FORECASTING CROP WATER DEMAND: STRUCTURAL AND TIME SERIES ANALYSIS

by

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(Under the Direction of Tharuvai N. Sriram)

ABSTRACT

The dearth of information and invalid modeling approaches restrict crop water demand forecasting and thereby, efficient allocation of limited water resources in Georgia. This study adopts econometrics, structural time series (STMS), and univariate time series (ARIMA) approaches to forecast corn and soybeans irrigation water demand. The expected utility maximization theory and crop acreage supply response models offer the theoretical backup needed for the study. Especial efforts have been made to improve the existing crop acreage response models by incorporating institutional variables and stochastic trend variable. In our analysis, economic and institutional variables yield expected signs and significant results reflecting the importance of these variables in crop water demand forecasting. Moreover, inclusion of different nature of trend variable also improves the corn and soybeans acreage supply models. Further analysis using ARIMA and STSM with stochastic trend and no explanatory variables presents pure statistical perspective of the water demand forecasting issue.

INDEX WORDS: Crop supply response, Corn, Soybeans, Crop water demand, Water demand forecasts, Slippage

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A Thesis Submitted to the Graduate Faculty of The University of Georgia in Partial Fulfillment of the Requirements for the Degree

MASTER OF SCIENCE

ATHENS, GEORGIA

2004

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August 2004

ACKNOWLEDGEMENTS

First, I wish to express my profound gratitude to my major professor, Dr. Sriram N. Tharubhai for his support, encouragement, and friendship through out my graduate program. With out his help, it was not possible to complete this work in time. Thanks Dr. Tharubhai.

I am also very thankful for Dr. Cesar Escalante and Lynn Seymour. Especial thanks goes for their critical supports and advises to improve the quality of my work. I also wish to express my heartfelt thanks and appreciation to my father and mother. Without their unbounded love and support to their children and grand children, it was not possible to work late night and complete this thesis work in time.

I also would like to thank my brothers, sisters, and brother-in-laws for supporting and me throughout the graduate study. Finally, words are not enough to express my appreciation to my wife, Laxmi, for her support, love, and faith and to children Anupam and Asim for making our family life a wonderful experience.

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CHAPTER ONE

FORECASTING IRRIGATION WATER DEMAND UNDER RISK AND UNCERTAINTY: ECONOMETRIC AND TIME SERIES ANALYSIS

Efficient management of existing water resources has become an increasingly important aspect of water policy in the United States. The importance of efficient water use and management is supported by rapidly growing water demand and constant or decreasing supplies of water in many parts of the United States. Seasonal and/or cyclical scarcity of water, and increasing levels and variation in demand for water by municipalities, agricultural farmers, and industries have created political conflicts leading to more scrutiny of the efficiency of water use in the United States (Frey, 1993).

The problems associated with water scarcity are further exacerbated due to the requirements of water to meet minimum in-stream flow for habitat restoration, recreation, and navigation. Because recreational, environmental, and other use values of water may exceed the potential values of most other natural resources, there is a great concern and an increased investment for efficient and equitable management of this natural resource.

During most of the previous century, water management mostly focused on a search for new water supplies. As a result, large water development projects dominated water resource economics (Jordan, 1998). Over the past 200 years, construction of dams, reservoirs, pumps, canals, and levees have been carried out to meet the growing demand for water resulting from population growth and increased industrial and development activities. In recent times, developments of additional large-scale water projects seem very unlikely, because of high financial and environmental costs associated with these prospective water projects. The limited opportunities for building additional dams and reservoirs to meet storage need for increasing demand for water diminishes the economic feasibility of large-scale water projects, shifting the focus away from new construction to efficient and equitable allocation of existing water supplies (Hatch et al., 2000).

Furthermore, recent changes in water management from supply oriented (focused on water storage and distribution by developing a large-scale water project) to demand oriented (focused on controlling demand by efficient allocation of existing water resources) raises a need for more economic analysis and better management of existing allocation practices (Frey, 1993). The prospect of global climate change and growing demand for water will change the trend of existing water supplies, exacerbating water supply problems. It will reinforce the need for new water management methods and analysis of alternative methods of efficient water use. Integrated management of existing supplies and infrastructure at the river basin and watershed levels may offer a potential cost-effective means of increasing reliable supplies and resolving water problems and conflicts in many regions of the country (Hatch, *et al.*, 2000).

Until the last few years, there had been very little concern or conflict related to water supply in Georgia. Substantial expansion of urban areas, including Atlanta, prolonged drought in South Georgia. Also, the tri-state water dispute between Georgia, Alabama, and Florida have drastically increased the public awareness and concern about potential scarcity and availability of water in the last few years, making water allocation a serious political and public issue in Georgia. There is a growing concern in Georgia whether insufficient water supply may be able to sustain agriculture and simultaneously meet all other demands during the low rainfall years. Since agriculture is the largest consumer of water, it can play a crucial role in efforts to efficiently utilize water in Georgia. An efficient allocation of water resources in agriculture can enhance the water conservation efforts in Georgia for both future needs of agriculture and for other competing uses.

Problem Statement

Georgia’s water resources include over 70,150 miles of streams, 418,000 publicly owned acres of lakes, 594 square miles of estuaries, and four major aquifers namely: Florida, Claiborne, Clayton, and Cretaceous. Annual rainfall in Georgia ranges from more than 75 inches in the extreme northeast corner to 40 inches in the east central area (Jordan, 1998). Inspite of abundant water resources and significant rainfall, Georgia still experiences water scarcity problems. The rapidly rising population and recent adverse climatic conditions are major reasons for the current water crisis in Georgia. A growing population in North Georgia has distorted the normal supply of water to Atlanta and its environs, threatening further expansion of municipal and industrial activities.

Concurrent with the rapid growth in the Atlanta metropolitan area, a prolonged drought and increasing water demand for agriculture and other activities have created a strong pressure in the existing water resources of the state. The U. S. Geological Survey (USGS) reports that the rainfall deficit for Georgia in calendar year 1999 was about 11.5 inches, and that deficit continued increasing in 2000. During the recent drought period, stream flows in North Georgia have been at or near their lowest levels of this century. Also, during 1999-2000, a new record low daily flow was recorded at three stream-flow gauging stations along the Flint River.

In recent years, ground water levels in most of the state have been affected by reduced rainfall and increased ground water usage during the drought period. It has been reported that in the 24-county area of southeast Georgia, ground water pumping has reduced the Florida aquifer system at Brunswick by 65 feet since pumping started in the late 1800s (USGS, 2000). In this area, salt water intrusion has been experienced in the ground water and restrictions on water use have been imposed. Furthermore, from January through August 2000, new record low water levels have been recorded in more than 40 wells in the statewide groundwater monitoring network, mostly at wells located in southwest Georgia (USGS, 2000).

Inspite of depleting water levels in the existing aquifers, there is another reverse trend of increased water use in Georgia. USGS reports show that Georgia’s use of 1.19 billion gallons per day (bgd) of ground water and 4.63 bgd of surface water in 1995 were up from 0.996 bgd of ground water use and 4.36 bdg of surface water use in 1990, respectively (USGS, 2000). USGS estimates show that water withdrawals in Georgia increased almost nine percent between 1990 and 1995. These two opposing scenarios of adverse climatic conditions and growing water demand by municipalities, agriculture, and other sectors have created negative impacts on the state’s surface and ground water resources, depleting them below normal levels in many parts of Georgia. If this trend of increasing use and withdrawals of its water resources continues without conservation efforts, the sustainability of Georgia’s water resources will likely be threatened.

Water conservation is one of the major goals of water planning and policy making in Georgia. All alternative ways of efficient water use are to be examined in order to find the most beneficial ways of water use. The growing water crisis and increasing damages on the economy and environment of Georgia demand judicious use of existing water resources of the state. Agriculture, and especially irrigated agriculture, is the largest consumer of water in Georgia. It is estimated that the quantity of water withdrawn for irrigation purposes was 722 million gallon per day (mgd) in Georgia, with ground water and surface water supplying 479 mgd and 243 mgd of water, respectively, in 1995 (USGS, 2000). As irrigated agriculture requires large amounts of water, reallocation of water resources from irrigated agriculture to other economic activities which can generate an equal or greater marginal productivity can play a crucial role in conserving the water resources of Georgia. Agriculture represents a critical sector of water use in Georgia because of its direct link with the welfare of thousands of farmers in Georgia.

In spite of the significant role of agriculture to ensure the efficient use and allocation of water, no scholarly works have been carried out to predict the precise amount of water demand by agriculture under the influence of economic, institutional, and other policy variables in Georgia. In this study, we make an attempt to understand the dynamics of irrigation water use and demand in Georgia through the use of statistical analysis of time series.

Rationale

Water is increasingly seen as a finite resource that needs to be managed sustainably and efficiently (Khan, 1999). Georgia faces many challenges in its search for a sustainable water supply and efficient water allocation. The management of water resources in Georgia requires complex balancing of competing interests of many sectors, including agriculture (Jordan, 1998). Unfortunately, the areas of economics of irrigation water use and management have been largely neglected in applied economics research. This study will devise a framework for more economic and effective water conservation while fulfilling the information gap existing in the area of irrigation water demand in Georgia.

Finding accurate information related to crop water use in Georgia is relatively a difficult task due to absence of past research and systematic records of water use data. Except for the aggregate irrigation water use data published by the US Geological Society, there exist very little information about irrigation water use in Georgia. A perfect knowledge of historical irrigation water use is imperative for making efficient decisions and policies related to water use in Georgia. But there still remains imperfect information for policy makers and water resource managers about present and future irrigation water use patterns in Georgia.

With accurate forecasting of irrigation water demand as a central focus, this study addresses the issue of limited and aggregate data, lack of scientific irrigation water demand forecasting models, and dynamic nature of irrigation water demand. Issues of ignorance of economic and institutional variables in irrigation water forecasting methods and absence of a link between the existing water forecasting methods (physical models) and a water forecasting model having economic and institutional variables (economic models) will be discussed.

USGS estimated the total amount of irrigation water use by agriculture in each county of Georgia (USGS, 2001). USGS irrigation water use data, which were estimated by multiplying the number of irrigated acres by a standard water use coefficient for each crop type, are highly aggregated and limited to some specific periods. Even though the water use data set provides general information about total amount of water use by crops, it does not provide any information on the exact amount of water use by each crop type. USGS irrigation water use information does not consider the economic, institutional, and other variables that may have impacted on the amount of irrigation water use and demand. Therefore, the report of the USGS provides benchmark but possesses severe limitations in its ability to trace the future irrigation water demand in Georgia.

In 1995, USDA Natural Resources Conservation Service in collaboration with Auburn University, University of Florida, and University of Georgia carried out an extensive study to assess the present and future water demand for all agricultural activities including different crops within Georgia, Alabama, and Florida (USDA Natural Resources Conservation Service, 1995). The Alabama-Coosa-Tallapoosa (ACT) and Apalachicola-Chattahocchee-Flint (ACF) comprehensive studies, which are considered as the most in-depth and detailed water use study of the region, also provide aggregate data for some specific areas of Georgia. By not adopting scientific modeling approaches and econometric techniques to predict the irrigation water demand, ACT/ACF comprehensive study carries the limitation of USGS's study and loses the validity of its water demand forecasting results.

An accurate forecasting of irrigation water demand first requires precise estimation of crop acreage. Supply of crop acreage by farmers is an economic decision, which is mostly driven by economic variables like expected future profit and cost of inputs. Supply of crops is also affected by changing international trade agreements, environmental laws, and government programs. A sound acreage supply response model and rigorous econometric analysis are needed to accurately predict the total crop acreage, and thereby the total amounts of irrigation water demand in Georgia.

The information provided by the USGS and the ACT/ACF studies offer benchmark information for understanding the irrigation water use pattern of Georgia. However, the information of these studies have an episodic scope and are limited in only examining physical relationships. Future irrigation water demand exclusively depends on crop production and acreage supply decisions of farmers as well. Also, acreage supply response is in turn, controlled by economic factors and government programs. The impacts of economic and institutional variables can be captured by acreage supply response functions. A comprehensive study of irrigation water demand, therefore, must consider the economic variables in addition to physical factors examined by the USGS and ACT/ACF studies. A deeper understanding of relationship between the physical irrigation water forecasting model and an economic irrigation water forecasting model contributes to correct the weaknesses of existing physical water forecasting model and thereby could provide more accurate forecasts of irrigation water demand in Georgia.

This study will adopt a systematic analysis approach based on economic principles (crop acreage response functions) to forecast the total crop acreage in coming years in Georgia. In the mean time, econometrics and statistical procedures will be adopted to disaggregate and simulate the data that would be necessary to forecast irrigation water demand in Georgia. The findings from this study could be useful to policy makers and regional planners at all levels to guide the allocation of limited water of Georgia in the most efficient ways. The results may assist in evaluations and planning of the region's water management policies. It will also provide suitable guidelines for similar studies of economics of irrigation water use elsewhere.

Objectives of the Study

The main objective of this proposal is to develop a method for forecasting irrigation water demand for particular crops in Georgia. Forecasting irrigation water demand for all crop types planted in Georgia is beyond the score of this study. Therefore, our study mostly focuses on irrigation water demand for corn and soybeans, two major agricultural crops of Georgia. Although the production features are different for different crop types, our model could serve as a representative model from which modification can be made to adapt to other crop enterprises.

Specially, the research objectives are:

I. To develop sound crop acreage response models for corn and soybeans in dynamic and microeconomic framework

II. To develop alternative models of crop acreage forecasting using univariate time series and structural time series models.

III. To predict present and future irrigation water demand of corn and soybeans by using three different models.

IV. To compare the accuracy of econometric, Univariate time series, and structural time series models in terms of irrigation water demand forecasting

V. To assess the impacts of economic and institutional variables in agriculture water demand

Procedures

Objective 1 is achieved by developing a Von-Neumann Morgenstern utility function. The proposed model assumes that representative farmers maximize expected utility from the total profit under competition and household preferences are represented by a utility function, U(G), satisfying $\delta U/\delta G>0$. Objective 2 of the study is accomplished by using a Box-Jenkins ARIMA time series model and a structural time series model. Scenarios of deterministic and stochastic trend components have been considered while analyzing crop acreage supply response using structural time series model. Objective 3 is accomplished by using the crop acreage coefficients obtained from objectives 1 and 2, and water use coefficient as reported by Blaney-Criddle formula. For objective 4, measures of root mean square percentage error (RMSPE) and mean absolute percentage error (MAPE) were used to measure both in-sample and out-of-sample forecasting accuracy for econometric, ARIMA, and structural time series models. Elasticity coefficients of different economic and institution variables obtained from objective 1 have been used to accomplish the objective 4.

In our study, the first chapter aims to introduce the reader to the suggested study to be conducted. The set of objectives offer glimpses of the activities to be covered in the study. These objectives outline the types of activities necessary to carryout the research and define some of the more technical aspects of the analyses. The statement of problem summarizes the underlying issues of irrigation water demand and identifies possible new research frontiers of this study. A secondary aim of the chapter one is to familiarize the novice reader with the irrigation water demand issue. This entails the understanding of acreage supply responses, limitations of the existing acreage supply response models, and discussion on the new models for irrigation water demand forecasting. A thorough analysis of crop acreage models is of importance in this instance since irrigation water demand basically depends on the acreage supply responses of farmers.

The remaining chapters of this thesis are organized as the follows. Chapter 2 covers the review of literature on crop acreage supply response and water demand forecasting, while chapter 3 presents the theoretical paradigms of the study. Chapter 4, 5, and chapter 6, analyze the irrigation water demand forecasting using econometric, ARIMA, and structural time series model, respectively. Finally, Chapter 7 summarizes the findings of the study and provides conclusions, implications and direction of future research. The findings from this study will be useful to policy makers and regional planners at all levels to guide the allocation of limited water of Georgia in the most efficient ways. The results may assist in evaluations and planning of the region’s water management policies. It will also provide suitable guidelines for similar studies of economics of irrigation water use elsewhere.

CHAPTER TWO

LITERATURE REVIEW

In recent years, many studies have dealt with the estimation and projection of water used by municipalities. Related reports have been published on quality and quantity issues, and on contingent valuation techniques to estimate demand parameters for an environmental amenity. So far, little attention has been given to estimating the irrigation water demand. This section presents a broad review of literature pertaining to the field of water demand and forecasting by municipalities, agriculture, and other users. Attempts will be made to cover the related areas of water demand forecasting to provide a background for further analyses and work.

Several researchers have made efforts to analyze water demand for municipalities along the various lines suggested above. These are mentioned next. Hogarty and Mackay (1975) used the annual average data collected on the amount of water use by household to analyze the impacts of seasons on water demand. In this study, researchers failed to draw any significant conclusions regarding the seasonal demands and peak-season pricing. George and King (1967) concluded that, if the demand conditions are fairly homogenous during the year, annual data may be sufficient to estimate demand equations (i.e., no seasonal variation exists). However, if demand conditions are not homogenous, then data with shorter intervals are required.

Wong (1973) also analyzed residential water demand by using time-series and cross-sectional data to estimate price, income, and other parameters affecting water demand. In his analysis, he found that price elasticities are suppressed by the time-series data relative to cross-sectional analysis. However, these studies were all limited to aggregate data and their validity for predicting how individuals and households respond to changes in water price, climate, size of households, income and other variables remains questionable (Danielson, 1977).

Few studies have utilized time-series data at the household level. Morgan (1973) analyzed a four-month time-series of data on 92 single family residences during 1971 but had no price variation and hence could not draw inferences about price responsiveness. Pope et al. (1975) analyzed three years of individual household observations on water consumption. Because of the difficult nature of the aggregate data, researchers were unable to analyze it without making extensive adjustments to the effect of season, climate and several other variables. In this study, researchers failed to draw any significant inferences about nature of water demand by households.

Thus, while economic theory suggests the appropriateness of using a time-series of cross-sections at the household level to estimate individual and household demand parameters, empirical water demand studies have by and large been unable to do so. Problems with both data availability and data analysis have been suggested (Morgan 1973).

Danielson (1977) developed an econometric model to estimate water demand equations and to analyze whether the policies of peak-load pricing and supply rationing through price adjustment would have an appreciable effect upon water demanded at the household level. In that study, residential demand for water was found to be negatively correlated with average price and monthly rainfall in summer and positively correlated with temperature, house value, and household size, as expected. Considerable variation was also found based upon the functional form selected and, in the case of price elasticity, whether real or nominal prices were used. The magnitude of adjustment to a policy of peak-load pricing depends upon price elasticities, the quantities of water used for various purposes, and the type of peak-load pricing policy adopted.

Dzisiak (1999) developed a forecasting model to examine the impacts of price changes on water usage. The study concludes that water demand is inelastic with respect to water prices, but, it appears to be more responsive during outdoor demand periods when extra consumption is supplemental to the set of water consuming goods held by each household. Consumers in general face complex water rate schedules, which complicates each consumer’s ability to determine the marginal water rate. On average, water costs are a very minor percentage of household income and water rates do not reflect the actual costs involved within a water distribution system with respect to system replacement and service costs. Research results indicate that at observed values, water demand is inelastic and increased water prices will result in system revenues increasing.

Knapp (1994) analyzed the impacts of climate, price, land use, and mandated conservation efforts on the water demand of a California retirement community. In his study, water consumption patterns for both the entire community and each land use were analyzed along with the corresponding climate data. In order to further understand the relationship between water consumption and climate, a statistical analysis was also performed. The results of the study indicate that, although they may be similar, the water consumption characteristics of the various land uses, such as water demand, seasonal variation, and degree of conservation, are specific to individual land uses. A comparison between his study's findings and selected data from the California Department of Water Resources (DWR) further revealed that the DWR's consumption figures are low and need adjustment.

Malla (1996) employed the Generalized Least Squares (GLS) procedure to estimate the demand equations for the residential, visitor industry, and commercial and industrial sectors. The Cochrane-Orcutt Procedure was also used to estimate the agricultural water demand equations. In the Malla’s study, the demand analysis did not display any consistency with respect to price sensitivity to water demand. Some of the sectors were responsive to an increase in water price by reducing water use, while the others did not appear to be affected by variation in water price.

