S. J., and A. N. Sharpley. 1990. "Soil nitrogen mineralization in the presence of surface and incorporated crop residues.", *Agronomy Journal*, 82:112116.

[103] Meso, B., K. S. Balkcom, C. W. Wood, and J. F. Adams. 2007. "Nitrogen Contribution of Peanut Residue to Cotton in a Conservation Tillage System.", *Journal of Plant Nutrition*, 30(7): 1153-1165.

[104] Holden S., B. Shiferaw and J. Penden. 2005. *Policy Analysis for Sustainable Land Management and Food Security in Ethiopia: A Bioeconomic Model with Market Imperfections*. Washington, DC: International Food Policy Research Institute, Research Report No. 140.

[105] R. E. Bellman. *Dynamic Programming*. Princeton N.J.: Princeton University Press, 1957.

[106] Zietz, J. 2007. "Dynamic Programming: An Introduction by Example.", *J. of Econ. Educ.*, 38(2):165-186.

[107] Novak, F.S., G. W. Armstrong, C.R. Taylor and L. Bauer. 1994. "An Analysis of Alternative Cropping Decision Rules", *Agricultural Systems*, (46):19-31.

[108] Danielson, J. 1993. "Optimal Crop Rotation to control Cephalosporium Stripe in Winter Wheat". *Applications of Dynamic Programming to Agricultural Decision Problems*. C. R. Taylor, ed. Boulder, CO: Westview Press.

[109] Duffy, P. A. 1993. "Optimal Farm Program Participation and Base Acreage Adjustment Under Alternative Program Provisions". *Applications of Dynamic Programming to Agricultural Decision Problems*. C. R. Taylor, ed. Boulder, CO: Westview Press.

[110] Economic Research Service USDA Climatic Data for the United States . Available at: `http://ars.usda.gov/Research/docs.htm?docid=19388` (Accessed November 9, 2011).

[111] Neitsch, S.L., J. G. Arnold,J. R. Kiniry, R. Srinivasan, J. R. Williams. 2010. *Soil and Water Assessment Tool Input Output File Documentation Version 2009*. Texas Water Resource Institute Technical Report No. 365.

[112] Dickey, D. and W. Fuller. 1981. "Likelihood Ratio Tests for Autoregressive Time Series with a Unit Root.", *Econometrica*, (49):1057-1072

[113] Cochrane, D. and G. Orcutt. 1949. "Application of least squares regression to relationships containing autocorrelated error terms.", *Journal of the American Statistical Association*, (44):32-61.

[114] Hamilton, J. D. *Time series analysis*. Princeton N.J.: Princeton University Press, 1994.

[115] Hamilton, J. D. 1989. "A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle.", *Econometrica*, 57(2):357-84.

[116] Kernighan, B. W. and D. M. Ritchie. 1988. *The C programming language*. 2nd ed. Englewood Cliffs N.J.: Prentice Hall.

[117] Sholar, J.R., R.W.Mozingo, and J.P. Beasley, Jr. 1995. "Peanut cultural practices.", *Advances in peanut science*. H.E. Pattee and H.T. Stalker ed. Stillwater, OK: Am. Peanut Res. Educ. Soc.

Appendices

Appendix A

GME - GCE Formulation

Heckelei and Wolff (2003)[28] assume disturbances in the data generation process of the model's variables[1]. These errors can be thought of as measurement errors or inefficiencies in productivity or in this case forecast errors made by the climatologists of the extension service. Therefore, after accounting for the errors, if the crop yield in the $k(=3)$ states of nature is $y_{ijk} - e^{y}_{ijk}$ and the observed land allocation is $\ell^{o}_{ij} - \sum_{k=1}^{3} \theta_k e^{\ell}_{ijk}$[2], where $\theta = [0.33, 0.30, 0.37]'$ is the vector of Markovian ENSO probabilities, the reparameterization of the disturbances and the own and cross price elasticities of supply $\varepsilon_{ii'}$ will be,

$$e^{y}_{ijk} = v^{y}_{ijk} w^{y}_{ijk}, \qquad e^{\ell}_{ijk} = v^{\ell}_{ijk} w^{\ell}_{ijk} \quad \text{and} \quad \varepsilon_{ii'} = v^{\varepsilon}_{ii'} w^{\varepsilon}_{ii'} \tag{A.1}$$