Paredes (1996) used a rigorous technique called meta-analysis to derive residential water demand elasticities for different sectors, seasons, and regions of the country. The elasticities of seven explanatory variables chosen for derivation were price, household income, house value, household size, precipitation, temperature, and bill difference. Once elasticities were derived, eight theoretical water demand equations corresponding to different sectors, seasons, and regions of country were derived using cross-sectional data. Results of Paredes' analysis indicate that the theoretical water demand equations performed well in predicting water use.

Acreage Response Model

Substantial literature exists in the area of acreage supply response. However, these studies involve different in specific products, geographic areas, explanatory factors, modeling approaches, and methods of analysis. The size and complexity of the market justify different modeling approaches, research efforts, and diversity of analyses. The primary purposes of analyzing acreage supply response include: developing outlook information, predicting the consequences of proposed changes in farm policy, and identifying the response to price levels.

Houck and Subotnik (1969) analyzed the effectiveness of government farm program on soybean acreage response by selecting major soybean producing areas such as the Lake States, the Corn Belt, and Delta States. The impact of government subsidies was examined by using effective support price which combines support price and acreage restrictions into an independent variable. The study used lagged prices of soybeans and other competitive crops as exogenous variables. In this study economic variables like the price of soybean and competitive crops yield expected signs and significant results.

Houck and Ryan (1972) used the model developed by Houck and Subotnik (1969) to analyze the acreage supply response of corn.

However, the study of Houck and Ryan focused on empirical measurement and analysis of government feed grain policy in 1948-1970 on corn acreage supply response. The study incorporates soybean price support and measures of corn-sorghum acreage competition to capture the substitution relationship among major competitive crops. The study's results suggest that a 10 percent increase in effective price would increase corn acreage by 0.9 percent. This mean that a 10 percent increase of effective acreage reduction payment would decrease corn acreage by 4.1 million to 4.5 million in the study area. Thus, empirical results support the hypothesized negative relationship between acreage and diversion payments, and a positive effect of support price on Corn acreage supply response.

Morzuch et al. (1980) modeled wheat acreage response as a function of expected relative price, trend, estimated diversion payment per bushels, and upper limit on the permissible land diversion. In order to analyze the impacts of institutional variables, the study period was subdivided into three sub periods: quota, non-quota, and free market situations. The years 1948, 1949, 1951, 1953, and 1974 were considered as a free market situation as no government programs were in effect. The 1965-1975 was a quota period dominated by a policy of land diversion for direct payments. The results of the estimation reveal that the response of wheat acreage to the price of wheat relative to the prices of competing crops would be higher if marketing quotas are not in effect. In this study, there exists considerable heterogeneity in supply response of major wheat producing areas. The study concludes that farm policy during the "quota years" would likely destroy the role of price in allocating acreage between wheat and competing crops.

Incorporating farm program provision and market prices in a single supply-inducing price, Bailey and Womack (1985) analyzed the wheat acreage response of five major wheat producing regions. The effective price variable used the higher value between the lagged-season average farm price or the loan rate. The study incorporates "effective price" and "effective voluntary diversion rate" as policy variables, and risk weather, and variable costs as non-policy variables. In this study, the major economic and institutional variables yield expected sign and significant results showing the importance of economic and policy variables while explaining variations in wheat acreage.

In 1985, Lee and Helmberger used a disaggregated approach while modeling acreage response for corn and soybeans in four Corn Belt states. The study divides the period 1948-1980 into a "farm program regime" and a "free market regime". The major logic behind disaggregating the dataset was an assumption of completely different nature of acreage supply response under farm programs and competitive market regimes. The researchers used a pooled cross-sectional and time series approach and estimated model using the restricted version of Park's three-state Aitken model to fix the serial autocorrelation problem. The empirical results of the study confirm the hypothesis of great supply elasticity for corn and lower supply elasticity for Soybeans under acreage-restricting feed grain programs. In the study, the supply elasticity for corn under the farm program regime was twice than the value obtained under the free market condition. Soybean acreage, however, showed less responsiveness to price under the program provisions than under competitive conditions.

Shideed, et al. (1987) developed an acreage response model for corn and soybeans by combining both market price and support price into a price expectation measure i.e. conditional expected prices. The main reason for combining these prices was high level of correlation among price variables. The corn and soybeans acreage response models also include exogenous variables such as weighted diversion payment of corn, conditional expected price of corn, conditional expected price of soybeans, trend, price risk of corn, PIK variables, and expected deficiency payment of corn. In this study, all exogenous variables were statistically significant. The R2 value shows that the model explains 92 percent of the variation in corn planting and 98 percent of the variation in soybean acreage. The study does show the significant impacts of policy variables in corn and soybeans acreage supply.

Duffy et al. (1987) analyzed the cotton acreage response model by following the modeling approach of Houck and Subotnik and using weighted combination of expected market price and government policy variables as a proxy of supply inducing price. In this model, the lagged acreage, supply inducing price of cotton, the expected price of competing enterprise, the expected per acre deficiency payment, and trend serve as explanatory variables. In this study, the estimated elasticities fall with in the general range as reported by previous studies. The estimate also shows that the price of a competing enterprise is an important factor in acreage allocation decision in the Southeast and Southern Plains. The study results further show that lowering government payment may lower crop acreage but jointly lowering government payments for cotton and competing crops would not reduce crop acreage to desired level. The negative and significant parameter estimates for effective diversion payment suggests the effective role of diversion payments in lowering acreage.

Hanthorn (1988) examined the competition between cotton and soybeans using soybean-cotton expected net revenue ratio and the lagged soybean acres as exogenous variables. Hanthorn argues that the net revenue ratio reflects relative returns more accurately than the price ratios when farmers make acreage allocation decision between cotton and soybeans. The model yields statistically significant parameters with expected signs. The results show that a 10 percent change soybean-cotton expected net revenue ratio increases soybean acreage by 1.9 percent in the same direction.

The impact of future prices also has generated substantial interest in the crop acreage supply research literature. Gardner (1976) used future prices of soybeans and cotton as the market's estimate of next year's cash period 1950-1974. This approach was justified as an alternative to Nerlovian adaptive expectation model where expected price is a distributed lag function of the past prices. Gardner suggests that when the future price represents the expected price, the coefficient of the lagged dependent variable arises from partial adjustment process. In this study, the coefficients and implied supply elasticities obtained by using the future price were very close to those obtained from the model using lagged price. Based on the finding of the study, Gardner concludes that future price can be valuable as an adjunct to and as a vehicle of evaluating lagged-price, lagged dependent variable models.

The findings of Morzuch et al. (1980) also suggest future price as a good alternative to lagged-price variables. Using expected utility model that includes output price and yield, Duffy et al. (1994) analyzed the acreage response under farm program for cotton, corn, and soybean. The model appeared to fit the soybean and corn data well, resulting in own-price elasticity estimate of 0.317 for corn and 0.727 for soybeans. When applied to cotton acreage, however, the model did not give the satisfactory results. In the study, when elasticity was allowed to change over time, more significant statistical results for the cotton equation was obtained, yielding an own price elasticities of 0.915 at data means. The study results show the significance of risk variability of soybeans and corn, and possibly cotton, but that price variability in corn and cotton has little effect on planting decisions.

In 1999, Houston et al. examined the leading indicator of regional cotton response using structural and univariate time series analysis. In this study, price, production, and yield of cotton and soybean serve as exogenous variables. The model also includes institutional variables like cotton loan rate, target price, deficiency payment, disaster payment, diversion payment, and PIK to capture the impacts of different government program on cotton and soybean acreage response. The study's results show the significant impacts of cotton price, loan rate, deficiency payments, lagged corn acreage, the PIK program, and previous cotton yield on regional acreage response. The best ARIMA model outperforms the structural model in term of forecasting accuracy. However, the econometric model seems more promising because of its ability to identify leading indicators of cotton acreage response.

Irrigation Water Demand

Harrington (1995) established a method for estimation of economic demand for irrigation water for the wiregrass region of Alabama. He used the profit function approach to estimate a system of factor demands and supply responses for three irrigated field crops and four inputs (water, fertilizer, labor, and machinery). A translog cost function method was employed to estimate cost share equations for irrigation equipment (traveler and center pivot) and crop insurance. The results of the study revealed that the price elasticities of demand for water vary across counties. Water price was a significant factor in the supply response of corn and peanuts (quota and additional). Furthermore, crop price levels for corn and peanuts (quota and additional) were the most important components affecting the demand for irrigation water.

Acharya (1997) used a combination of simulation, econometric, and optimization models to develop a methodology that can be applied to examine the effect of water scarcity on net farm income. A biophysical simulation model, known as Erosion Productivity Impact Calculator (EPIC), was used to simulate the relationship between water from rainfall and/or various irrigation management practices, and crop yields. The water yield response functions for selected crops were estimated using EPIC simulated data, and the estimated parameters were used to develop a recursive stochastic linear programming model. The optimization model was designed to solve a series of irrigation decision problems faced by a representative farm, which was growing corn, cotton, and peanuts. Different irrigation decision rules were derived for dry and normal weather conditions. Using a preference scale and the flow data of the Chattahoochee River measured at Columbus, the residual flow that could be used for crop irrigation was calculated.

Acharya’s results indicated that, even if the historical flow could be maintained in the future, it would not be enough to meet the total irrigation demand in many instances. The aggregate optimal demand for irrigation water in the Middle Chattahoochee Sub Basin was estimated to be 3.211 million gallons per week. The contribution of this optimal irrigation level to net farm income would be $1.175 million per year for dry years and $0.711 million per year for normal years. That is, the aggregate impact of a water shortage, measured relative to the optimal use level, would be higher in dry years by $0.464 million as compared to normal years. Since the impact of water scarcity on net farm income was expected to be much higher in dry years than in normal years, two separate marginal relationships were estimated. Once the existing supply and weather conditions are known, these marginal functions can be used to derive the impact of reduced stream flow on net farm income. For the Middle Chattahoochee Sub

Basin, the average impact of a 15 percent draw down in downstream flow on net farm income was calculated to be less than $3.10 per acre in dry years and $0.57 per acre in normal years.

Quality and Quantity Issue

Zachariah (1999) examined interrelationships between extractive and non-extractive uses of water with the aid of a dynamic programming model that maximized the net present value of drinking water benefits and agricultural waste assimilation benefits under a common pool institutional arrangement and integrated management strategies. Agricultural waste assimilation in the aquifer was used to model the non-extractive use. A central result of the optimization problem was that optimal choices of groundwater extraction and agricultural waste assimilation were determined simultaneously in an integrated management approach. Thus, a common pool groundwater management regime or any regime that emphasizes only one area of concern (e.g., extraction or pollution) would be sub-optimal.

Zachariah’s study, the model was applied to an aquifer management problem in Wilmot Township, Ontario. Extractive benefits were measured by using water demand functions, and agricultural waste assimilation benefits were obtained using farmers' marginal abatement cost functions for nutrient waste. Empirical results showed that the present value of aquifer benefits achieved under current common pool institutional arrangements were sub-optimal. Where the cost of switching from one management approach to another would be zero, the integrated approach was always optimal. The estimated welfare loss under common pool institutions was less than 1% of potential economic benefits under an integrated approach.

Opaluch (1981) examined the optimal method of achieving water quantity and quality standards in a dynamic framework. The instruments under control were groundwater use, investment in treatment facilities, waste water disposal, an effluent tax, and imported water from two sources such as inexpensive, poor quality water and expensive, good quality water. In the first step, the supply of pollution disposal services was derived by minimizing the cost of achieving the standards with various quantities of pollution generated. The demand functions for these services were assumed to be linear stochastic functions with unknown slope. The slopes of the demand functions were estimated in an adaptive manner over the time horizon using Bayesian methods. The optimal price for the pollution disposal was found as the price which optimizes the interdependent goals of control and learning. In addition, construction of the Santa Ana Regional Interceptor and the constraints imposed on water flow from the Upper to the Lower Santa Ana Watershed were evaluated.

Assuming salinity control of the Colorado River, the benefit to the Upper Watershed for the availability of the Peripheral Canal in 1980 was $33.9 million. If the Peripheral Canal was not built, the willingness to pay for salinity control of the Colorado River would be $923,000. Opaluch also concluded that a somewhat more stringent constraint for water flow out of the Upper Watershed was probably justified. Monte Carlo methods were used to evaluate the net benefits derived from incorporating an effluent charge into the pollution control policy. Results from the Upper Santa Ana Watershed were extrapolated to other affected river basins to evaluate the total benefits derived from the Peripheral Canal in a speculatory manner, tentatively estimated at $7.5 billion.

CHAPTER THREE

THEROTECIAL MODELS

Consider a farmer that produces '*n*' crops where A_i is the size of irrigated acres devoted to the ith irrigated crop, P_i is the market price of the ith crop, and Y_i is the corresponding yield per acre, (i = 1, 2,...,n). The total revenue of a representative farmer is given by

$$R = \sum_{i=1}^{n} p_i \, y_i \, A_i$$

Letting C_i be the cost of production per acre of the ith crop,the total cost of agricultural production would be

$$C = \sum_{i=1}^{n} C_i \, A_i$$

Information about output prices **P** = (P_1, P_2,....,P_n) and crop yield **Y**= (Y_1,Y_2,....,Y_n) are not available to a farmer when the production decisions are made, Therefore, the revenue *(R)* is treated as an uncertain variable. In the meantime, input prices and per acre costs *(C_i)* are available to the producers at the time of crop acreage allocation. Given this situation, a producer faces a budget constraint which can be defined as (Chavas and Holt, 1990)

$$I + R - C = qG$$

$$I + \sum_{i=1}^{n} p_i \, y_i \, A_i - \sum_{i=1}^{n} C_i \, A_i = qG \qquad (1)$$

where the variables *I*, *G*, and *q* are defined as follows;

I = Exogenous income (wealth)

G = Index of producer consumption of goods

q = Consumer price index

Equation 1 shows that exogenous income *(I)* plus farm profit *(R-C)* equals consumption expenditure *(qG)* of a household. Let the constraints on the crop acreage decision be represented by

$$f(A) = 0 \tag{2a}$$

where A = (A_1, A_2,....,A_n). Constraints on the acreage require that total crop acreage is allocated to either soybeans or corn production and that total crop acres should not exceed the total available acreage.

$$\sum_{i=1}^{n} A_{iy} = A_Y \tag{2b}$$

Assuming that representative farmers maximize expected utility from total profit "Π" under competition, and household preferences are represented by a Von-Neuman Morgensten utility function, U(G), satisfying δU/ δG > 0, the decision model is

$$Max\ A\ \{EU\ [\frac{I}{q} + \sum_{I=1}^{n} [\frac{Pi}{q} Yi - \frac{Ci}{q} Ai]]\}\ \text{s.t. (2), or} \tag{3a}$$

$$Max\ A\ \{EU\ [\ W + \sum_{i=1}^{n} \Pi_i A_i\ ]\}\ \text{s.t. (2)} \tag{3b}$$

where W = I/q is normalized initial wealth subject to acreage constraints in equation 2b; Π is Normalized profit per acre of the ith crop, i = 1,2. All prices are deflated by the consumer price index.

Equation (3a and 3b) shows that a producer makes the irrigation acreage allocation decision '*A*' under both price and production uncertainty. Here, both yield *(Y)* and output price (P) represents random variables with given subjective probability distributions. Consequently, the expectation E in equation (3) over the stochastic variables *P* and *Y* relies on the information available to producer at the time of planting.

Optimization problem (3) has direct economic implications for the optimal irrigation acreage decision (A). If the producer is risk averse, the optimal acreage decision depends on normalized initial wealth (W), Expected normalized profit per acre (π_i), and second or higher moments of distributions of normalized profits (σ) per acre. In the case of normally distributed returns, expected values and variances of returns define the criterion of expected utility. Otherwise, it is a second-order Taylor series approximation to all risk-averse utility functions. In other words, the optimal irrigation acreage decision can be represented as

$$A^* = A(W, \overline{\Pi}, \sigma, Z) \tag{4}$$

Where,

W = normalized Initial wealth,

$\overline{\Pi}$ = expected normalized profit per acre,

σ = higher moments of distributions of normalized profits (σ) per acre, and

Z = Institutional variables for corn and soybeans.

In order to analyze the producer supply behavior under risk, adaptive expectations for untruncated normalized prices are used. The final econometric model is represented as:

$$A_{it} = \alpha_i + \zeta_i W_{it} + \sum_i \beta_i \pi_{it} + \sum_i \sum_j \gamma_i \sigma_{ijt} + \theta T_{it} + \sum_i \eta_i Z_{it} + \varepsilon_{it} \quad (5)$$

where

A_{it} = total irrigated acreage for ith crop at time t,

W_{it} = wealth of ith crop's farmers at time t,

π_{it} = mean expected profit for ith crop per acre at time t,

σ_i = coefficient of variance of profit of ith crop at time t;

σ_{ijt} = covariance of profit between the ith and jth crops at time t,

t = time variable,

Z_i = matrix of institutional variables, such as deficiency payments, diversion payments, disaster payments, ppayments-in-kind (PIK) for corn and quota and government support prices for soybeans,

ε_{it} = errors

Univariate Time Series Forecasting Model

Time series analysis modeling offers a powerful means of understanding value-generating mechanisms, forecasting of future values, and optimal control of system. Time series arises in agriculture production might be dependent or correlated. This intrinsic nature of a time series makes statistical procedures that rely on independence assumption invalid. Basically, time series analysis is used to model the mechanism that generates the value and forecast the future value using the fitted model. In our study, forecasting of future crop acreage is critical to predict future irrigation water demand by corn and soybeans. Time series analysis of crop acreage also allows us to compare forecasting results with econometric and USGS physical model.

There exist different time series modeling approaches to analyze the stationary time series. However, many applied time series, mostly arising in agriculture are non-stationary in nature. Non-stationary time series can have non-constant mean μ_t non-constant variance σ^2_t or both of the properties (Wei, 1989). Therefore, in our analysis, the autoregressive integrated moving average (ARIMA) model was used. Box Jenkins (ARIMA) offers a powerful modeling tool for stationary, non-stationary, seasonal, and non-seasonal time series data analysis. A process non-stationary in the mean presents a series problems for estimation of the time dependent mean function without multiple realizations. Techniques of mean differencing correct the time series non-stationary in mean.

Box and Jenkins (1976) refers non-stationary behavior as the homogenous non-stationary. In ARMA models, the non-stationary process arises, if some roots of AR polynomial do not lie outside the unit circle. However, by the nature of homogeneity the local behavior of this kind of homogenous non-stationary series is independent of its level (Wei 1989). Let ψ (B) be the autoregressive operator defining the behavior

$$\Psi_B(Z_t + C) = \psi(B)Z_{t+1} \tag{1}$$

If C is constant, it implies that ψ (B) must be of the form

$$\psi(B) = \phi(B)(1-B)^d \tag{2}$$

if d >0, where ϕ (B) is a stationary autoregressive operation. By appropriate differencing of the general series, a homogenous non-stationary series can be reduced to stationary. In an alternative, the series $\{Z_t\}$ is non-stationary but d^{th} difference series $\{(1-B)^d Z_t\}$ for some integer $d \geq 1$ is stationary.

If the d^h difference series follows a white noise phenomenon

$$(1-B)^d Z_t = a_t \tag{3}$$

Let consider d=1 in equation 3. The implication of this kind of homogenous non-stationary series

$$(1-B)Z_t = a_t \tag{4}$$

$$Z_t = Z_{t-1} + a_t \tag{5}$$

Given the past information Z_{t-1}, Z_{t-2},…….the level of the series at time 't' is

$$\mu_t = Z_{t-1} \tag{6}$$

The General ARIMA Model

We now define a general autoregressive integrated moving average model, also known in short as an ARIMA model. The stationary process resulting from a properly differenced non-stationary series may not be white noise (Neimi,1984). More generally, the series $(1-B)^d Z_t$ follows the general stationary ARMA (p,q) process, defined as

$$\phi_p(B)(1-B)^d Z_t = \theta_0 + \theta_q(B)a_t \tag{7}$$

In equation 7, the AR operator $\phi_p(B) = (1-\phi B - .... - \phi_p B_p)$ and the MA operator $\theta_a(B) = (1-\theta_1 B - .... - \theta_q B^q)$ share no common factors. The parameter θ_0 plays important role for d=0 and d >0. When d =0, the original process is stationary and θ_0 is related to the mean of the process i.e . $\theta_0 = \mu(1-\phi_1 - .... - \phi_p)$. If d ≥1, θ_0 is the deterministic trend term. The resulting homogenous non-stationary model is autoregressive integrated moving average model of order (p, d,& q). Where p, d, and q represent the order of autoregressive process, degree of differencing, and order of the moving average process respectively.

Variance of Autocovariance of the ARIMA (p, d, and q)

Being stationary in mean does not necessarily translate to stationarity condition in the variance and the autocovariance. However, a non-stationary time series in mean will also be non-stationary in the variance and autocovariance. Although the model is stationary, the finite number of parameters i.e. Φi, the θj and σ^2 define the complete characteristics of time series process (Weiss, 1984). Therefore, given data set {Z_1, Z_2,Z_3,…………Zn)}, the future evaluation of the process can be developed using ARIMA. Suppose we fix IMA (1,1) or ARIMA(0,1,1)model.

$$(1-B)Z_t = (1-\theta B)a_t \qquad (8a)$$

OR $$Z_t = Z_{t-1} + a_t - \theta a_{t-1} \qquad (8b)$$

To a series of n_o observation , if time origin number for t > n_o . we can write

$$Z_t = Z_{t-1} + a_t - \theta a_{t-1}$$

$$= Z_{t-2} + a_t + (1-\theta)a_{t-1} - \theta_{at-2}$$

$$=Z_{n_0}+a_t+(1-\theta)a_{t-1}+.......+(1-\theta)a_{n_0} \qquad (9)$$

If t-k > no

$$Z_{t-k}=Z_{n_0}+a_{t-k}+(1-\theta)a_{t-k-1}+...........+(1-\theta)a_{n_0+1}-\theta a_{n_0} \qquad (10)$$

Hence, with respect to the time origin number

$$Var(Z_t)=\left[1+(t-n_0-1)(1-\theta)^2\right]\sigma^2{}_a \qquad (11)$$

$$Var(Z_{t-k})=[1+(t-k-n_0-1)(1-\theta)^2]\sigma_a^2 \qquad (12)$$

$$Cov(Z_{t-k,}Z_t)=[(1-\theta)+(t-k-n_0-1)(1-\theta)^2]\sigma_a^2 \qquad (13)$$

Equation 11 and 12 summarize (Wei, 1989) that

I. Variance, var (Z_t), of the ARIMA process is time dependent and var (Z_t)≠var (Z_{t-k})

II. The variance var (Z_t) is unbounded as t → ∞

III. The autocovariance cov (Z_{t-k},Z_t) and the autocorrelation (Z_{t-k},Z_t) of the process are also time dependent, and hence not variant with respective to time.

Nonetheless, it is difficult or impossible to make statistical inference of a process that is non-stationary in both mean and the autocovariance or autocorrelation function. However, by using the technique of differencing, we can reduce it to stationary time series data. Therefore, the original series Z_t is non-stationary. The differenced series $W_t=(1-B)^dZ_t$ is stationary ARIMA process where

$$\phi(B)W_t=\theta(B)a_t$$

$\phi(B)=(1-\phi_1B-..........-\phi_pB^p$ and

$$\theta(B)=(1-\theta_1B-............-\theta_qB^q)$$

Therefore, the parameter Φ_i, θj, and σ^2 that control the evolution of the non-stationary phenomenon of Z_t can be estimated from the differenced series W_t.

Forecasting

Time series analysis is also used for forecasting purposes. Consider the general ARIMA (p, d, q) model

$$\phi(B)(1-B)^d Z_t = \theta_q(B)a_t \tag{14}$$

where $\phi(B) = (1-\phi(B) - .... - \phi_p B^{\phi})$ and $\theta(B) = (1-\theta_1 B - .... - \theta q B^q)$ represents stationary AR operator and MA operator, respectively. Under these conditions, the mean and the second order moments such as the variance and autocovariance functions, vary over time. The complete evaluation of the process is completely determined by a finite number of fixed parameters (Φ_i, θ_j, σ^2). Basically forecasting is a process of estimation of these parameters and obtains the minimum mean square error forecasting using Bayesian approach (Wei 1989).

Structural Time Series with Exogenous Variables

Crop acreage response has traditionally been modeled as a function of cost of production, expected price of output, interest rate, institutional variables, and lagged dependent variables. Despite economic and institutional variables, unobservable factors, such as technological improvements, seasonal dummies, demographic features, and other exogenous variables, also affect acreage supply responses. In the crop acreage supply response literature, impacts of these unobservable variables were either ignored or modeled by a simple linear deterministic time variable which assumes fixed underlying trend effect overtime (Kapombe and Colyer, 1998). In most cases, the trend variable was used to capture the underlying technological improvements in the crop production sector.

In a similar way, potential impacts of non-stationary seasonal data have been ignored. Crops response models, which use quarterly time series data, have traditionally incorporated deterministic seasonal dummy variables to account for the underlying seasonal effects. Deterministic seasonal dummies implicitly assume fixed effects of seasonal variables throughout the period. However, assuming deterministic seasonality and trend as *a priori* when it is actually stochastic might yield a misspecified model and false inferences. To fully understand the crop acreage response, and more importantly, to predict more accurately future crop acreage supply and future irrigation water demand, it is critical that acreage supply response be modeled appropriately. Therefore, a preferable approach would be to test a model having stochastic trend and seasonal variables as an alternative model to the existing models having deterministic trend and seasonal components.

In this section, the corn and soybeans acreage supply models were further analyzed by developing a structural time series model especially to accommodate the unobservable underlying trend in a more general way. So far, no researchers have examined the impacts of stochastic trend variable in their analysis of crop acreage response.

Therefore, this study significantly departs from the acreage response models of other researchers.

Structural Time Series Model

The structural time series model (STSM) allows for the unobservable trend and seasonal components to change stochastically over time (Harvey, 1997). The STSM models are generally developed directly in terms of components of interest, trend, seasonal, cyclical and residual or irregular components (Kapombe and Colyer, 1998). In an STSM model, the exogenous variables enter into the model along with the unobserved components. STSM models revert to a standard regression model in the absence of unobservable components (Harvey and Scott,1994).

Consider the following STSM acreage supply model

$$AR_t = \mu_t + \gamma_t + Z_t^{'}\delta + \varepsilon_t \tag{1}$$

where

AR_t = Quarterly acreage response for corn and soybeans;

μ_t = the trend component;

γ_t = the seasonal component;

Z'_t = a vector of explanatory variables (price of output, production cost);

δ = k x1 Vector of unknown parameters; and

ε_t = White noise

The trend component ε_t is assumed to have the following stochastic process

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \tag{2}$$

$$\beta_t = \beta_{t-1} + \xi_t \tag{3}$$

where $\eta_t \sim NID\ (0,\ \sigma_\eta^2)$ and $\xi_t \sim NID\ (0,\ \sigma_t^2)$

Equations (2) and (3) represent the level and the slope of the trend, respectively. A stochastic trend variable (μ_t) is incorporated into the acreage supply model to capture the technological progress and structural change in the corn and soybeans production sectors in recent years. The exact form of the trend depends upon whether the variances, σ_η^2 and σ_t^2 , also known as the hyper parameters, are zero or not. If either σ_η^2 and $\sigma_{t,}^2$ are non-zero then the trend is said to be stochastic. If both are zero, then the trend is linear and the model reverts to a deterministic linear trend model as follows;

$$AR_t = \alpha + \gamma_t + \beta_t + Z_t^{'}\delta + \varepsilon_t \tag{4}$$

A stochastic seasonal component (γ_t) is included in the crop response model to capture the effect of weather and other seasonal factors in the crop production function. Accordingly, in equation (1), the seasonal components (γ_t) follows the following stochastic process:

$$S(L)v_t = \omega_t$$

where $\omega_t \sim NID\ (0,\ \sigma_\omega^2)$, $S(L) = 1 + L + L^2 + L^3$ and L = lag operator. If $\sigma_\omega^2 = 0$ the model becomes a deterministic seasonal dummy variable model. If not, seasonal components are moving stochastically over time.

Proposed Procedure

This study will adopt a systematic analysis approach based on economic principles (acreage response functions) to forecast future corn and soybeans acreage in Georgia. Objective 1 will be achieved by developing an expected utility maximization model constrained by the total irrigated acreage. Proposed econometric model captures the underlying risk and uncertainty of corn and soybeans production by incorporating variance price and co-variance of price and yield of corn and soybeans. The objective 2 will be carried out by developing a Univariate ARIMA time series model as proposed by Box and Jenkins (1976). The objective 2 will further be analyzed by using a structural time series model with exogenous variables as proposed by Harvey (1989). Proposed structural time series model will assess three different scenarios of trend components namely: no trend, deterministic trend, and stochastic trend. The best structural time series model will be selected by using measures of root mean square percentage error (RMSPE) and mean absolute percentage error (MAPE). The future irrigation water demand of corn and soybeans (objective 3) will be predicted by using the information available after analyzing objective 1 and 2, and corn and soybeans water use coefficient as reported by Blaney-Criddle formula.

CHAPTER FOUR

ECONOMETRIC IRRIGATION WATER DEMAND

Forecasting Irrigation Water Demand under Risk and Uncertainty: An Econometric Analysis

In the last few years, Georgia has suffered a severe water shortage problem. The causes of the crisis are both natural and man-made. The increase in water demand for domestic uses due to population growth, rising standard of living, climate variations, and droughts have resulted in an increased water shortage in Georgia. The growing population, expanding urban areas, and increasing competition among the different sectors of water use are likely increase the water scarcity problem in the coming years making water a critical local issue (Jordan, 1998). The water issue would be more crucial if Georgia, Florida, and Alabama failed to reach an agreement on their negotiation to achieve an equitable allocation of water for its shared river.

Inspite of substantial research works on water scarcity, allocation, and management issues, very few studies have exclusively examined the issue of water demand estimation and forecasting for different sectors of water uses, an area highly critical for any efficient water allocation and management decisions. The lack of credible information about the present and future water demand by different sectors of water use creates obstacles in efficient allocation of water resources. In many cases, the policy makers and water managers are constrained by the lack of accurate information about the present and future trend of water demand. In the absence of this information, any policy proposals regarding water management are made under incomplete and potentially inaccurate information. Irrigation water use comprises of nearly 41.1% of total water use in Georgia (USGS, 2003). Being the major sector of water use, precise prediction of present and future irrigation water demand is very critical for any strategic water management and planning proposal.

So far, the county-wise aggregate irrigation water use data published by the United Stated Geological Survey (USGS) and Apalachicola-Chattahoochee-Flint (ACF) comprehensive irrigation study (hereafter refer as ACT/ACF study) report remain the main source of irrigation water use information in Georgia. However, water demand estimates of USGS and the ACT/ACF study are based on the static physical model, where future water demand is a function of temperature, daylight, and other physiological variables or based on the guess of expert. The USGS and ACT/ACF water demand models carry the limitations of physical models by failing to capture impacts of economic and institutional variables in irrigation water demand and forecasting. It makes USGS and ACT/ACF model inappropriate for water demand forecasting purposes.

Given the dearth of past research and systematic records of irrigation water use data, it is very difficult to find accurate information about the present and future water demand for agricultural crops in Georgia. Irrigation water demand of crops directly depends on crop acreage supply. The more precise estimation of irrigation water demand is only possible if researchers are able to closely predict the present and future crop acreage supply by developing a sound crop acreage supply response model. Crop production is an economic decision which is mostly driven by variables such as expected profits, costs of inputs, and government policies such as price support, target price, loan rate, deficiency payment, and payment-of-kind (PIK). Therefore, the estimation of sound acreage supply response model is of obvious important for precise water demand forecasting purposes. Moreover, while estimating irrigation water demand, it is very difficult to model irrigation water demand directly as a function of economic and institutional variables. Use of crop acreage response model offers an alternative way to indirectly capture the impacts of economic and government support program variables on irrigation water demand estimation and forecasting (Banerjee, 2004).

Because of a direct relationship between crop acreage supply and irrigation water demand, the first step of any irrigation water demand forecasting study would be to identify factors or explanatory variables likely to explain the variation in crop acreage and thereby, in irrigation water demand. Therefore, the present study intends estimate and forecast the irrigation water demand by developing a sound acreage supply response model. Different studies have confirmed the implications of risk in production and uncertainly in market conditions (Just, 1975; Traill, 1978; Chavas and Holt, 1990) in crop acreage supply decision. Therefore, present study focuses on econometric analysis of time series data with explicit use of risk involved in agricultural production to improve the estimated supply response relationship.

Forecasting irrigation water demand for all crops is beyond the scope of our study. Therefore, we analyze irrigation water demand by selecting two major crops of Georgia: Corn and Soybeans. Although the production processes and biological nature vary among different crops, our model serves as a representative model for crop irrigation water demand study and can be extended to other crops with little modifications. In this study, the acreage response supply model proposed by Chavas and Holt (1990) serves as a basic model. However, our study further extends the model of Chavas and Holt by explicitly incorporating government program variables such as deficiency payment, loan rate, and production flexibility contract.

Model Development

The proposed behavioral model of crop acreage response was developed by Chavas and Holt (1990) incorporating price and yield risks involved in agricultural production using a revenue risk variable (R). The details of the model are given in chapter 3. The final econometric model is represented as:

$$A_{it} = \alpha_i + \varsigma_i W_t + \sum_i \beta_i \pi_{it} + \sum_i \sum_j \gamma_i \sigma_{ijt} + \theta T_t + \sum_i \eta_i Z_{it} + \varepsilon_{it} \qquad (1)$$

Here

A_{it} = Total crop acreage for i^{th} crops at time t

w_t = wealth of crop farmers at time t

π_{it} = Mean expected profit for i^{th} crop per acre at time t

σ_{it} = Coefficient of variance of price of i^{th} crop at time t

σ_{ijt} = Covariance of price between the i^{th} and j^{th} crop at time t

t = time variables

Z_i = Matrix of institutional variables such as corn deficiency payment (CDP), soybeans deficiency payment (SDP), corn loan rate (CLR), and production flexibility contract (PFC)

ε_{it} = random errors

The market prices and yields for corn and soybeans will not be known to the farmers in advance. In the literature different methods have been used to calculate the expected market price ranging from simply one-period lagged price to one period lagged price, plus a constant (Chavas and Holt, 1990). Implicitly, the Chavas and Holt specification of expected normalized prices, P, is defined by the equation:

$$E_{t-1}(P_t) = \alpha + \beta P_{t-1} \tag{2}$$

With β constrained to equal 1.

However, rather than assuming, β=1, as Chavas and Holt proposed, we improve the equation (2) by directly estimating the value of β using regression analysis. Therefore, we assume that expected price and yield for corn and soybeans would be a linear function of lagged price and yield; and a time variable respectively.

$$E(P) = \beta_0 + \beta_1 P_{i,t-1} + \beta_2 T \tag{3}$$

$$E(Y) = \alpha_0 + \alpha_1 Y_{it-1} + \alpha_2 T \tag{4}$$

where β_0, β_1, and β_2;and α_0, α_1, and α_2 are parameters to be estimated with the price and yield using OLS.

$$E_{t-1}(\Pi_{it}) = E_{t-1}(P_{it} * Y_{it}) + Cov(P_i * Y_i) - C_{it} \quad (5)$$

Where Cov (P_i*Y_i) represents the covariance between price and yield of corn and soybeans. The risk avert behavior of the farmers was captured by incorporating the price variance of corn and soybeans in analysis. The variance of price for three-year period proceeding year t is defined as dispersion of observed profits about their mean i.e.

Var (P_{it}) = $\sum_{j=1}^{3} \lambda_j [P_{i,t-j} - E_{t-j-1} P_{i,t-j}]^2$ where,

$$E_t(P_{it}) = \frac{(P_{i,t-1} + P_{i,t-2} + P_{i,t-2})}{3}$$

represent three year moving average of observed profits and γ_1, γ_2 and γ_3 represents the weights from an adaptive expectations having 0.5, 0.3 and 0.2 weighted average for the first, second and third year respectively. Covariance between the price of corn and soybeans was also incorporated in to model to capture the mechanism of risk-spreading by farmers via the portfolio effect in an expected value-variance (EV) setting.

Data

Corn and Soybeans annual time series data (1975-2002) was used for acreage supply equations estimations. Crop acreage, crop yield, and seasonal average price of corn and soybeans were obtained from the U.S. Department of Agriculture (USDA). The costs of production were obtained from USDA economic research service (ERS). The price, cost, and wealth variables are deflated by using the consumer price index (1982-84=100) as reported by the Bureau of Labor Statistics for all items. Deflating the variables by the CPI satisfies the homogeneity condition as required by the economic theory and helps to reduce multicollinearity problems among explanatory variables (Shalishali, 1993). Initial wealth, w, was estimated by the farm equity as reported by ERS, weighted by the percentage of Georgia income plated to corn and soybeans.

Forecasting Data

Our study aims to forecast the crop acreage and thereby, the irrigation water demand for corn and soybeans in Georgia for coming years (2003-2008). The future price, yield, and cost data of corn and soybeans, which are required for forecasting purposes, are mostly taken from the USDA baseline projects. The USDA baseline projections consists of 10-year projections for agriculture, assuming continuation of current farm law, as well as specific conditions for the economy, weather, and global situation. The remaining data were estimated by using the Box-Jenkin’s ARIMA models.

Results and Discussions

Given the economic hypothesis of expected utility in (6), the preliminary investigation on the data set involved the used of ordinary least square (OLS) and seemingly unrelated regressions (SUR). The t and F statistics were used for the statistical inference purposes. All variables were tested for 5 or 10 percent level, an acceptable level of significance in applied economic research. Ordinary regression analysis (OLS) is based on the several statistical assumptions including independence of the stochastic errors term. However, with the use of time series data, the ordinary regression residuals might correlate over time violating the assumptions of OLS. The OLS estimates of the autoregressive model are generally biased and inconsistent leading to incorrect statistical test results and/or false inferences.

Our study use the time series data (1975-2003), therefore, first we examine the validity of data in terms of auto correlation, multicollinearity, and heteroscedasticy. To check for serial correlation in the residual, Durbin-Watson statistic was used. The analysis yield DW, d, statistics of 2.112 and 1.335 for corn and soybean, respectively. With the K=9 and N=29, the'd' values fall in to the indecision region (0.691-2.342) failing to clearly reject or accept the null hypothesis of no autocorrelation. Idea of non-parametric runs test or Geary test was also proposed to solve the problem of indecision (Gujrati, 1995). Therefore, we further examine the autocorrelation by using the runs test.

The Runs Test for Auto-correlation

In this test, a sequence of positive or negative residuals (K or the number of runs) is used to analyze the autocorrelation problem. Let consider,

N= total number of observations= $n_1 + n_2$

n_1= number of + symbols (+ residuals)

n_2= number of – symbols (- residuals)

k= number of runs.

Under the null hypothesis that successive residuals are independent, and assuming that $n_1>10$ and $n_2> 10$, then $k \sim N(\mu, \sigma^2)$ which is the number of runs is distributed asymptotically normally with mean and variance.

Where,

$$\mu = E(k) = \frac{2n_1 n_2}{n_1 + n_2} + 1$$

$$\sigma^2 = \sigma^2_k = \frac{2n_1 n_2 (2n_1 n_2 - n_1 - n_2)}{(n_1 + n_2)^2 (n_1 + n_2 - 1)}$$

If the hypothesis of randomness is sustainable, we should expect k, the number of runs, to lie between $[E(\kappa) + 1.96\sigma_\kappa \le \kappa \le E(\kappa) - 1.96\sigma_\kappa]$ with 95% confidence. Our analysis yields 12 positive residual (n_1) and 15 negative residual (n_2) for soybeans. Similarly analysis yields 14 positive residual (n_1) and 13 negative residual (n_2) for corn. Further analysis, using the procedure described in the runs test shows that the K (number of the runs) lies between the interval and clearly failed to reject the null hypothesis of no autocorrelation. Therefore, we concluded no autocorrelation problem in our data. The residual plotting also confirms the no heteroscedacity problem for corn and soybeans (Figure 4.1 and 4.2). The correlation matrix among the variables shows no multicollinearity problem among the explanatory variables. In order to detect the heteroscedasticy, the Breusch-Pagan (BP) test was used. The Breusch-Pagan analysis yields (Pr>ChiSq) values of 0.79 and 0.58 for corn and soybeans, respectively. The BP test is distributed chi-squire, and high value of the chi-square statistic (or a low p-value) allows you to reject the null hypothesis of homoscedasticity. In our analysis high p value of 0.79 and 0.58 for corn and soybeans, respectively, failed to reject the null hypothesis of homoscedasticity.