where $\boldsymbol{ws}$ are the posterior probabilities of the vs supports. In particular the support of the error of the crop yield v^{y}_{ijk} was centered around zero and the upper and lower bounds (variance) have been calculated as plus or minus the difference between the average yield in the ENSO state of nature and the most recent observed crop yield when the respective ENSO event occurred $y_{ijk} - y^{o}_{ijk}$. For the land allocation normally distributed errors have been added with support point centered at zero and standard deviations equal to 10% of the average land allocation. As supports for the own and cross price elasticities of supply, a range of elasticities from a previous study by Shumway (1986)[29] in the South U.S. has been employed. The support points have been centered on the midpoint of the intervals reported in table A.1.

[1] The authors assume random errors around land allocations, input allocations and supply quantities. See Heckelei and Wolff (2003)[28] p. 39.

[2] The expected value of the disturbances is taken because the observed land allocation is one of the possible allocations from the discrete probability distribution set.

Table A.1: Range of own and cross price elasticities of supply

Quantity	Price			
	corn	cotton	peanuts	soybeans
corn	[0.340 ; 1.590]	[-0.810 ; 0.092]	[-0.230 ; -0.060]	[-1 ; +0.91]
cotton	[-0.090 ; 0.120]	[0.150 ; 0.360]	[-0.110 ; -0.061]	[-0.01 ; +0.02]
peanuts	[-0.230 ; -0.050]	[-0.300 ; 0.020]	[0.340 ; 0.150]	[-0.02 ; 0.06]
soybeans	[-0.030 ; 0.030]	[-0.300 ; 0.030]	[-0.490 ; 0.270]	[0.940 ; 3.300]

Source: Shumway (1986). *Notes:* Because the elasticities for peanuts were not available, elasticities range of oil crops has been used as substitute.

Golan *et al.* (1996)[31] suggest that relaxing the bounds of the support will give more power to the data reducing the power of the prior information. According to this suggestion the 3σ[3] rule has been used to set the upper and lower bounds of the elasticities support.

Because the problem is well–posed and the number of observation is larger than the number of parameters to be estimated, including the errors is a straight econometric consequence that alleviates the computational burden of estimating 38×3[4] non-linear cost functions.

After the reparameterization, the GME - GCE formulation of the problem is

$$\max_{w^{\ell}_{ijkm},w^{y}_{ijkm},w^{\varepsilon}_{im},d,q,h,\lambda_{jk}} I(w^{\ell}_{ijkm}, w^{y}_{ijkm}, w^{\varepsilon}_{im})$$

$$= -\sum_{i=1}^{4}\left[\sum_{j=1}^{38}\sum_{k=1}^{3}\sum_{m=1}^{2} w^{\ell}_{ijkm} log\left(\frac{w^{\ell}_{ijkm}}{\theta_k}\right)\right. \tag{A.2}$$

$$\left.+\sum_{j=1}^{38}\sum_{k=1}^{3}\sum_{m=1}^{2} w^{y}_{ijkm} log\left(\frac{w^{y}_{ijkm}}{\theta_k}\right) + \sum_{m=1}^{2} w^{\varepsilon}_{im} log\left(w^{\varepsilon}_{im}\right)\right]$$

Subject to

[3] The rule is a direct application of the Chebychev inequality, see Golan *et al.* (1996)[31] p. 88. Heckelei and Wolff (2003)[28] use even a wider interval equal to 5σ.

[4] Because the goal is to estimate the quadratic cost function that calibrates model (1.1), an alternative way could be estimating a cost function for each county for each ENSO scenario.

$$\begin{aligned}\sum_{k=1}^{3}\sum_{m=1}^{2}\theta_k\, p_i(y_{ijk}-v^{y}_{ijk}w^{y}_{ijkm})-c_i+s^{o}_{ij}-\lambda_{jk}-d_i \\ -\sum_{i'=1}^{4}\left[q_{ii'}(\ell^{o}_{i'j}-v^{\ell}_{ijk}w^{\ell}_{ijkm}\right]=0\end{aligned} \tag{A.3}$$

$$\sum_{i=1}^{4}\sum_{k=1}^{3}\sum_{m=1}^{2}\left(\ell^{o}_{ij}-v^{\ell}_{ijk}w^{\ell}_{ijkm}\right)\leq b^{o}_{j} \tag{A.4}$$