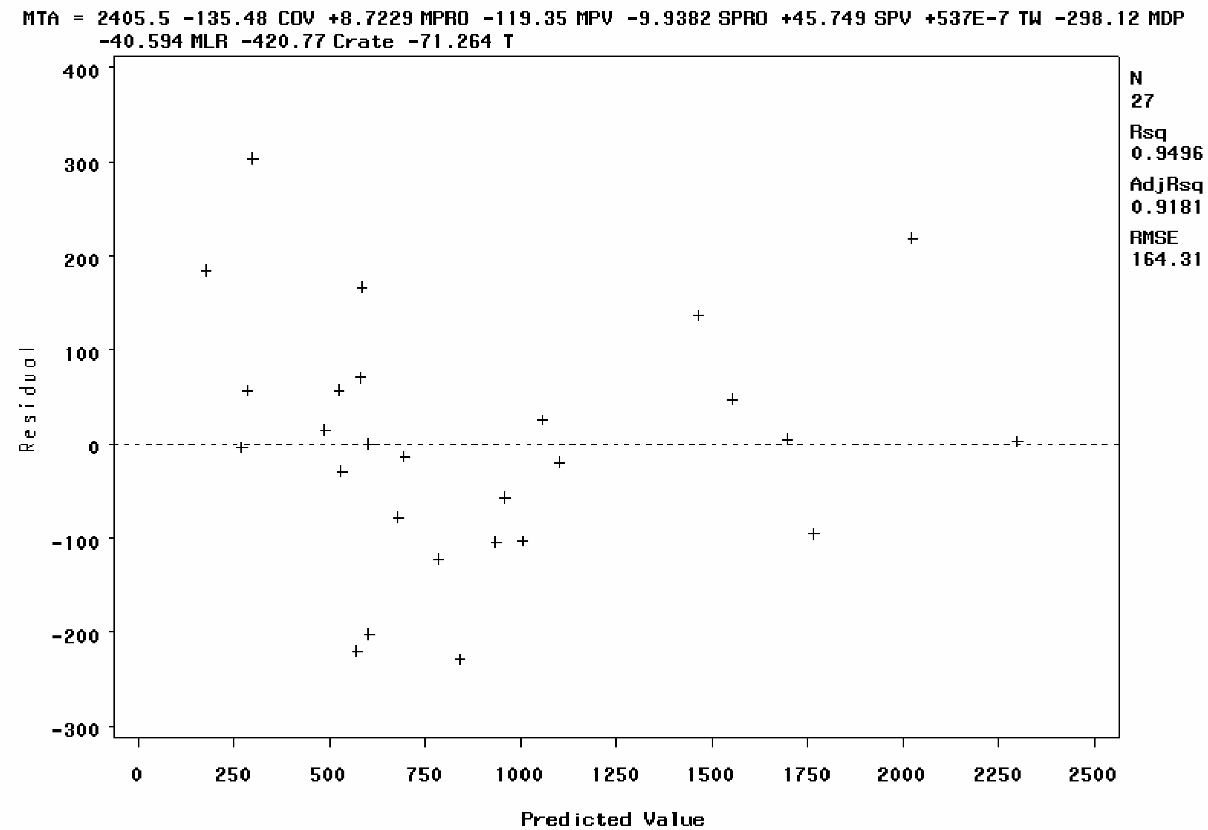


Figure 4.1 Residual Plotting of Corn

The parameter estimates for acreage supply from the Georgia corn and soybeans are presented in Table 4.1 and Table 4.2, respectively. With the exception of few variables, statistical results for corn and soybeans were generally strong in terms of statistical significance of parameters. In our analysis, the F statistics and p value (p=0.0001) strongly reject the null hypothesis that all parameters expect intercept is zero. The R^2, which explains total variation in the model due to explanatory variables, for corn and soybeans were 0.95 and

0.94, respectively. Therefore, the estimated model explains historical variations in corn and soybeans acreage well as reflected by the high R^2 value.

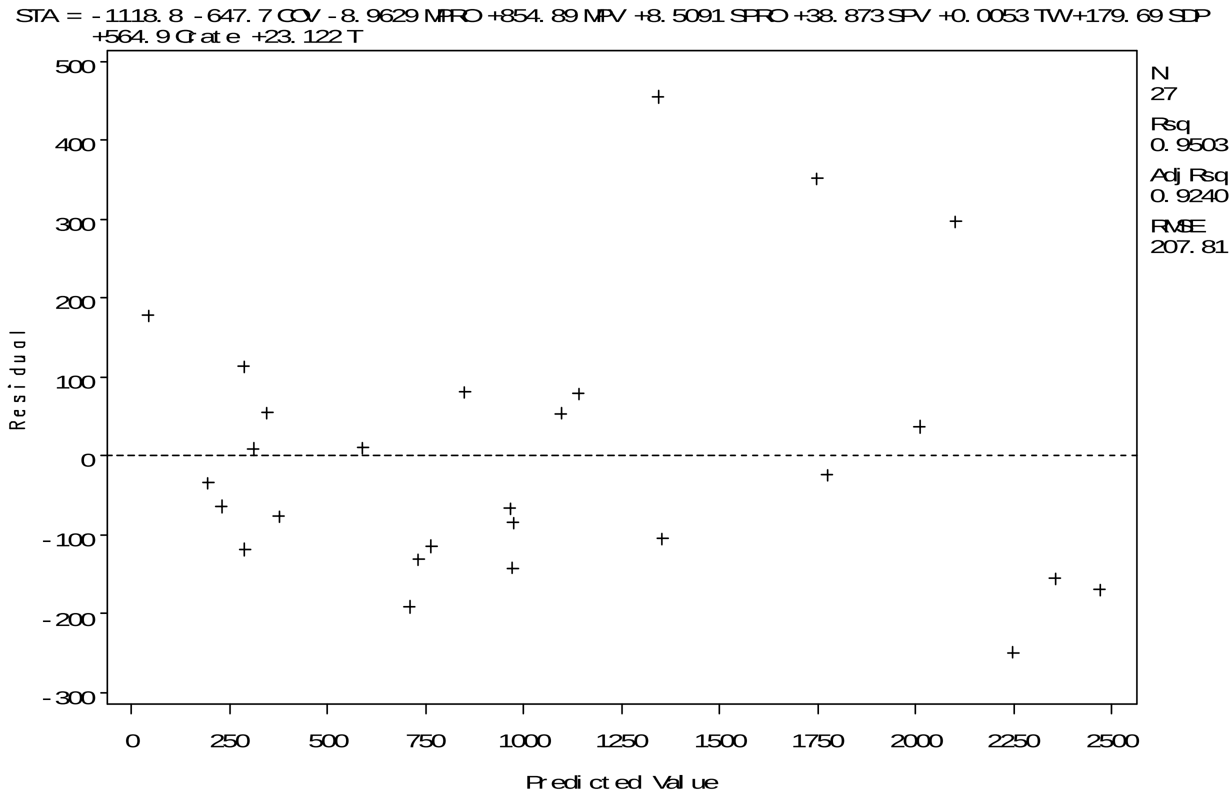


Figure 4.2 Residual Plotting of Soybeans

As expected, the own-expected profit yields positive signs for corn and soybeans. However, only expected profit of corn found to be statistically significant at 5 percent level of significance. With P value of 0.1145, the expected profit of soybeans was not statistically significant at the usual levels of significance. Own expected profit elasticity of corn and soybeans were 0.66 and 0.49, respectively. The measure of elasticity suggests that for every 1 percent increase in the expected profits, corn and soybeans acreage will increase by 0.66 percent and 0.49 percent, respectively.

Table4.1. Estimated Corn Acreage and Elasticity with Mean

Parameter	Estimates	Std.Error	Elasticity
Intercept	2405.53**	575.31	
Time	-71.26**	16.83	
π_1	8.72**	2.99	0.662
w	0.000053	0.0007	0.017
σ_{11}	-119.35	547.32	-0.025
π_2	-9.94**	4.33	-0.668
σ_{22}	45.74	102.86	0.043
σ_{12}	-135.48	495.51	-0.045
CDP	-298.12**	103.54	
CLR	-40.59	176.37	
PFC	-420.77	305.65	
Adj- R^2	0.92		
R^2	0.95		
RMSE	164.31		
P> F-Value	<.0001		

Note: ** indicates the corresponding variables are significant at less than and equal to 10% level. Coefficients in the bracket show elasticity.

The competing expected profits yield negative sign and were statistically significant at 5 percent level of significance for both corn and soybeans. The competing expected profit elasticities were -0.66 and -0.58 for corn and soybeans, respectively. The finding was consistent with the finding of Chavas and Holt (1990), and Duffy et al. (1994). The higher magnitude of elasticities of corn and soybeans in Georgia might have resulted from the availability of production substitutes such as peanut, cotton, and horticultural crops. The accessibility of the different substitute crops would make farmers more responsive to change in profitability. A trend variable was incorporated to capture the effects of omitted variables on acreage decision of corn and soybeans over time. In our analysis, only trend variable of corn yields negative but significant result showing a decreasing trend of corn production in Georgia. Increased timber acreage and to a lesser extend hay crops might have contributed to reduced corn acreage in Georgia.

Table4.2 Estimated Soybeans Acreage and Elasticity with Mean

Parameter	Estimates	SE	Elasticity
Intercept	-1118.80	666.73	
T	23.12	19.29	
π_1	8.51	5.11	0. 058
w_1	0.0053*	0.0008	1.472
σ_{11}	38.87	124.51	0.032
π_2	-8.96*	3.48	-0.586
σ_{22}	854.89	658.57	0.158
σ_{12}	-647.70	602.95	-0.188
SDP	179.69	147.15	
PCF	564.89	355.10	
Adj- R^2	0.92		
R^2	0.95		
RMSE			
P> F-Value	<.0001		

Note: * indicates the corresponding variable is significant at less than and equal to 10% level.

The wealth variable was included in the acreage response equations of corn and soybeans to facilitate tests of hypotheses about risk attitudes. As expected, the study result shows a positive and significant wealth effect for soybeans farmers. This finding was consistent with the results of other researchers (Duffy et al. 1994;

Chavas and Holt, 1990; Shalishali, 1993) and supports the Chavas and Holt findings of decreasing absolute risk aversion for soybeans growers in the United States. In our analysis, the wealth variable failed to yield significant results for corn farmers.

Variance of price captures the influence of the risk involved in the crop production. As expected, the own price variance of corn and soybeans yield negative sign but were statistically insignificant. Even though, the results were not consistent with the finding of other researchers for corn and soybeans, a similar situation exists in Duffy et al's analysis of cotton and soybeans, and cotton and corn acreage supply response. These results might have results from the diversity of crops in Georgia. Given the availability of many possible substitute crops, it is difficult to isolate one alternative crop with a significant influence on corn and soybeans acreage in aggregate. In Georgia, cotton is most often grown on croplands where corn, soybeans, and peanuts are grown. Therefore, the factors outside the corn and soybeans market can affect the corn and soybeans acreage supply response of farmers.

In our analysis, expect deficiency payment for corn, other institutional variables such as loan rate and production flexible contact yield statistically insignificant results. These results are both consistent (Duffy et al. 1994) and, findings inconsistent with other researchers (Houston et al.1999), In our opinion, this result might have resulted from the inconsistent government cotton support programs and conflicting goals of governmental policies in the last decades.

Water Demand Forecasting

Traditionally, the Blaney and Criddle formula (B-C Formula) was used to estimate consumptive or irrigation water demand for agricultural crops. The B-C Formula estimates consumptive water use of crops by using mean monthly temperature and daylights. The B-C Formula develops coefficients that could be used to transpose the consumptive water use data for a given area for which climatological data are available. In our analysis, the B-C formula based irrigation water use coefficients reported by the USDA Soil Conservation Service (in Georgia Irrigation Guide) serve as proxy water use estimates for corn and soybeans. The Georgia Irrigation Guide reports irrigation water demand estimates for lower, middle, and upper flint regions of Georgia. However, we have developed a weighted average water use coefficient to forecast corn and soybeans irrigation water demand in Georgia (Table 4.3).

Table 4.3 also presents the net irrigation demand (inches per acre) coefficients for corn and soybeans as reported by the Georgia Irrigation Guide. While estimating irrigation water demand using B-C Formula, the net amount of irrigation water necessary to satisfy consumptive use of crops was obtained by subtracting the efficient rainfall from the consumptive water requirement for a crop during a growing season. The net irrigation water demand requirement data are based on 30 years average of climatological data (Banerjee, 2004). In order to forecast corn and soybeans irrigation water demand,we first forecast the corn and soybeans acreage supply response using the econometric model (Table 4.4). In our analysis, the Theil's U statistic was 0.68 and 0.73 for corn and soybeans models, respectively showing a forecasting power of the models.

Table 4.3 Net Irrigation Requirements (acre- inches) in Normal and Dry Years by Crop and Region of the Flint River Basin as Given by Blaney-Criddle Coefficients.

Crop	Lower Flint	Middle Flint	Upper Flint	Weighted. Avg.(L,M,U)
Corn				
Normal Year[a]	11.14	12.15	12.32	11.75
Dry Year[b]	12.71	13.65	3.69	13.23
Soybeans				
Normal Year	7.58	8.38	7.65	7.72
Dry Year	9.04	9.75	8.79	9.06

[a] A normal year is defined as a growing season with average rainfall of 49, 44 and 55 inches of rain in Lower, Middle, and Upper Flint River Basin regions respectively.
[b] Dry year is defined as a drought on the magnitude of 20% or an average of the two driest years in a ten –year period over the last 30 years of weather data.
Conversion rate: 1 ac-in=27,150 gallons per day, 1 ac-ft = 325,800 gallons per day

Using the acreage coefficients available from the econometric forecasting of corn and soybeans (Table 4.4) and irrigation water use coefficients calculated for Georgia by using the Blaney-Criddle (BC) formula (Table 4.3), we forecast the water demand for corn and soybeans up to 2008 for dry and normal season. For example, predicted irrigation water for corn for 2005 was estimated by calculating multiplying forecasted corn acre of 2005 (221.01) by the BC coefficients (weighted average) of 11.75 inch per acre (normal year) and 13.23 inch per acre (dry year). Therefore, total corn irrigation water demand would be 408.8 and 400.28 feet per acre for normal and dry season, respectively in Georgia, respectively.

Table 4.4 Forecasted value for corn and soybeans (Thousand Acres)

Year	Soybeans		Corn	
	Real	Forecasted	Real	Forecasted
1997	400	406.00	500	634.30
1998	300	285.35	500	603.10
1999	220	100.28	350	554.82
2000	170	254.45	360	279.10
2001	165	170.94	265	177.87
2002	160	197.00	340	239.24
2003		214.28		367.24
2004		173.86		318.78
2005		168.89		199.09
2006		130.22		243.62
2007		109.71		79.93
Theil's U: Corn = 0.68, Soybeans = 0.73				

Normal year is defined as a growing season having average rainfall of 49, 44, and 55 inches in lower, middle, and upper Flint River basin of Georgia, respectively. While a dry year refers as a drought on the magnitude of 20% or an average of the two driest years in a ten year period over the last 30 years averages of climatological data. Table 4.5 presents the irrigation water demand for corn and soybeans in Georgia for normal and dry season from 2003-2008.

Table 4.5 Net Irrigation Water Demand Forecasting Net (acres feet) in Normal and Dry Years by Corn and Soybeans in Georgia (2003-2007)

Year	Soybeans		Corn	
	Normal Year	Dry Year	Normal Year	Dry Year
1997	261.1933	306.53	621.0854	699.3158
1998	183.5752	215.4393	590.5354	664.9178
1999	64.51347	75.7114	543.2613	611.6891
2000	163.6962	192.1098	273.2854	307.7078
2001	109.9714	129.0597	174.1644	196.1017
2002	126.7367	148.735	234.2558	263.7621
2003	137.8535	161.7814	359.5892	404.8821
2004	111.8499	131.2643	312.1388	351.455
2005	108.6526	127.512	194.9423	219.4967
2006	83.77487	98.3161	238.5446	268.5911
2007	70.5801	82.83105	78.26479	88.12283

Conclusions

Irrigation water demand depends on crop producers’ acreage allocation and supply decisions. The crop acreage supply decision of farmers is affected by own crop profit, competing crops’ profits, and government programs. While allocating crop acreage, producers attempt to minimize the risk involved. Because of the risk aversion behavior of the farmers, understanding of the variance of own crop profit and competing crops’ profit is also equally important. In this study, we have examined the corn and soybeans acreage allocation decision and thereby, the irrigation water demand of farmer under production risk and price uncertainly by using the expected utility model. The proposed model incorporates expected own profit, expected profit of competing crop, variance of own price, variance of competing crop price, covariance of price of competing crops, and institutional variables.

In our analysis, most of economic and institutional variables were statistically significant. In spite of significant contributions of this article in policy arena, our study is constrained by limited data and/or lack of related information and inconsistent government programs. Our study also shows the pitfall associated with disregarding the changes in crop acreage when economic and government programs change.

CHAPTER FIVE

IRRIGATION DEMAND FORECASTING

A Structural Time Series Analysis

The serious lack of information on past, present and future irrigation water demand restricts the efficient allocation of limited water resource in many parts of the United States including Georgia (Jordan, 1998). The aggregate data, absence of economic model of agriculture water demand, and lack of a proper link between the economic and engineering water demand, represent the major irrigation water demand problems in Georgia (Tareen, 2001). So far, irrigated crop acreage estimates compiled by county extension agent, irrigation permits recorded by the Georgia Environmental protection Division (GEPD), county level agricultural water demand data reported by the United States Geological society (USGA), and irrigation water information collected by the Alabama-Coosa-Tallapoosa (ACT) and Apalachicola-Chattahoochee-Flint (ACF) comprehensive study (ACT/ACF study) remain the major sources of irrigation water demand in Georgia.

However, lack of systematic record, invalid modeling approaches, and missing data problem limit the scope and applicability of these studies for irrigation water demand estimation and forecasting purposes. For example, USGS reports agricultural water demand for each county of Georgia without disaggregating crop water demand into an individual crop. In the absence of information on a specific crop water demand, prediction of future water demand would be incomplete.

The ACT/ACF study, which is considered as one of the most detailed study of the region, forecasts irrigation water demand for some specific counties of Georgia up to the year 2050. However, ACT/ACF study's crop acres and thereby irrigation water demand is based on the guess of experts (see page 21, ACT/ACF River Basins Comprehensive Study, 1995). Simply, the guess or opinion of any expert does not offer enough justifications necessary to validate the findings of any study. Therefore, existing physical irrigation water demand models in Georgia are of narrow scope to reach any logical conclusions regarding present and future crop water demand.

Being the major source of water use in Georgia, precise information on present and future crop water demand is very crucial for water allocation and conservation efforts. Realizing the importance of accurate estimates of crop water demand, presently a multi-million dollars project is underway at the University of Georgia. As a part of this project, the Department of Agricultural Engineering of the University of Georgia (DAE-UGA) has been recording irrigation water use in 400 different agricultural farms of Georgia (Banerjee, 2004). The DAE-UGA study aims to accurately assess the individual crop's irrigation water demand and thereby, to develop proxy coefficients of crop water demand for future uses. The DAE-UGA would contribute to refine the existing crop water use coefficients which are mostly based on the Blaney-Criddle formula. However, by failing to capture the changes in crop acres and thereby crop irrigation water demand, this study is also of limited applicability for irrigation water demand forecasting purposes.

In this paper, we argue that irrigation water demand is directly related to crop acreage allocation decision of farmers, which in turn, driven by different economic and government program variables such as expected profit, cost of production, government support price, deficiency payment, loan rate and related factors. Therefore, any irrigation water demand forecasting study, first, should capture these possible adjustments in the crop acreages by developing a sound acreage supply response model and finding the elasticities associated with the significant economic and institutional variables. An acreage model traces the change in crop as economic and institutional variables vary (Houston et al., 1999). Use of crop supply response function offers an alternative modeling approach to indirectly capture the impacts of economic and institutional variables on crop irrigation water demand. Therefore, our study aims to forecast irrigation water demand for corn and soybeans by developing a structural time series model (STSM) with exogenous variables as proposed by Harvey, 1989. Rather than using a classical econometric model, we use STSM to capture the impacts of technological change on crop acreage response.