$$q_{ii'}=\sum_{i'=1}^{4}h_{ii'}h_{i'i} \qquad \text{with } h_{ii'}=0 \quad \forall i'>i \tag{A.5}$$

$$\begin{aligned}\sum_{m=1}^{2}v^{\varepsilon}_{i}w^{\varepsilon}_{im} \\ =\sum_{j=1}^{38}\sum_{k=1}^{3}\sum_{m=1}^{2}\theta_k\left\{\left[q^{-1}_{ii'}-\left(\sum_{i'=1}^{4}\frac{a_{ijk}}{q_{ii'}}\right)q_{ii'}\right]^{-1}\frac{p_i}{(y_{ijk}-v^{y}_{ijk}w^{y}_{ijkm})\bar{\ell}^{o}_{ij}}\right\} \\ \forall i,i'\text{with} i\neq i'\end{aligned} \tag{A.6}$$

$$\sum_{k=1}^{3}\sum_{m=1}^{2}\theta_k w^{\ell}_{ijkm}=1,\ \ \sum_{k=1}^{3}\sum_{m=1}^{2}\theta_k w^{y}_{ijkm}=1 \text{ and } \sum_{m=1}^{2}w^{\varepsilon}_{im}=1 \tag{A.7}$$

where the superscript '^{o}' refers to observed variables, subscript i refers to the crop while i' is the crop subscript transposed, j are the counties, k the ENSO states of nature and m is the number of supports. The objective function (A.2) is cross–entropy that needs to be minimized to reduce the distance between the posterior probabilities of the errors and the prior information of the Markovian probabilities θ_k. Because the cross–entropy is taken with the negative sign, the problem now is to find the maximum value of the negative cross-entropy. Equation (A.3) is the reparameterized first order condition (1.10), (A.4) is the land constraint with the error, (A.5) is the Cholesky factorization that ensures the proper curvature of the quadratic cost function[5], (A.6) is the reparameterized relationship (1.15) where a_{ijk} are the elements of the matrix of technical coefficients calculated as the inverse of

[5]See Lau (1978)[39], Appendix A.4 p. 422.

the crop yield and expressed in acres/lb. As mentioned in the chapter, such a relationship holds because land is the only limiting factor considered in the analysis. Constraints (A.7) are the adding up conditions imposed to the supports' probabilities.

Appendix B

Net Energy Value and Carbon Emissions Calculation

The total net energy of biofuels produced in the state can be calculated as

$$NEG = \sum_{i=1}^{4} \sum_{j=1}^{38} \left(E_i^{biofuel} + E_i^{coproducts} - E_i^{farm} - E_i^{trip} - E_i^{process} \right) \ell_{ij} \tag{B.1}$$

where the first two addends under the summation indicate respectively the energy content of bioethanol or biodiesel and the stochastic biomass of the energy crop i expressed in MMbtu/acre. The subtrahends are the energy expenditures, also expressed in MMbtu/acre, respectively for farm practices such as energy content of nitrogen, phosphate, potash, pesticides and fossil fuels used for farming activities in addition to energy used to transport the crop i from the farm to the processing plant and the energy expended during the industrial process of biofuel production.

$$\begin{aligned} CO_2 = \sum_{i=1}^{4} \sum_{j=1}^{38} \Big(& CO_{2i}^{diesel} + CO_{2i}^{gasoline} + CO_{2i}^{LPG} + CO_{2i}^{farm} \\ & + CO_{2i}^{electricity} + CO_{2i}^{trip}) \ell_{ij} \end{aligned} \tag{B.2}$$

Equation (B.2) is the total emission of carbon dioxide derived from the entire process of biofuel production and takes into account the emission from diesel, gasoline, LPG used by the farmers in Alabama during the farming activities in addition to the emission due to the electricity used during the industrial process and the transportation of the energy crops from the farm to the conversion plant. The addends of the summation can be expressed in metric ton of CO_{2eq}/acre.

Net Energy values are calculated, in general, using the methodology of Pimentel and Patzek (2005) and Persson *et al.* (2009) with data from the sources reported in table B.1.

With reference to equation (B.1), table B.1 shows the values of the energy costs of the agricultural inputs and the energy gains of the outputs of four different types of biofuels considered in this study. The energy embodied in the cement, stainless steel and steel of the conversion plant has been omitted. This amount of energy can be thought of as a *fixed cost* in energy terms and its value will vanish in the long run.