Issue of Technological Changes in Crop Acreage Response Model

Many researchers have analyzed the crop acreage supply response of corn and soybeans (Shideed et al., 1987; Krause and Koo, 1996; Parrott and McIntosh, 1996; Guyomard et al., 1996; Park and Garcia, 1994). These studies differ in specific products, geographic areas, explanatory factors, modeling approaches, and method of analysis. The size and complexity of the issue justify the different modeling approaches, research efforts, and diversity of analyses. The primary purposes of analyzing corn and soybeans acreage supply response include: forecasting of future supplies, identifying the response of government program on corn and soybean acreage, and identifying the response to price levels.

However, traditionally crop acreage supply responses have been modeled as a function of expected price or profit, cost of production, expected profit of the substitute crops, and government program variables (Krause et al., 1996; Houston et al., 1999; McIntosh and Shideed, 1989). In addition to the traditional economic and government program variables, crop acreage supply response might be influenced by unobservable factors such as improvement in production efficiency, crop management, plant variety, and production technologies. However, majority of researchers in the crop acreage response studies ignore the role of technological changes (Parrot and McIntosh, 1996; Chembezi and Womack, 1992; Ghatak and Seale, 2001).

Even though highly overlooked in the crop acreage supply response literature, the issue of technological changes warrants a through analysis because of the far-reaching changes in the corn and soybeans productivity in the last few decades. The USDA reports show that the corn yield increases from 28.06 bushels per acre in 1900 to 136.87 bushels per acre in 2000. Similarly, soybean yield increases from 11 bushels per acre in 1924 to 38.1 per acre in 2000 (USDA, 2001). These drastic increases in per acre corn and soybeans yield might have been attributed by the ongoing changes in improved breeding, biotechnology, and management practices. An increase in per acre production level would affect the acreage supply decisions of farmers. Therefore, the issue of technological changes can not be simply disregarded.

Some of the researchers also incorporated trend dummy variables to capture of the impacts of technological progress (Chavas and Holt, 1990; Shideed et al., 1987). However, one of the severe limitations of these studies was the assumption of deterministic trend component in crop acreage response, implying that a model with a constant intercept, a time trend, and is correctly specified. These unobservable variables can be embodied, disembodied, endogenous, exogenous, or of different forms (Hunt et al. 2003). Therefore, whether a simple linear deterministic time trend correctly specified the model is an empirical issue. Moreover, assuming deterministic trend implies an unchanged rate of technological changes throughout the sample period, an assumption seems unreasonable.

Contrary to the tremendous research efforts on the issues of expected price and government programs and its impacts on crop acreage supply responses, we shift our focus on trend or a technological proxy variable, a variable highly ignored in crop acreage response literature. We argue that ignoring trend variable and/or assuming trend as deterministic variable as *a priori* might lead to a mis-specified model and false inferences. A deterministic trend may or may not be correct, but it should not be assumed *a priori*. Therefore, we suggest let data prove it. The main objective our study is to develop a correctly specified corn and soybean acreage response model, especially incorporating trend as stochastic components. So far, none of the researchers have considered the role of stochastic trend variables in crop acreage supply response function. Therefore, this study would be a first of its kind and departs significantly from the modeling approaches of the existing crop acreage model.

Expected utility model discussed in the econometric analysis of corn and soybeans offers theoretical justification needed for the study. We begin our study by selecting a corn and soybeans acreage response model. The selected model was further improved by assuming three different versions of technological changes namely: no trend effect, fixed trend effect, and stochastic trend effect. In the case of corn and soybeans acreage supply response, we ignore the role of seasonality. No seasonality was assumed because of the unavailability of quarterly data and existing pattern corn and soybeans production in Georgia. Three versions of acreage supply response were developed separately for corn and soybeans as:

i. No trend and no seasonality (NTNS)

ii. Deterministic trend and no seasonality (DTNS)

iii. Stochastic trend and no seasonality (STNS)

NTNS represents the basic acreage response model where role of trend and seasonality is ignored. STAMP offers options to run the proposed versions of corn and soybeans acreage supply response models.

Structural Time Series Model

First proposed by Harvey in 1989, the STSM allows the unobservable trend and seasonal components to change stochastically over time. The STSM is generally developed directly in terms of components of interest, such as trend, seasonal, cyclical, and residual or irregular components. The STSM relates to regression model in both technical formulation and model selection methodology. The Kalman filter, which is a simple statistical logarithm, and a state-space model play fundamental roles in analyzing structural time series models (Gonzalez and Moral, 1995). In STSM, the exogenous variables enter in to the model side by side with the unobserved components. Unlike the traditional ARIMA models, STSM explicitly consists of unobserved stochastic trend and seasonality components. STSM model reverts to a standard regression model in the absence of unobservable components (Harvey, 1989). Consider the following STSM corn and soybeans acreage supply model:

$$AS_t = \mu_t + \gamma_t + Z_t^{'}\delta + \varepsilon_t \quad (1)$$

Where,

AS_t = Crop acreage supply

μ_t = the trend component

γ_t = the seasonal component

Z'_t = Vector of explanatory variables (expected price, price variance, government program variables)

δ = k*1 Vector of unknown parameters

ε_t = Random white noise disturbance term

With deterministic trend and seasonality variables, the model coefficients of μ_t and γ_t in equation 1 are assumed to be constant. If these coefficients are statistically significant, the corn and soybeans acreage supply response will be driven by deterministic trend and seasonality. However, this would be a highly restrictive assumption. Technical and genetic progress may lead to changes in the value of these coefficients over time. Changes in the values of μ_t and γ_t may take different forms, leading to either structural break or a smoothly changing stochastic trend. Proposed STSM allows specifying a possible alternative of the above problem by allowing a test for deterministic trend and seasonality against a stochastic trend and seasonality alternative. The stochastic trend, which represents the long term movement in the series can be represented by

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \tag{2}$$

$$\beta_t = \beta_{t-1} + \xi_t \tag{3}$$

Where $\eta_t \sim NID\ (0,\ \sigma_\eta^2)$ and $\xi_t \sim NID\ (0,\ \sigma_\xi^2)$

Equations (2) and (3) represent the level and the slope of the trend, respectively. Here, μ_{t-1} is a random walk with a drift factor, β_t, which follows a first-order autoregressive process as represented by equation 3. A stochastic trend variable (μ_t) captures the technological progress and structural change in corn and soybeans sector in recent years. The exact form of the trend depends upon whether the variances, σ_η^2 and σ_ξ^2 (also known as the hyper parameters) are zero or not. If either σ_η^2 or σ_ξ^2 is non-zero, then the trend is said to be stochastic. If both are zero, then the trend is linear and the model reverts to a deterministic linear trend model as follows:

$$DS_t = \alpha + \gamma_t + \beta_t + Z_t^{'}\delta + \varepsilon_t \tag{4}$$

In our study, the seasonality component was ignored while developing STSM for corn and soybeans. Therefore, the seasonality specification is not elaborated.

Economic Model Specification for Corn and Acreage Supply

Following the corn and soybeans acreage supply model developed in the chapter 4, STSM for corn and soybeans were specified as:

$$A_{it} = \mu_t + \zeta_i W_t + \sum_i \beta_i \pi_{it} + \sum_i \sum_j \gamma_i \sigma_{ijt} + \sum_i \eta_i Z_{it} + \varepsilon_{it} \qquad (5)$$

Here

A_{it} = Total crop acreage for i^{th} crops at time t

μ_t = the trend component

w_t = wealth of crop farmers at time t

π_{it} = Mean expected profit for i^{th} crops per acre at time t

σ_{it} = Co-efficient of variance of price of i^{th} crops at time t

σ_{ijt} = Co-variance of price between the i^{th} and j^{th} crop at time t

Z_i = Matrix of institutional variables such as corn deficiency payment (CDP), corn loan rate (CLR), Soybeans deficiency payment (SDP), production flexibility contract (PFC)

ε_t = Random white noise disturbance term

If $\sigma_\eta^2 = \sigma_\xi^2 = 0$, equation 5 collapses to a standard regression model having a linear deterministic time trend and no seasonal component. Therefore, the STSM with explanatory variables in equation 6 is a generalization of the classical linear regression model used by Chavas and Holt (1990) and Shideed et al.(1987)

The market price and yield for corn and soybeans will not be known to the farmers in advance. In the analysis, the expected price and expected yield were estimated using the procedure used in chapter 4.

Data

Corn and Soybeans annual time series data (1975-2002) were used for acreage supply equations estimations. Crop acreage, crop yield, and seasonal average price of corn and soybeans were obtained from the U.S. Department of Agriculture (USDA). The costs of production were obtained from USDA economic research service (ERS). The price, cost, and wealth variables are deflated by using the consumer price index (1982-84=100) as reported by the Bureau of Labor Statistics for all items. Deflating the variables by the CPI satisfies the homogeneity condition as required by the economic theory and helps to reduce multicollinearity problems among explanatory variables (Shalishali, 1993). Initial wealth, w, was estimated by the farm equity as reported by ERS, weighted by the percentage of Georgia income plated to corn and soybeans. Information about corn and soybean loan rate, target price, and production flexibility contract were obtained from the ERS, USDA.

Results and Discussions

Structural Time Series Analyzer, Modeller, and Predictor (STAMP) 6.0 version was used for the analysis purposes. STAMP allows options to run different versions (NTNS, DTNS, and STNS) of corn and soybeans acreage supply models. Table 5.1 and Table 5.2 report the estimates of all three different models of corn and soybeans acreage supply, respectively.

Table 5.1 Estimation Results of Corn Acreage Supply Response under Different Assumptions of Trend

Parameter	NTNS	DTNS	STNS
μ_t		410.14	-162.38
β_t		-71.264	-10.497
π_1	4.62	8.72**	5.24**
		(0.66)	(0.398)
w	0.0028**	5.37e-005	0.00091
	(0.906)		
σ_{11}	1486.1**	-119.035	-250.04
	(0.320)		
π_2	0.548	-9.93**(-0.668)	5.24
σ_{22}	390.24**	45.74	1.83
	(0.374)		
σ_{12}	-1751.11**	-135.48	164.82
	(-0.592)		
CDP	-468.44**	-298.12**	-143.23**
CLR	18.22	-40.59	141.56
PFC	-155.39	-420.77	-267.32
DW	1.95	1.90	1.71
Q	7.92	5.06	4.14
R^2_d	0.22	0.55	0.61
AIC	11.15	11.53	10.75
BIC	11.58	11.75	11.37
N	0.99	0.44	0.23
H(g)	0.62	1.57	0.54
Theil U	0.86	0.76	0.49

Note: **shows variables statistically significant at 10 percent level. The number in the parenthesis shows corresponding elasticity

Also included in tables are measures of diagnostic and goodness-of-fit of the model such as Durbin-Watson (DW) test, Ljung-Box Q statistic, Jarque and Bera normality statistic, standard error of the estimated equation (σ’), Aikake information criterian (AIC), and Bayes information criterian (BIC). The conventional R^2 is not very useful to measure the goodness of fit in our model due to the use of quarterly time series model. Therefore, we report R^2_d, a coefficient of determination, as suggested by Harvey (1989).

Table 5.2 Estimation Results of Soybeans Acreage Supply Response under Different Assumptions of Trend

Parameter	NTNS	DTNS	STNS
μ_t		-471.37*	-126.52
β_t		23.12	-68.35
π_1	1.51	8.50**(0.492)	-2.84
w	0.0039**(1.087)	0.0052**(1.472)	0.0029**(0.808)
σ_{11}	-107.88	38.87	22.12
π_2	-6.81**(-0.445)	-8.96**(-0.586)	-0.04
σ_{22}	148.34	854.89	-39.36
σ_{12}	10.306	-647.71	-146.75
SDP	151.50	179.69	-23.44
PCF	277.52	564.90**	-120.35
DW	1.23	1.27	1.83
Q	14.11	7.94	1.71
R^2_d	0.42	0.51	0.71
AIC	10.98	10.08	10.56
BIC	11.36	11.06	11.14
N	6.84	1.55	0.35
H(g)	0.44	0.30	0.17
Theil U	0.87	0.72	0.82

Note: ** shows variables statistically significant 10 percent level. The number in the parenthesis shows corresponding elasticity

The time-varying parameter estimates of Tables 5.1 and 5.2 are related to the final state vector when the information in the full sample has been utilized. The trend variable (μ_t) and the slope of the trend (β_t) in Tables 5.1 and 5.2 are equivalent to the constant and coefficient of trend variable, respectively, in the standard regression equation.

Results of Corn Models

In our analysis all NTNS, DTNS, and STNS corn acreage supply models show a strong convergence, reflecting successful maximum likelihood estimation by the numerical optimization procedure of STAMP. As indicated by the R^2_d, the goodness of fit diagnostics for all corn acreage supply models was satisfactory. N value in Table 5.1 is the Jarque and Bera normality test, which follows asymptotically a χ^2 distribution with two degree of freedom under the null hypothesis (Gaujrati, 1995). At 5% critical level, $\chi^2_{(2)}$ yields a value of 5.99. With N= 0.99 (NTNS), N=0.44 (DTNS), and N=0.23 (STNS), all corn models fail to reject the null hypothesis of the presence of normality. Therefore, the diagnosis shows that there is no indication of non-normality in the residuals.

The Box-Ljung Q statistic, Q (p,q), is a test for serial correlation, which is based on the first ‘p’ residual autocorrelations and should be tested against a chi-square distribution with ‘q’ degree of freedom. In our analysis NTNS, DTNS, and STNS corn acreage models yield “p” values of 0.24, 0.53, and 0.65 for Box-Ljung serial correlation test, respectively. The decision rule is to reject the null hypothesis of the presence of no serial correlation if the p value is great than 0.05 (at 5 percent level of significance). This diagnostic test is clear-cut indicating that there is no serial correlation in the residuals.

The Darbin-Watson d statistic examines the presence of serial correlation in the model. In our analysis, the NTNS, DTNS, and STNS corn acreage supply models yield DW d values of 1.95, 1.90, and 1.71, respectively. With the sample size (N) of 26 and 9 explanatory variables (K), the critical d_L and d_U values range from 0.657 to 2.379. All of the DW d values of our corn acreage supply models fall between these critical d_L and d_U values, and therefore, fail to reject the null hypothesis of no autocorrelation. The results suggest that there is no autocorrelation in the disturbances. These conclusions are consistent with the results of Box-Ljung Q statistic.

H(g) is a test for heteroscedasticity and the 1% critical values of F(g,g), for NTNS, DTNS, and STNS corn acreage supply models are 3.44, 3.44, and 3.18 respectively. These values fail to reject the null hypothesis of presence of homoscedasticity in the residuals. In our analysis, the estimation procedures converge and the results of diagnostic tests appear satisfactory for the different models of corn acreage supply response models suggesting that NTNS, DTNS, and STNS models were appropriately specified. After confirming the validity of the models using different diagnostic tests, we further analyze the three corn models by using STSM with explanatory variables as proposed by Harvey 1989. The parameter estimates of corn acreage response models and hyper parameters are given in Table 5.1.

Except the NTNS model, own-expected profit yield positive and significant results for DTNS and STNS corn acreage supply response model. Own expected profit elasticity of DTNS and STNS corn model were 0.66 and 0.49, respectively. The measure of elasticity suggests that for every 1 percent increase in the expected profits, corn acreage will increase by 0.66 percent and 0.49 percent in DTNS and STNS corn acreage response model, respectively.

In our analysis, the competing expected profits of soybeans yield negative sign and were statistically significant at 5 percent level of significance only for DTNS corn model. The competing expected profit elasticity was -0.67 in DTNS corn model, respectively, a finding consistent with Chavas and Holt (1990), and Duffy et al. (1994). Wealth variable was included in all of three corn acreage response models to facilitate tests of hypotheses about risk attitudes. Except NTNS, the study results fail to show significant wealth effect on DTNS and STNS corn models. This finding was consistent with the results of other researchers such as Duffy et al. 1994; Chavas and Holt, 1990; Shalishali, 1993.

Variance of price captures the influence of the risk involved in the corn production. In our study, DTNS and STNS corn model yield expected negative sign but the results were statistically insignificant. These results might have been influenced by the diversity of crops in Georgia. Given the availability of many possible substitute crops, it is difficult to isolate one alternative crop with a significant influence on corn acreage in aggregate. Except for the NTNS corn model, the covariance between prices of corn and soybeans also fail to show significant affect on corn acreage allocation decision. In our analysis, all corn models yield statistically significant results for the corn deficiency payment variable. However, corn loan rate and production flexibility contract (PFC) failed to yield any statistically significant impacts on corn acreage response. These results are both consistent (Duffy et al. 1994) and inconsistent with other researchers (Houston et al.1999). In our opinion, this result might have resulted from the inconsistent government support programs and conflicting goals of governmental policies in the last decades.

The Best Corn Model

The main goal of our analysis was to select a correctly specified corn acreage supply response model for corn irrigation water demand forecasting purpose in Georgia. The values of AIC, BIC and R^2_d values were considered as the main criteria of the best model specifications. In our analysis, STNS corn acreage response model yields the smallest AIC and BIC values of 10.75 and 11.37 respectively (Table 5.1). The STSS model also yields highest R^2_d value of 0. 61 (Table 5.1). These statistics are significantly different from the remaining corn acreage supply models making STSS a superior and correctly specified model of corn acreage supply. The study results clearly reject the classical ideas of ignoring technological change and/or incorporating deterministic trend as a proxy of technological changes in corn acreage supply response model as *a priori* and suggest the critical role of stochastic trend variable in crop acreage response study. The analysis confirms that the best corn acreage supply model be specified by incorporating trend as a stochastic variable.

In order to assess the forecasting accuracy of the selected model, we further analyze the forecasting performance of NTNS, DTNS, and STNS corn acreage supply model using out-of-sample predictions (Table 5.3). Forecasts are made for all corn acreage response models for the next 7 years. The forecasts, together with their estimated RMSE and MAPE are reported in the table 5.3. To further assess the robustness, structural integrity, and forecasting accuracy, and thereby to confirm the superior corn acreage supply model, we also report the Theil U statistics (Table 5.1). In our analysis, with small Theil U statistics of 0.47 the STNS corn model emerges as the best model.

Soybeans Acreage Supply Models

The estimates of trend and explanatory variables along with measures of diagnostic and goodness-of-fit of the model such as Durbin-Watson (DW) test, Ljung-Box Q statistic, Jarque and Bera normality statistic, Aikake information criterian (AIC), and Bayes information criterian (BIC) for NTNS, DTNS, and STNS models of soybeans acreage response models are presented in Table 5.2. In our analysis, NTNS, DTNS, and STNS soybeans acreage supply response models show a strong convergence and successful maximum likelihood estimation by the numerical optimization procedure of STAMP. Further diagnostic tests using *t*he Jarque and Bera normality test, the Durbin-Watson d test, Box-Ljung Q statistic and heteroscedasticity suggest the presence of normality, homoscedasticity, and the presence of no serial autocorrelation in the model (Table 5.2).

Table 5.3 Net Irrigation Requirements (acre- inches) in Normal and Dry Years by Crop and Region of the Flint River Basin as Given by Blaney-Criddle Coefficients.

Crop	Lower Flint	Middle Flint	Upper Flint	Weighted. Avg.(L,M,U)
Corn				
Normal Year[a]	11.14	12.15	12.32	11.75
Dry Year[b]	12.71	13.65	3.69	13.23
Soybeans				
Normal Year	7.58	8.38	7.65	7.72
Dry Year	9.04	9.75	8.79	9.06

[a] A normal year is defined as a growing season with average rainfall of 49, 44 and 55 inches of rain in Lower, Middle, and Upper Flint River Basin regions respectively.
[b] Dry year is defined as a drought on the magnitude of 20% or an average of the two driest years in a ten –year period over the last 30 years of weather data.
Conversion rate: 1 ac-in=27,150 gallons per day, 1 ac-ft = 325,800 gallons per day

The parameter estimates for NTNS, DTNS, and STNS soybeans acreage supply equations are presented in Table 5.2. Own expected profit showed positive sign for NTNS and DTNS models, however only DTNS soybeans model was statistically significant. The own profit elasticity of DTNS soybeans was 0.49. The soybeans own-profit estimates in Georgia are in line with the previous estimates of own price elasticity. The competing expected profit carried negative signs and were found to be statistically significant for NTNS and DTDS soybeans models thereby suggesting that increasing profitability of corn may result in a decrease in soybeans acreage. The competing expected profit elasticities were -0.44 and -0.58 for NTNS and DTNS soybeans models, respectively, which are consistent with Chavas and Holt (1990), and Duffy et al. (1994).

As expected all three soybeans models yielded a positive and significant wealth effect. The finding supports the Chavas and Holt assumption of decreasing absolute risk aversion for soybean farmers. Expect NTNS soybeans models, the remaining soybeans acreage response model yield positive results for the variance of price. However, in all three models the results were not significant, a finding inconsistent with the results of other researchers (Chavas and Holt, 1990; Duffy et al. 1994). The covariance between corn and soybeans prices also was not significant in our study. In the case of institutional variables, the production flexibility contract (PFC) variable yielded positive and statistically significant results for DTNS soybeans model. The insignificant impacts of other institutional variables might have been caused by the highly inconsistent government farm policies in the last few decades.

The Best Soybeans Model

The criteria of AIC, BIC, and R^2_d were used to select the best model of among the NTNS, DTNS, and STNS soybeans acreage response models. With the smallest AIC and BIC values of 10.08 and 11.06 respectively, the DTNS soybeans acreage supply model emerges as the best model. The best model is further confirmed by the highest R^2_d values of 0.67. Even though the analysis rejects the idea of incorporating trend as a stochastic variable, the results explicitly show the significance of adding trend variable in soybeans acreage response study. The finding suggests that soybeans acreage response model should consider trend variable for correct modeling specification purposes. The Theil U statistic of 0.72 shows the robust forecasting power of DTNS soybeans acreage model and further confirms it as the best model.

Water Demand Forecasting

After selecting the best model of corn acreage response model, we forecast the corn irrigation water demand for the coming 7 years. The Blaney and Criddle model's (B-C Formula) crop water use coefficient reported by the USDA Soil Conservation Service serves as baseline information of present and future irrigation water demand for corn. Even though Georgia irrigation guide reports irrigation water coefficient for lower, middle, and upper flint regions of Georgia, we have developed a weighted average water use coefficient for forecasting purposes (Table 5.3).

Table 5.3 also presents net irrigation water demand (inches per acre) coefficients for corn and soybeans as reported in the Georgia Irrigation Guide by USDA Soil Conservation Service. The net amount of irrigation water necessary to satisfy consumptive use of crops was obtained by subtracting the efficient rainfall from the consumptive water requirement for a crop during a growing season. The net irrigation water demand requirement data are based on 30 years average of climatological data (Banerjee, 2004). Table 5.4 and Table 5.5 present the corn and soybeans acreage forecasting for the next 7 years and corresponding room mean square error (RMSE).

Table 5.4 Corn and Soybeans Acreage forecasting Using STNS Model (thousand acres)

Period	corn		Soybeans	
	Forecast	RMSE	Forecast	RMSE
2001	287.89	73.51	227.41	33.50
2002	347.71	87.20	198.65	35.21
2003	367.39	89.85	187.59	37.02
2004	347.33	94.81	183.48	43.92
2005	321.57	99.74	178.51	50.93
2006	317.29	102.29	169.53	63.03
2007	301.13	105.72	163.56	85.23
2008	298.31	113.10	159.58	107.52
2009	284.35	127.45	151.61	119.89
2010	270.39	241.7	141.63	142.35

Using the acreage coefficients available from the STSM forecasting of corn and soybeans (Table 5.4) and irrigation water use coefficients calculated for Georgia by using the Blaney- Criddle (BC) formula (Table 5.3), we forecast the water demand for corn and soybeans up to 2010. For example, predicted irrigation water for corn for 2005 was estimated by multiplying forecasted corn acre of 2005(270.19 thousands acres) by the BC coefficients (weighted average) of 11.75 inch per acre (normal year) and 13.23 inch per acre (dry year). Therefore, total 2005 corn irrigation water demand would be 3174.73 thousands acres inches for normal year and 3574.61 thousands acres inches for dry year in Georgia. Normal year is defined as a growing season having average rainfall of 49, 44, and 55 inches in lower, middle, and upper Flint River basin of Georgia, respectively. While a dry year refers as a drought on the magnitude of 20% or an average of the two driest years in a ten year period over the last 30 years averages of climatological data. Table 5.5 presents the irrigation water demand for corn and soybeans in Georgia for normal and dry season from 2003-2010

Table 5.5 Net Irrigation Water Demand Forecasting Net (acres inches) in Normal and Dry Years by Corn and Soybeans in Georgia (2001-2010)

	Corn		Soybeans	
Year	Normal	Dry	Normal	Dry
2001	281.8923	317.3987	146.3004	171.6946
2002	340.466	383.3503	127.7982	149.9808
2003	359.736	405.0475	120.6829	141.6305
2004	340.094	382.9313	118.0388	138.5274
2005	314.8706	354.5309	114.8414	134.7751
2006	310.6798	349.8122	109.0643	127.9952
2007	294.8565	331.9958	105.2236	123.4878
2008	292.0952	328.8868	102.6631	120.4829
2009	278.426	313.4959	97.53577	114.4656
2010	264.7569	298.105	91.1153	106.9307

Conclusions

Our analysis aims to forecast the corn and soybeans irrigation water demand in Georgia by developing a sound crop acreage supply response model having an excellent forecasting accuracy. We first improve the existing corn and soybean model explicitly modeling different version of trend components. Three versions of corn and soybean acreage supply models with different assumptions trend were considered to select the best corn and soybeans supply response model. Analysis using different assumptions on trend variable confirms the role of technological changes on corn and soybeans. In our study, stochastic and deterministic trend variable offers the most promising modeling option for corn and soybeans, respectively. The findings show that ignoring trend variable might lead to model misspecification and false conclusions. The results also demonstrate that the out-of-sample forecasting power of the correctly specified model is superior. In our analysis, all economic variables were statistically significant showing the importance of incorporating economic variable while forecasting corn and soybeans acreage and thereby future dairy water demand.

CHAPTER SIX

UNIVARIATE TIME SERIES ANALYSIS

Univariate and Structural Time Series Analysis

The impact of economic, technological, and institutional changes is manifested by the drastic changes in corn and soybeans acreage in Georgia in the last few decades. For instance, during the past decade the corn acreage ranged from a high of 4710 thousand acres in 1935 to a low of 265 thousand acres in 2001. Between 1982 to 2002, soybeans acres also changed from a high of 2400 thousand acres in 1982 to a low of 180 thousand acres in 2002 (USDA, 2002) in Georgia. Understanding of absolute movement and the variations of crop acreage time series is very critical from different perspectives including irrigation water allocation and forecasting. The incorrect anticipation of crop acreage supply and fluctuations affect the irrigation water allocation decision directly. Therefore, it is crucial that feasibility of using several crop acreage forecasting techniques including univariate time series be explored.

The previous chapters have analyzed the corn and soybeans water demand estimation and forecasting issues using econometric and structural time series (STSM) techniques. This chapter further assesses the issue of corn and soybeans water demand forecasting by using a Univariate or ARIMA modeling approach, a technique highly ignored in the crop acreage supply response studies. Using Univariate time series not only blends pure statistical outlook in the ongoing study but also offers alternative benchmark information of comparing water demand forecasting among different modeling techniques. The analysis will be further extended using STSM with no explanatory variables.

Data

The corn and soybeans annual acreage time series (1926-1999) used in this study were secondary data taken from National Agricultural Statistics Services (NASS) of the United States Department of Agriculture (USDA). The annual corn and soybeans acres of the last three years (2000-2003) were taken from the Georgia Agricultural Fact. The aggregate nature of these state data may not offer the detailed or actual account of variability for each corn and soybeans farm as the variability contained in the state level aggregate data is less than that of a particular farm.

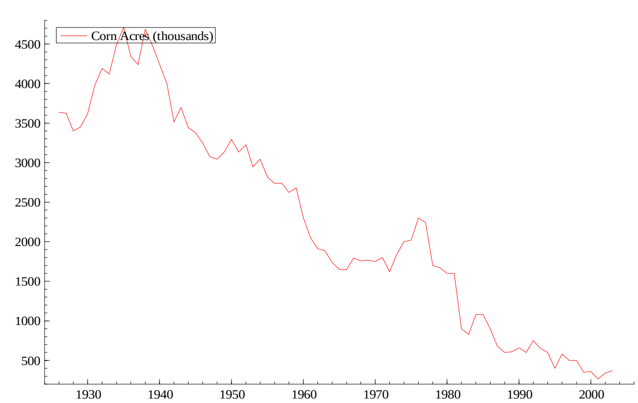
Materials and Methods

In 1976, Box-Jenkins suggested four chronological steps of ARIMA model building namely: identification, estimation, diagnostic checking, and forecasting. In this study, modeling procedures as outlined by Box-Jenkins are used to construct ARIMA models for corn and soybeans in Georgia. The ARIMA model comprises of two methods of representing the behavior of observed time series processes, namely the autoregressive (AR) and the moving average (MA) model. The AR model describes a time series in which the current observation depends on the preceding values (Bergstrom, 1983), where as the moving average

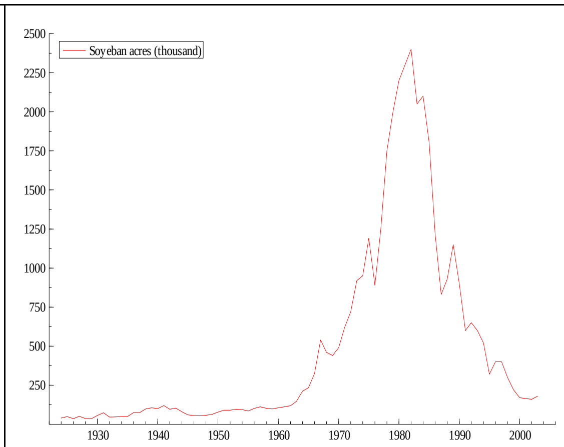
(MA) assess a time series process as linear function of current and previous random errors. The standard ARIMA analysis rests on the simplifying assumption that the process that generates a single time series is stationary. Therefore, we first test the series for stationarity.

Stationarity of the Time Series Data

Let us denote the corn and soybeans areas (unit in thousand) in Georgia in year t as Z_t, where t ranges from year 1924 to 2003; then the realization of the Z_t can be plotted as shown in Figure 6.1 for corn and soybeans, respectively. The visual observation of Figure 6.1 shows mean and variance non stationarity in corn and soybeans acreage.



Corn



Soybean

Figure 6.1 Time Series Plotting of Corn and Soybeans Acreage in Georgia in Thousands Acres (1924-2003)

Further analysis of ACF and PACF of corn (Figure6.2) and soybeans (Figure6.3) shows a slow tapering of the autocorrelation suggesting non-stationarity problem of the data. The white noise test and Augmented Dickey-Fuller test for unit roots also confirm the non-stationarity problem of the data.

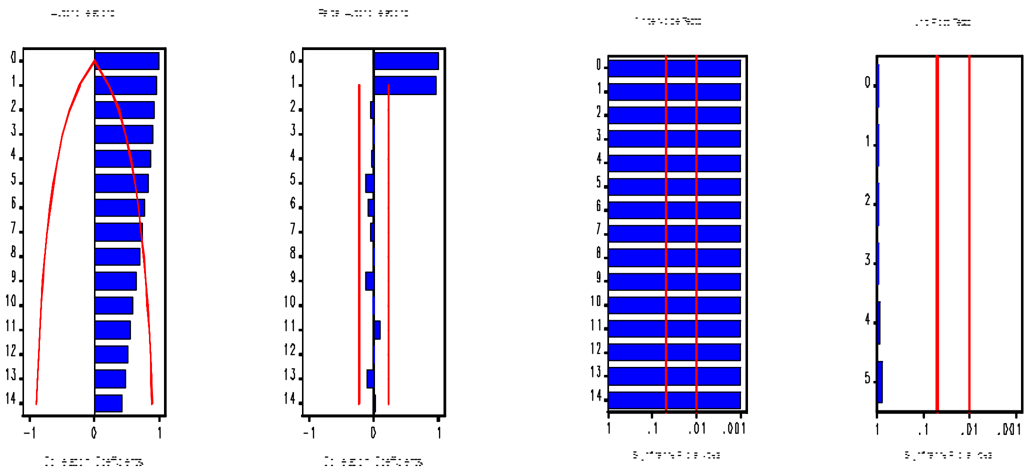


Figure 6.2 ACF, PACF, White Noise Test, and Unit Root Test of Corn Acreage Data

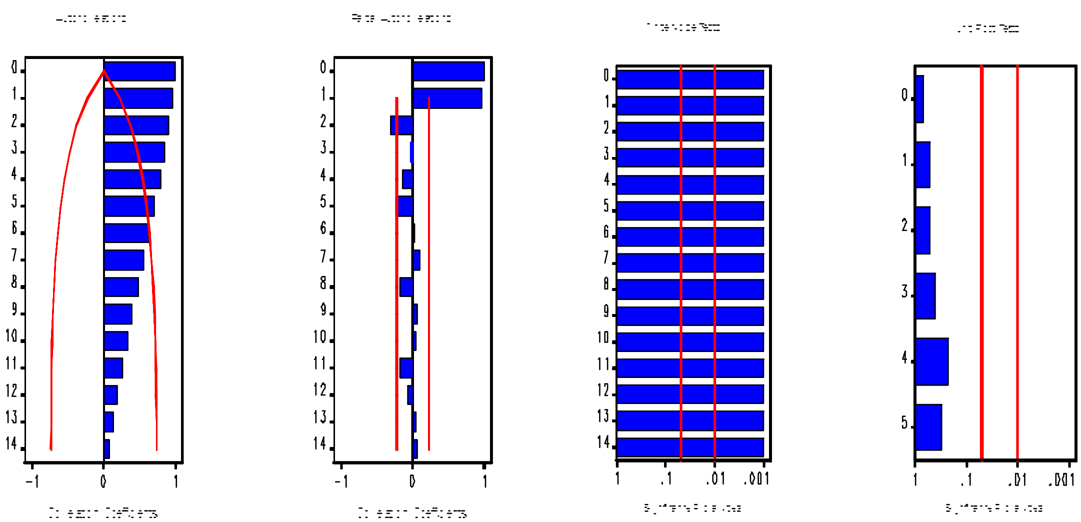


Figure 6.3 ACF, PACF, White Noise Test, and Unit Root Test of Soybeans Acreage Data

To cope with the deficiencies resulting from the non-stationarity, differencing and Box Cox transformation techniques have been used. Correcting non-stationarity is highly essential and crucial in the identification stage to minimize the distortions that might exclude the consideration of pertinent model patterns (Wei, 1990) SAS gives the best lambda value of 0.7 and 0.5 for corn and soybeans, respectively. Transformation using the best lambda value and first difference technique yields stationarity of corn and soybeans data (Figure 6.4).

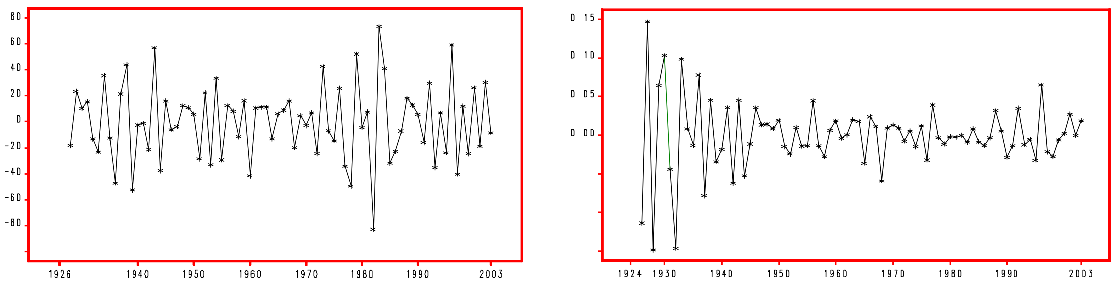


Figure 6.4 Time Series Plotting of Corn and Soybeans Acreage Data After Transformation

The data stationarity is further assessed by the ACF and PACF plotting of corn (Figure 6.5) and soybeans (Figure 6.6). If series is characterize by white noise, that is, consisting of random shocks then the error terms would be approximately normally independently distributed with mean and variance (0, 1/n) and the ACF and PACF estimates would not be significantly different from zero (Lin,1987). In our analysis both ACF and PACF plot of corn and soybeans acres tail off. However, neither are statistically significant indicating white noise error terms.

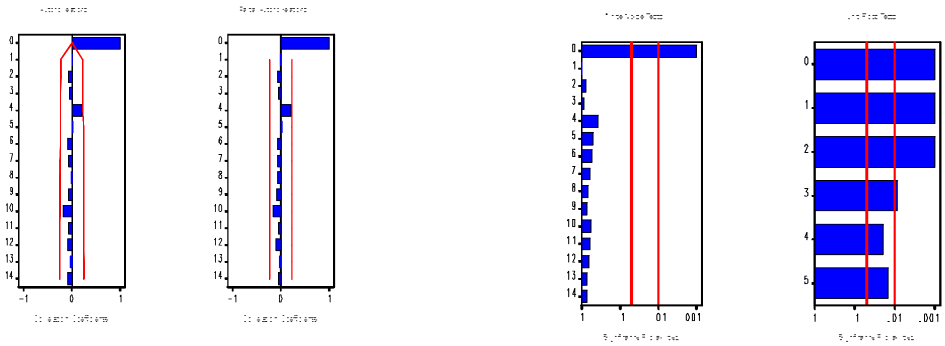


Figure 6.5 ACF, PACF, White Noise Test, and Unit Root Test of Transformed Corn Acreage Data

The white noise bar chart shows significance probabilities of the Ljung-Box Chi Square statistic. Each bar shows the probability computed on autocorrelations up to the given lag. Longer bars favor rejection of the null hypothesis that the prediction errors represent white noise (Tsay,1984). In our analysis, probabilities of the Ljung-Box Chi Square statistic were 0.9843 for corn and 0.5265 for soybeans, respectively. These values were insignificant beyond the .001 probability level, so that we failed to reject the null hypothesis of white noise errors.

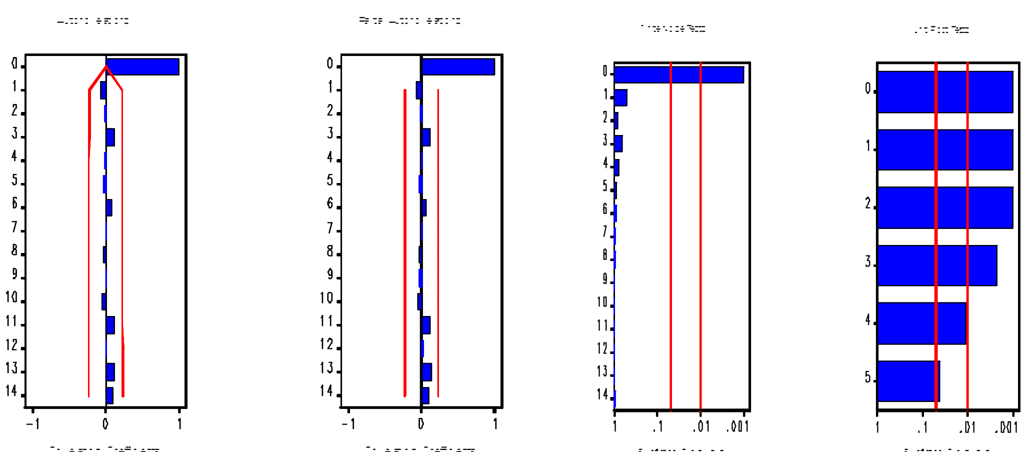


Figure 6.6 ACF, PACF, White Noise Test, and Unit Root Test of Transformed Soybeans Acreage Data

The second bar chart shows significance probabilities of the Augmented Dickey-Fuller test for unit roots. The bar at lag three indicates a probability of 0.0086 for corn and 0.0023 for soybeans, respectively rejecting the null hypothesis of data nonstationarity.