The crop residues include 50% moisture. Assuming a natural drying process, the crop residues are able to support self-combustion (Jenkins *et al.*, 1998)[40]. This calculation assumes that the conversion of oil seed crops to biodiesel would occur at the processor of Decatur, Alabama (LAT 34.58, LON -86.98) while the ethanol conversion would be processed by the plant located at Olbion, Tennessee (LAT 36.26, LON -89.19).

Direct carbon emissions have been calculated using data and guidelines from the 2010 U.S. Greenhouse Gas Inventory Report of US-EPA[41] assuming 99% as an oxidation factor to carbon dioxide, while the emissions due to the electricity required by the conversion are available for the states of Tennessee and Alabama at the US Energy Information Administration.

Table B.1: Energy Gains and Energy Costs

Energy Content	Units	Corn	Cotton	Peanuts	Soybeans	Source
			Outputs			
biofuel	MMBtu/ lb seeds	0.0040	0.0003	0.0004	0.0002	C, ORNL
Crop residues	MMBtu/ lb	0.0073	0.0073	0.0073	0.0073	J, ORNL
			Inputs			
Seeds	MMBtu/ acre	0.8360	0.0840	1.0900	0.1850	PP, D
Nitrogen	MMBtu/ Kg	0.0633	0.0633	0.0633	0.0633	S
Phosphate	MMBtu/ Kg	0.0121	0.0121	0.0121	0.0121	S
Potash	MMBtu/ Kg	0.0044	0.0044	0.0044	0.0044	S
Herbicides	MMBtu/ Kg	0.2049	0.2049	0.2049	0.2049	Sh
Pesticides	MMBtu/ Kg	0.2109	0.2109	0.2109	0.2109	Sh
Fuel for farming	MMBtu/ acre	2.0043	2.0043	2.0043	2.0043	USDA, ORNL
Conversion process	MMBtu/ ton	20.7800	55.9100	148.3900	40.4300	PP, B
Electricity during the conversion	MMBtu/ ton	392.0000	270.0000	270.0000	270.0000	PP
trip	MMbtu/ (Km lb)	$1.50 \cdot 10^{-6}$	$1.50 \cdot 10^{-6}$	$1.50 \cdot 10^{-6}$	$1.50 \cdot 10^{-6}$	PP

C: Collins *et al.* (2005)[42], D:Duke (1983)[43], J:Jenkins *et al.* (1998)[40], ORNL:Oak Ridge National Laboratory[44], PP:Pimentel and Patzek (2005)[12], S:Sheehan *et al.* (1998)[36], Sh:Shapouri *et al.* (2002)[11], USDA: Census (2007)[45].

Appendix C

Biomass Crop Residue

A biophysical analysis has been performed at the watershed level using the Soil and Water Assessment Tool (SWAT) supported by the United States Department of Agriculture – Agricultural Research Service (USDA-ARS) at the Grassland Laboratory to estimate the potential biomass residue for the 4 major crops modeled. Given the substantial soil heterogeneity (US class B, C and D), the analysis has been conducted on 84 sub-basins in Lawrence county which have been further divided into 303 pedologically and phenologically independent hydrological response units (HRUs) with a territory that has three different geomorphological classes. The total cropland modeled lies on 44 HRUs. Data on soil came from the detailed Soil Survey Geographic (SSURGO2.2) Database for Lawrence County from the Natural Resource Conservation Service of USDA while the land use has been modeled using the National Land Cover Data of United States Environmental Protection Agency (US-EPA, 2001). The climate has been modeled using data on precipitation, minimum and maximum temperatures. These data, at daily frequency from 01/01/1950 to 10/30/2009, for the rain gauge-climatic stations located at (LAT 34.71, LON -86.58) and (LAT 34.75, LON -87.65) are available at USDA-ARS.

The SWAT model has been calibrated to replicate the farming management practices in the use of agricultural chemical inputs (fertilizers and pesticides) that are common in non-irrigated agriculture in Alabama. Parameters of the runoff curve, soil evaporation and plant uptake compensation factors have been adjusted in the attempt to match the annual yields of corn, cotton, soybeans for Lawrence County as reported in 2009 by the National Agricultural Statistical Service (NASS) while peanuts has been modeled using data from Dale County.