Model Identification

After stationarity of the data is achieved, the ACF and PACF of the differenced series are then examined to determine the number of autoregressive (AR) and moving average (MA) parameters of the model. We examine several candidate models to select the best ARIMA corn and soybeans model capable of capturing underlying phenomenon of the data using different orders of P and Q. The AIC, BIC, and statistical significance of AR and MA coefficients are considered as criteria of the best model selection. Table 6.1 presents the AIC and SBC values of different corn and soybeans ARIMA models considered in our analysis.

Table 6.1 AIC and SBC of Different Corn and Soybeans ARIMA models.

	AIC	SBC
Corn		
ARIMA (1,1,0)	683.67	688.30
ARIMA (2,1,0)	685.26	692.29
ARIMA (0,1,2)	685.37	692.40
ARIMA (1,1,1)	687.11	696.49
ARIMA (2,1,1)	687.23	696.61
ARIMA (1,1,1)	684.75	691.78
ARIMA (0,1,1)	683.67	688.36
ARIMA (0,1,0)	681.67	684.01

Table 6.1 Continued……..

Soybeans	AIC	SBC
ARIMA (1,2,0)	489.52	494.23
ARIMA (2,2,0)	479.21	486.28
ARIMA (0,2,2)	468.70	475.77
ARIMA (1,2,1)	469.55	478.98
ARIMA (2,2,1)	468.20	477.63
ARIMA (1,2,1)	468.31	475.30
ARIMA (0,2,1)	465.76	468.12
ARIMA (1,2,2)	466.49	471.49
ARIMA (3,2,0)	465.64	461.11

In our analysis, corn ARIMA model (0,1,0) and soybeans ARIMA (3,2,0)yield the smallest AIC and SBC values and emerge as the best corn and soybeans model, respectively.

The MINIC Method

We further use the Minimum Information Criterion (MINIC) method) to confirm the best model. The MINIC procedure tentatively identifies the order of a stationary and invertible ARIMA process. Given a stationary and invertible time series {Zt:1 $\leq$ t $\geq$ n} with mean corrected form $Z_t = Z_t - \mu_2$ with a true autoregressive order of *p*, and with a true moving-average order of *q*, the MINIC method computes information criteria (or penalty functions) for various autoregressive and moving average orders (Wei, 1990). Table 6.2 and Table 6.3 present the MINIC results.

Table 6.2 The Minimum Information Criterion of Corn Acreage Models

Lags	MA 0	MA 1	MA 2	MA 3	MA 4	MA 5
AR 0	5.8229	5.8646	5.8472	5.8661	5.9045	5.9561
AR 1	5.8744	5.9008	5.8782	5.9052	5.9357	5.9814
AR 2	5.8619	5.8787	5.9346	5.9614	5.9920	6.0367
AR 3	5.8863	5.9150	5.9708	6.0117	6.0415	6.0847
AR 4	5.9126	5.9310	5.9839	6.0288	6.0769	6.1266
AR 5	5.9602	5.9802	6.0360	6.0816	6.1307	6.1803
Minimum Table Value: BIC(0,0) = 5.82293						

Table 6.3 The Minimum Information Criterion of Soybeans Acreage Models

Lags	MA 0	MA 1	MA 2	MA 3	MA 4	MA 5
AR 0	3.485709	3.23418	3.258447	3.310908	3.308814	3.351640
AR 1	3.405397	3.281533	3.308405	3.354883	3.352171	3.399219
AR 2	3.300624	3.272447	3.328263	3.194788	3.246513	3.270968
AR 3	3.176244	3.229657	3.284949	3.245159	3.298211	3.316606
AR 4	3.227692	3.283393	3.338964	3.290264	3.339054	3.372176
AR 5	3.27107	3.326767	3.382621	3.323892	3.376036	3.425171

Note: Minimum Table Value: BIC (3,0) = 3.176244

The MINIC results also confirm the ARIMA (0,1,0) and ARIMA (3,2,0) as the best corn and soybeans model, respectively. Further diagnostic of selected corn (table 6.4) and soybeans (table 6.5) using the Ljung Box test suggest non-significant residual autocorrelation and the white noise process of the errors terms. The validity of the selected corn and soybeans models are further supported by the ACF and PACF plot of corn and soybeans respectively.

Table 6.4 Ljung Box Test on Residual Autocorrelations for Corn ARIMA (0,1, 0) With Intercept

Lag	Chi-Square	DF	Pr> ChiSq	Autocorrelations			
6	4.89	6	0.5584	-0.002	-0.073	-0.046	0.207
12	9.54	12	0.6559	-0.077	-0.008	-0.062	-0.176
18	14.29	18	0.7099	-0.023	-0.094	-0.099	0.031
24	16.30	24	0.8769	0.098	-0.029	0.034	0.054

Table 6.5 Ljung Box Test on Residual Autocorrelations for Soybeans ARIMA (3,2,0)

Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations				
6	3.53	3	0.3167	-0.03	-0.041	-0.107	-0.085	0.015
12	7.23	9	0.6135	0.074	-0.019	-0.138	-0.005	0.122
18	10.63	15	0.7781	-0.09	0.102	0.067	-0.030	0.087
24	21.27	21	0.4425	-0.01	-0.307	-0.039	0.000	0.015

In order to find where the parameters coefficients of the selected modes are statistically significant or not, maximum likelihood estimation of the best corn and soybeans models were carried out. As expected, all estimated parameters are significant suggesting the robustness of the best corn and soybeans models (Table 6.6, and Table 6.7).

Table 6.6 Maximum Likelihood Estimation of Corn ARIMA (0,1,0)

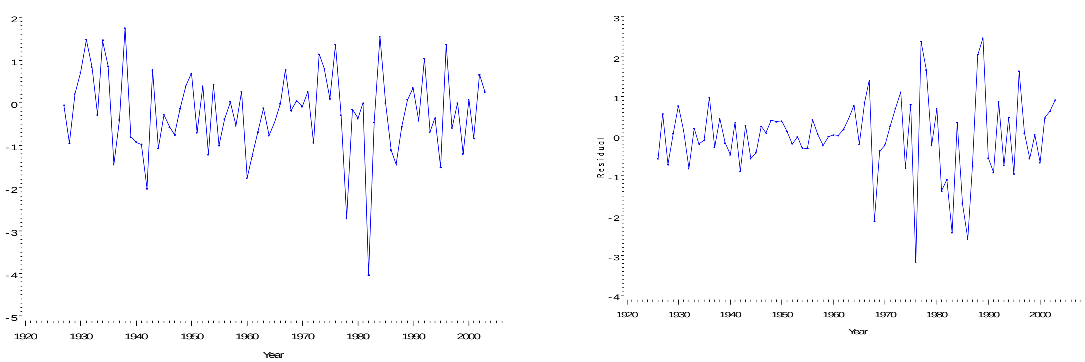
Lag	Estimate	T-value	Pr>|t|
Intercept	-4.6022	-2.0085	0.0481
Model Variance	404.29		

Table 6.7 Maximum Likelihood Estimation of Soybeans ARIMA (3,2,0)

Lag	Estimate	Error	t-value	Pr >|t|
AR1,1	-0.62797	0.10494	-5.98	<.0001
AR1,2	-0.56643	0.10891	-5.20	<.0001
AR1,3	-0.39662	0.10523	-3.77	0.0002

Normality Checking

Once the optimal parameters have been estimated, we examine the normality assumptions to further confirm the validity of the selected corn and soybeans model. Analysis of normality using residual plot (Figure 6.7) and QQ plots (Figure 6.8 and Figure 6.9) suggest no serious violation of variance stationarity and normality assumption. However, there exists variability in residual plotting which might have attributed by the inconsistent government programs.



Corn

Soybeans

Figure 6.7 Residual Plotting of Corn ARIMA (0,1,0) and Soybeans ARIMA (3,2,0)

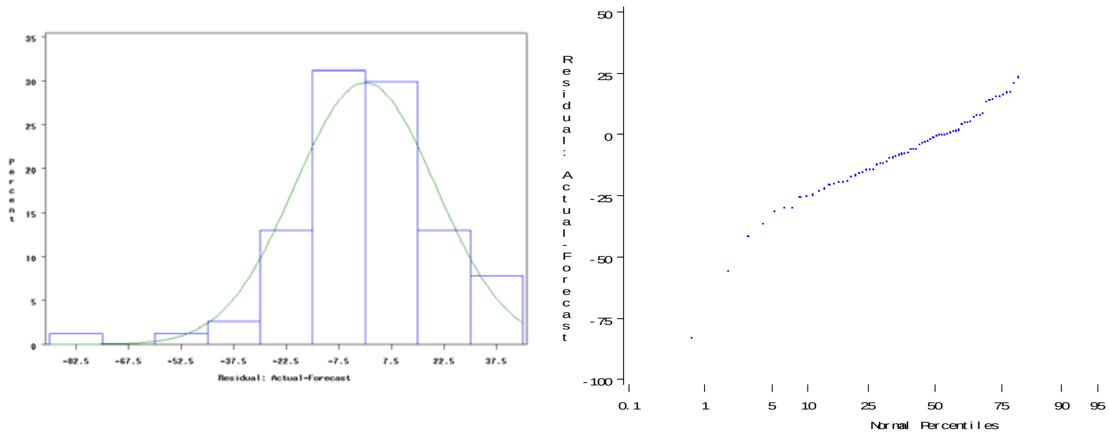


Figure 6.8 Histogram and Normality Testing of Corn ARIMA (0,1,1)

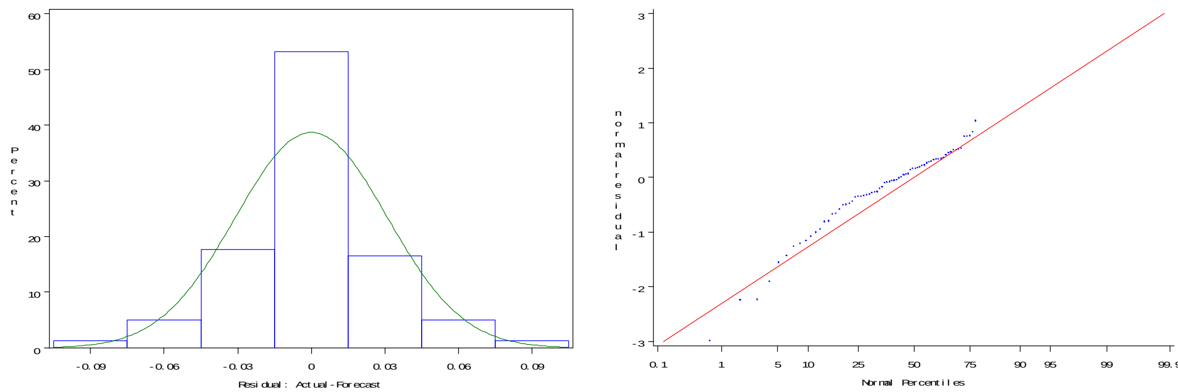


Figure 6.9 Histogram and Normality Testing of Soybeans ARIMA (3,2,0)

Forecasting and Its Accuracy

After selecting the appropriate corn and soybeans model, estimates of future acreage observation that are optimal in a minimum mean square errors sense have been forecasted. Table 6.8 reports the estimates of the forecast acres of corn and soybeans. The mean squared errors (MSE), the root mean square errors (RMSE), the mean absolute error (MAE), the Theil U statistics measures have been used to assess the forecasting accuracy of the selected model. The MSE is a non parametric statistic that provides a measure of the size of individual forecast errors from the actual values. The MAE is simply average of the absolute values of the forecast errors. The Theil’s coefficient represents a comparison of the sum of square of the one-step-ahead forecast errors of a model with those of a random walk model (Lin,1987). Thus for a random walk model, U=1 always. When U is less than unity, it is implied that the forecasting technique is better than the naïve model. The smaller the U-statistics, the better the relative performance of the forecasting technique.

Irrigation Water Demand Forecasting

We estimate corn and soybeans irrigation water demand (Table 6.10) by multiplying corn and soybeans acreage (Table 6.8) with net corn and soybeans irrigation requirements (acre- inches) in normal and dry years as reported (Table 6.9). For example, the predicted irrigation water for corn for 2005 was estimated by multiplying forecasted corn acre of 2005 (316.96 thousands acres) by the BC coefficients (weighted average) of 11.75 inch per acre (normal year) and 13.23 inch per acre (dry year). Therefore, total 2005 corn irrigation water demand would be 310.35 thousands acres feet for normal year and 349.44 thousands acres feet for dry year in Georgia.

Table 6.8 Acreage Forecasts of Corn ARIMA (0,1,0) and Soybeans ARIMA (3,2,0) in Thousands Acres

Year	Corn		Soybeans	
	Actual Acres	Forecasted Acres	Actual Acres	Forecasted Acres
1999	350	470.57	220	268.38
2000	360	323.63	170	197.49
2001	265	333.40	165	155.44
2002	340	240.80	160	161.30
2003	370	313.86	180	155.26
2004		343.17		181.86
2005		316.96		177.76
2006		291.38		172.67
2007		266.46		167.67
2008		242.22		162.66
2009		218.69		157.88
2010		195.89		153.25
2011		173.87		148.76
2012		152.65		144.41
2013		132.28		140.19
Theil U		0.98		0.99

Table 6.9 Net Irrigation Requirements (acre-inches) in Normal and Dry Years by Crop and Region of the Flint River Basin as Given by Blaney-Criddle Coefficients

Crop	Lower Flint	Middle Flint	Upper Flint	Weighted. Avg.(L,M,U)
Corn				
Normal Year[a]	11.14	12.15	12.32	11.75
Dry Year[b]	12.71	13.65	3.69	13.23
Soybeans				
Normal Year	7.58	8.38	7.65	7.72
Dry Year	9.04	9.75	8.79	9.06

Table 6.10 Net Irrigation Water Demand Forecasting (thousand acres feet) in Normal and Dry Years by Corn and Soybeans in Georgia (2004-2013)

Year	Corn		Soybeans	
	Normal	Dry	Normal	Dry
2004	336.0206	378.3449	116.9966	137.3043
2005	310.3567	349.4484	114.3589	134.2088
2006	285.3096	321.2465	111.0844	130.3659
2007	260.9088	293.7722	107.8677	126.5909
2008	237.1738	267.0476	104.6446	122.8083
2009	214.1341	241.1057	101.5695	119.1994
2010	191.8091	215.9687	98.59083	115.7038
2011	170.2477	191.6917	95.70227	112.3138
2012	149.4698	168.2966	92.90377	109.0296
2013	129.5242	145.8387	90.1889	105.8435

Structural Time Series Analysis

In spite of its popularity, ARIMA analysis has many limitations. Univariate time series forecasting just represents an extrapolation of the observed past behavior of the series (Harvey, 1989). Moreover, ARIMA time series analysis is an *ad hoc* forecasting procedure, which places relatively more weight in to the recent observations (Engel, 1978). This discounting of the past observations is intuitively sensible but lack explicit statistical justifications. Furthermore, traditional assumption of reducing time series to stationarity by differencing is also misconceived (Harvey, 1989).

A time series comprises of salient trend and seasonal features and a correctly specified time series modeling approach must have mechanisms to capture these underlying components of the series.

Conventional ARIMA follows the stationarity assumptions and not flexible enough to incorporate the underlying characteristics especially the trend components of the data (Harvey, 1989). To overcome the limitation of ARIMA procedure, we propose the idea of structural time series model (STAMP). The STSM, which allows trend variable to evolve gradually over time, captures the underlying stochastic processes of the time series and provides an alternative modeling approach to ARIMA *ad hoc* procedures In our opinion, with a well defined statistical model, STSM is likely to yield a better description of the series and its components which may have widely differing properties.

Structural Time Series Model

The details of STSM are given in the previous chapters. However, a simple STSM comprises of:

$$AR_t = \mu_t + \gamma_t + Z_t^{'}\delta + \varepsilon_t \qquad (1)$$

AR_t = Annual corn and soybeans acreage in Georgia

μ_t = the trend component;

γ_t = the seasonal component;

Z'_t = a vector of explanatory variables (price of output, production cost);

δ = k*1 Vector of unknown parameters; and

ε_t = Random white noise disturbance term.

The details analyses of STSM with different exogenous variable and trend components have been carried out in the previous chapters. Therefore, present STSM analysis ignores exogenous variables. We also ignore the seasonality component for the reason given in chapter 5 and only focus on the stochastic trend variable of the corn and soybeans acreage data. After ignoring trend and exogenous variables, equation 1 will be reduced to

$$AR_t = \mu_t + \varepsilon_t \tag{2}$$

where, the trend components ε_t are assumed to have the following stochastic process

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \tag{3}$$

$$\beta_t = \beta_{t-1} + \xi_t \tag{4}$$

where $\eta_t \sim$ NID $(0, \sigma_\eta^2)$ and $\xi_t \sim$ NID $(0, \sigma_t^2)$

Equations (3) and (4), which represent the level and the slope of the model, are still capable of capturing the stochasticity of trend in data.

Estimation Results

In our analysis STSM corn and soybeans model a strong convergence and successful maximum likelihood estimation by the numerical optimization procedure of STAMP. Further diagnostic test using the Jarque and Bera normality test, the Durbin-Watson d test, Box-Ljung Q statistic and heteroscedasticity suggest the presence of normality, homoscedasticity, and the presence of no serial autocorrelation in the model (Table 6.11).

Table 6.11 Diagnostic summary report of STSM corn and soybeans models

Statistics	Corn	Soybeans
Std.Error	0.12807	0.21647
Normality	29.719	1.4042
H(23)	10.606	0.85757
r(1)	-0.015998	-0.0021518
r(8)	0.054694	0.020666
DW	1.9925	1.9427
Q(8,6)	8.5312	3.2284

Water Demand Forecasting

After confirming the validity of STSM corn and soybeans model, we forecast corn and soybeans acreage for the year up to 2013. Table 6.12 and Table 6.13 present the forecasts of corn and soybeans acreage, respectively.

Table 6.12 Corn Acreage Forecasts Using STSM in Thousand Acres (2004-2013)

Period	Forecast	RMSE
2004	345.11	51.331
2005	331.75	66.284
2006	318.91	78.121
2007	306.57	88.039
2008	294.71	96.600
2009	283.30	104.12
2010	272.34	110.82
2011	261.80	116.82
2012	251.67	122.24
2013	241.93	127.15
Theil U	0.74	

Table 6.13 Soybeans Acreage Forecasts Using STSM in Thousand Acres (2004-2013)

Period	Forecast	RMSE
2004	165.14	40.477
2005	151.58	59.005
2006	139.14	73.956
2007	127.72	87.080
2008	117.24	99.071
2009	107.62	110.30
2010	98.785	120.99
2011	90.677	131.32
2012	83.235	141.41
2013	76.403	151.36
Theil U	0.51	

Also present in the table are RMSE value and its confidence intervals. The forecasting robustness of STSM corn and soybeans model was examined using the Theil U statistics. Theil U, which is based on the RMSE was estimated by dividing the RMSE of forecasting model by RMSE of naïve model. In our analysis, 5 years average (2004-2008) RMSE of STSM was used.

A Note on Theil U

Theil U statistic, which measures the forecasting accuracy of model, suggests the robustness of structural time series model over univariate time series model. In our analysis Theil U value of corn ARIMA (0,1,0) and soybeans ARIMA (3,2,0) were 0.98 and 0.99, respectively. These Theil values of corn and soybeans ARIMA models are higher than corresponding Theil values of STSM corn (0.74) and soybeans (0.51) respectively.

Water Demand Forecasting Using STSM

Table 6.14 presents the net irrigation water demand forecasting (thousand acres feet) in normal and dry years for Corn and Soybeans in Georgia (2004-2013) using STSM. The irrigation water demand was estimated by multiplying corn and soybeans irrigation water demand coefficients (Table 6.9) with forecasted corn and soybean acreage (Table 6.12, and Table 6.13).

Table 6.14 Net Irrigation Water Demand Forecasting (thousand acres feet) in Normal and Dry Years by Corn and Soybeans in Georgia (2004-2013) Using STSM

	Corn		Soybeans	
Year	Normal	Dry	Normal	Dry
2004	337.9202	380.4838	106.2401	124.6807
2005	324.8385	365.7544	97.51647	114.4429
2006	312.266	351.5983	89.5134	105.0507
2007	300.1831	337.9934	82.16653	96.4286
2008	288.5702	324.9178	75.4244	88.5162
2009	277.3979	312.3383	69.23553	81.2531
2010	266.6663	300.2549	63.55168	74.58268
2011	256.3458	288.6345	58.33554	68.46114
2012	246.4269	277.4662	53.54785	62.84243
2013	236.8898	266.7278	49.1526	57.68427

Conclusions

In this chapter, we forecast corn and soybeans acreage and thereby, corn and soybeans irrigation water demand (2004-2013) using ARIMA time series analysis and structural time series analysis (STSM). Use of ARIMA and STSM improves the ongoing analysis of irrigation water demand forecasting by adding a pure statistical outlook with no economic and government program variables. Moreover, STSM addresses the limitation of ARIMA model by incorporating stochastic trend variable in the model. The STSM outperforms the ARIMA model in terms of forecasting accuracy.

CHAPTER SEVEN

SUMMARY, CONCLUSIONS AND IMPLICATIONS

Summary

Since the last few years, Georgia has been experiencing water shortage problem because of the exploding population in metro areas especially Atlanta and reoccurring drought conditions. In Georgia, approximately 1.5 million acreage of irrigate agricultural lands use nearly 41.3 percent of total water representing a single major source of water use (Benerjee, 2004). Therefore, understanding of dynamics of irrigation water demand has far reaching impacts on efficient water allocation and conservation efforts. In spite of its crucial role, still there exists dearth of reliable information on past, present, and future water demand in Georgia.

Presently, USGS and ACT/ACF study offers limited bench mark information about crop irrigation water demand in Georgia. However, aggregate nature of data and invalid modeling approaches limit the applicability UGGS and ACT/ACF study. Though cited as the most in-depth study of the region, the ACT/ACF study's water forecasting is simply based on the crop acreage projection of crop experts, a water forecasting effort with no statistical and theoretical justification.

Crop irrigation water demand fluctuates with the changes in crop acreage. Therefore, complete analysis of irrigation water demand requires an in-depth understanding of crop acreage supply response behaviors of farmers. Supply of crop acreage by farmers is an economic decision and mostly determined by the expected economic outcomes. No water forecasting study can be complete without analyzing the roles of these variables. Therefore, our study overcomes the deficiencies of USGS and ACT/ACF study by adopting a systematic modeling approach based on the expected utility maximization theory. The proposed model incorporates expected own profit, expected profit of competing crop, variance of own price, variance of competing crop price, covariance of price of competing crops, and institutional variables.

Behind the successful water demand forecasting study remains the ability of model to trace the crop acreage fluctuations under different economic and institutional variables. Therefore, especial efforts have been made to improve the existing corn and soybeans models and its forecasting accuracy by incorporating government program variables and different assumptions of trend (stochastic trend, determinist trend, and no trend), a proxy variable of technological changes. The analysis was further extended using ARIMA and STSM with stochastic trend and no explanatory variables.

Econometric models were analyzed using ordinary regression analysis (OLS). The OLS relies on no serial autocorrelation, no multicolianerity, and homoscedasticity statistical assumptions. The Durbin-Watson statistic, the runs test for auto-correlation, Breusch-Pagan analysis, and correlation matrix confirm none of these problems in data. The STSM further improves the existing corn and soybeans acreage response models by examining different versions of trend variable. The STSM uses all economic and institutional variables that were included in econometric analysis of crop acreage response. In the case of STSM analysis, we consider different measures of diagnostic and goodness-of-fit such as Durbin-Watson (DW) test, Ljung-Box Q statistic, Jarque and Bera normality statistics, standard error of the estimated equation, AIC, and BIC. The forecasting accuracy of different corn and soybeans acreage response models was examined by using mean square percentage error (MAPE) and root mean square percentage error (RMSPE) criteria for both in-sample and out-sample forecast values. To blend the pure statistical outlook in to the ongoing study, we further analyzed the issue of corn and soybeans water demand forecasting using ARIMA and STSM with stochastic trend but no explanatory variables.

Conclusions

In our analysis of econometric and STSM, with the exception of few variables, statistical results were strong in terms of statistical significance of parameters. In our analysis, the F statistics and p value (p=0.0001) strongly reject the null hypothesis that all parameters expect intercept is zero. Most of the economic and institutional variables yield expected sign and statistically significant impacts. Further Analysis using STSM and different assumptions on trend variable confirms the role of technological changes on corn and soybeans. In our study, stochastic and deterministic trend variable offers the most promising modeling option for corn and soybeans, respectively. The findings show that ignoring trend variable might lead to model misspecification and false conclusions. The results also demonstrate that the out-of-sample forecasting power of the correctly specified model is superior. Further analysis using ARIMA and STSM with stochastic term suggests forecasting robustness of STSM.

Implications and Future Research

So far, there exist no systematic efforts to estimate and forecast crop irrigation water demand by using a valid modeling approach. A major contribution of this research is to develop econometric and time series crop water demand forecasting models incorporating economic and institutional variables. Analysis also shows the importance of systematic modeling approaches and econometric/time series analysis for valid results. In our study, efforts mostly center on improving the existing crop acreage supply response models and its forecasting accuracies. However, precise forecasting of irrigation water demand is a difficult task in the light of limited data, inconsistent government policies, and variations in the factors that affect the crop water demand.

Our econometric forecasting of irrigation water demand depends on the USDA projection of crop yield, price, and profit up to the year 2014. However, the reliability of forecasted crop yield, price, and profits and thereby crop acreage response and crop water demand are highly controversial issues. The irrigation water demand forecasting information of ARIMA and STSM analysis only offer bench mark information as time series models fail to capture the impacts of individual economic and institutional variables. Changes in crop management practices, irrigation technologies, soil conditions and related factors also affect irrigation water demand. Therefore, whether water demand coefficient of Blaney-Criddle formula presents real information is also an important issue. Therefore, future irrigation water demand forecast study should focus updating BC formula as management and irrigation technologies change.

References

Acharya, R. "Economics Simulation and Optimization of Irrigation Water in Humid Regions." Ph.D. Dissertation, Department of Agricultural Economics and Rural Sociology, Auburn University. 1997.

Banarjee, S.B. "Multiproduct Rational Expectations Forecasting of Irrigation Water Demand: An Application to the Flint River Basin in Georgia." Ph.D. Dissertation, Department of Agricultural and Applied Economics, the University of Georgia. 2004.

Bailey, K.W. and A.W. Womack. "Wheat Acreage Response: A Regional Econometric Investigation." S.J.Agr.Econ.17 (1985): 171-80

Bergstrom, A.R. "Gaussian Estimation of Structural Parameters in Higher Order Continuous Time Dynamic Models." *Econometrica* 51(1983): 117-52

BoX, G.E.P. and Jenkins, G.M. "Time Series Analysis Forecasting Control." 2nd edition, Holden-Day, SanFrancisco, 1970.

Chavas, J.P. and A.F. Kraus. "Polulation Dynamics and Milk Supply Response in the US Lake States." Journal of Agricultural Economics, (January 1990):75-84.

Chavas, J.P., and Johnson, S.R. " Supply Dynamics: The Case of US Broilers and Turkeys." American Journal of Agricultural Economics. (1982): 558-564

Chavas, J.P., and Mathew T.Holt. " Acreage Decision Under Risk: The Case of Corn and Soybeans." American Journal of Agricultural Economics. 72 (1990) 529-538

Chembezi, D.M. and A.W. Womack. " Regional Acreage Response for US Corn and Wheat: The Effect of Government Programs." Southern Journal of Agricultural Economics 24(1992): 187-98

Danielson, L.E. "Estimation of Residential Water Demand." Economics Research Report No 39. Department of Economics and Business. North Carolina State University at Raleigh, 1977.

Duffy, P.A., J.W. Richardson, and M.K. Wohlgenant. "Regional Cotton Acreage Response." Southern Journal of Agricultural Economics 19(1987):99-109.

Duffy, P.A., K.Shaishali, and H.W. Kinnucan. "Acreage Response Under Farm Programs for Major Southeastern Field Crops." Journal of Agricultural and Applied Economics 26 (1994): 367-378.

Dzisiak, R.N. "The Role o Price Determining Residential Water Demand: Water Pricing and Residential Water Demand in Municipalities in the Western Prairies." Master Thesis. The University of Manitoba. 1999

Engel, R.F. "Estimating Structural Models of Seasonality." In A. Zellner (ed.) *Seasonal Analysis of Economic Time Series*, pp. 281-308 (1978). Washington D.C.: Bureau of the Census

Frey, F.W. "Power, Conflict, and Co-operation." National Geographic Research and Exploration. Water Issue 9 (1993):18-37.

Gardener, B.L. "Future Prices in Supply Analysis." American Journal of Agricultural Economics 58(1976):81-84.

Ghatak, S., and J.Seale, Jr. "Supply Response and Risk in Chinese Agriculture." The Journal of Development Studies 37, 5(2001): 141-150

Gillespie, J., "Modern Livestock and Poultry Production" Delmar Learning, 5th Edition, 1995.

George, P.S. and King G.A. "Consumer Demand for Food Commodities in the United States With Projections for 1980. Giannini Foundation Monograph No. 26. University of California, Davis. 1971.

Gonzalez, P. and P. Moral. "An Analysis of International Demand in Spain." *International Journal of Forecasting.* 1(1995):233-251.

Gujrati, N.D. "Basic Econometrics." McGraw-Hill International Edition, 1995.

Guyomard, H., Marc Baudry, and Alain Carpentier. "Estimating Crop Supply Response in the Presence of Farm Programmes: Application to the CAP." European Review of Agricultural Economics. 23 (1996): 401-420

Godolphin,E., and M. Stine. "On the Structural representation for Polynomial Predictor Models." Journal of the Royal Statistical Society, Series B 42(1980): 35-45.

Harvey, A.C. "The Formulation of Structural Time Series Models in Discrete and Continuous Time." Invited Paper at First Catalan International Symposium on Statistics, Barcelona, September 1983, Questiio 7: 563-75

Harvey, A.C. and J.Durbin. "The effect of seat belt Legislation on British Road Causalities: A Case Study in Structural Time Series Modeling." Journal of the Royal Statistical Society, Series A 149(1986):187-227

Harvey, A.C. and S. Peters. ”Estimation Procedures for Structural Time Series Models.” LSE Econometrics Programme Discussion Paper A44.1984

Harvey, A.C. and P.H.J. Todd. “Forecasting Economic Time Series with Structural and Box Jenkins Models.” Journal of Business and Economic Statistics 1(1983):299-315

Harvey, A.C. “Forecasting Structural Time Series Models and the Kalman Filter, Cambridge University Press, 1989.

Harvey, A. C. “Forecasting, Structural Time Series Models and the Kalman Filter.” Cambridge, UK: Cambridge University Press. 1989.

Harvey, A. C. and A. Scott. “Seasonality in Dynamic Regression Models.” Economic Journal 104 (1994): 1324-1345.

Houston, J.E., Christopher S. McIntosh, Paul A. Stavriotis, and Steve Turner. “ Leading Indicators of Regional Cotton AcreageResponse: Structural and Time Series Modeling Results.” Journal of Agricultural and Applied Economics, 31, 3 (1999):507-517

Hatch, U., Paudel, K., Cruise, J., Lamb, M., Masters, M., Limaye, A., and Perkey, D. “Hydrolic-Economic Evaluation of Use and Value of Irrigation Water.” Department of Agricultural and Rural Sociology, Auburn University, 2000.

Houck, J.P. and M.E. Ryan. “ Supply Analysis of Corn in the United States: The Impact of Changing Government Programs.” Amer.J.Agr.Econ. 54(1972): 184-91

Houck, J.P. and A. Subtonik. “The US Supply of Soybeans: Regional Acreage Functions.” *Agr.Econ.Res*. 21(1969):99-108

Hatch, U., Paudel, K., Cruise, J., Lamb, M., Masters, M., Limaye, A., and Perkey, D. " Hydrolic-Economic Evaluation of Use and Value of Irrigation Water." Department of Agricultural and Rural Sociology, Auburn University, 2000.

Harrington, J.A. "Demand for Supplemental Irrigation Water in Humid Regions." Ph.D. Dissertation. Auburn University. 1995.

Hunt, L. C. and Y. Ninomiya. "Unraveling Trends and Seasonality: A Structural Time Series Analysis of Transport Oil Demand in the UK and Japan." *The Energy Journal* 3(2003): 63-96.

Jordan, L.J., "An introduction to Water: Economic Concepts, Water Supply, and Water Use." Dept. of Ag and Applied Economics. Faculty Series 98-13, 1998.

Jarvis, L.S. "Cattle as Capital Goods and Ranchers as Portfolio Mangers: An Application to the Argentine Cattle Sector." Journal of Political Economics. 82 (1974): 480-520

Just, R.E. "The Investigation of the Importance of Risk in Farmers' Decision." Amer.J.Agr.Econ. 56(1974): 14-25

Khan, M.S. "Economic Significance of Water Use Function in Some Desert Livestock. In: Report Advances in Management of Arid Ecosystem. Proceeding of a Symposium, Jodhpur, India. 1999.

Kapombe, C. M., and D. Colyer. "Modeling US Broiler Supply Response: A Structural Time Series Approach." Agricultural and Resource Economic Review (1998): 241-251.

Knapp, K.C. Irrigation Management and Investment Under Saline, Limited Drainage Conditions: Characterization of Optimal Decision Rules. Water Resources Research, (December 1992):3091-97.

Krause, M.A., J.H. Lee and W.W. Koo. " Program and nonprogram Wheat Acreage Responses to Price and Price Risk." Journal of Agricultural and Resources Economics 20(1995): 96- 107

Lee, T.C., and S.K. Seaver. "A Simultaneous Equation Model of Spatial Equilibrium and It's Application to the Broiler Markets." American Journal of Agricultural Economics (1982): 286-98.

Lin, K.S. (1987). "A Comparative Study of Various Univariate Time Series Models: Canadian Lynx Data." Journal of Time Series Analysis, 8, No. 2,(1987):161-176.

Malla, P.B., "The Economics of Urban Water In Hawaii; Empirical Analysis and Case Studies. Ph.D. Dissertation. University of Hawaii. 1996.

Morgan, W.D. "Residential Water Demand: The Case from Micro-Data. Water Resources Research, Vol. 9, No. 4. 1973.

Opaluch, J. "River Basin Management: The Optimal Control of Water Quantity and Quality." Ph. D. Dissertation. University of California, Berkley. 1981

Paredes, A.M. "Meta-Analysis of Residential Water Demand Elasticities with respect to Selected explanatory Variables." Ph.D. Dissertation. Southern Illinois University at Carbodale. 1996.

Park, W.I., and P. Garcia. " Aggregate Versus Disaggregate Analysis: Corn and Soybean Acreage Response in Illinois." Review of Agricultural Economics 16(1994):17-26

Parrott, S.D., and C. S. McIntosh. " Nonconstant Price Expectations and Acreage Response: The Case of Cotton Production in Georgia."

Journal of Agricultural and Applied Economics, 28, 1(1996):203-210.

Pope, R.M, Stepp, J.M., and Lytle J.S. "Effects of Price Upon the Domestic Use of Water Over Time. Water Resources Research Institute, Report No.56, Clemson University. Clemson, South Carolina. 1975.

Shalishali, K.M. " Acreage Decision Under Risk: The Case of Three Crops (Corn, Cotton, And Soybeans) in the Southeast Production Region of the United States." Ph.D. Dissertation. Department of Agricultural Economics and Rural Sociology, Auburn University. 1993.

Shideed, K.H., F.C. White, S.J.Brannen, and R.S.Glover. "Structural Changes of Corn Supply Response in Georgia." Georgia Agricultural Experiment Station Bulletin No. 367, 1987.

Tarren I.Y, Rose, C.E. and Bramblett, J.R. "Estimating Irrigated Acres with Missing Data." Paper presented at Proceedings of the 2001 Georgia Water Resources Conference, held March 26-27, 2001 at University of Georgia.

Tareen, Y.T. "Forecasting Irrigation Water Demand: An Application to the Flint River Basin." Ph.D. Dissertation. Department of Agricultural and Applied Economics, The University of Georgia. 2001.

Traill, B. "Risk Variables in Econometric Supply Models." J. Agr. Econ. 29(1978): 53-61.

Tsay, R.S. and Tiao, G.C. (1984). "Consistent Estimates of Autoregressive parameters and Extended Sample Autocorrelation

Function for Stationary and Non- Stationary ARIMA Models." Journal of American Statistical Association, 79, 84-96.

United States Department of Agriculture- Natural Resource Conservation Services "ACT/ACF Rivers Basins Comprehensive Study: Agricultural Water Demand." 1995.

Wei, W.S. W., "Time Series Analysis: Univariate and Multivariate Method" Addison Wesley Publishing Company, Inc. 1990.

Wong, S.T. "A Model on Municipal Water Demand: A Case Study of Northeastern Illinois." Land Economics, Vol. 48, Feb. 1972.

Zachariah, O.E. "Optimal Economic Management of Ground Water Quantity and Quality: An Integrated Approach." Ph.D. Dissertation. University of Guelph. 1999.

APPENDICES

A: Econometric Analysis of Complete Dataset (SAS Output)

The REG Procedure
Model: MODEL1
Dependent Variable: STA STA (Soybeans Model)

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	9	14045340	1560593	36.14	<.0001
Error	17	734177	43187		
Corrected Total	26	14779517			

Root MSE	207.81452	R-Square	0.9503
Dependent Mean	1047.22222	Adj R-Sq	0.9240
Coeff Var	19.84436		

Parameter Estimates

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	Intercept	1	-1118.80402	666.73367	-1.68	0.1116
COV	COV	1	-647.70225	602.95280	-1.07	0.2977
MPro	MPro	1	-8.96293	3.48233	-2.57	0.0197
MPV	MPV	1	854.89465	658.57908	1.30	0.2116
SPRO	SPRO	1	8.50912	5.11489	1.66	0.1145
SPV	SPV	1	38.87339	124.51872	0.31	0.7587
TW	TW	1	0.00528	0.00088114	5.99	<.0001
SDP	SDP	1	179.69435	147.15819	1.22	0.2387
Crate	Crate	1	564.89891	355.10859	1.59	0.1301
T	T	1	23.12248	19.29380	1.20	0.2472

SAS output for CORN

The REG Procedure
Model: MODEL1
Dependent Variable: MTA MTA

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	10	8134604	813460	30.13	<.0001
Error	16	431946	26997		
Corrected Total	26	8566550			

Root MSE	164.30658	R-Square	0.9496
Dependent Mean	901.66667	Adj R-Sq	0.9181
Coeff Var	18.22254		

Parameter Estimates

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	Intercept	1	2405.53345	575.30973	4.18	0.0007
COV	COV	1	-135.48103	495.51637	-0.27	0.7880
MPro	MPro	1	8.72294	2.99208	2.92	0.0101
MPV	MPV	1	-119.35448	547.32074	-0.22	0.8301
SPRO	SPRO	1	-9.93820	4.33467	-2.29	0.0358
SPV	SPV	1	45.74865	102.86871	0.44	0.6625
TW	TW	1	0.00005371	0.00078874	0.07	0.9466
MDP	MDP	1	-298.11544	103.54410	-2.88	0.0109
MLR	MLR	1	-40.59431	176.37586	-0.23	0.8209
Crate	Crate	1	-420.76866	305.65950	-1.38	0.1876
T	T	1	-71.26414	16.83400	-4.23	0.0006

Forecasting Values from Econometric Model for Soybeans

The REG Procedure
Model: MODEL1
Dependent Variable: STA STA

Output Statistics

Obs	Dep Var STA	Predicted Value	Std Error Mean Predict	95% CL Mean		95% CL Predict		Residual
1	890.0000	1219	41.1082	1134	1303	783.0386	1654	-328.5958
2	1250	1484	59.9848	1361	1608	1040	1929	-234.3395
3	1750	1827	71.3660	1680	1975	1375	2279	-77.2371
4	2000	2207	87.5955	2026	2388	1743	2671	-206.9764
5	2200	2542	93.0763	2350	2734	2074	3011	-342.1560
6	2300	2289	92.3876	2098	2479	1821	2757	11.2378
7	2400	1939	74.5032	1785	2092	1484	2393	461.4627
8	2050	1956	105.3218	1739	2174	1477	2436	93.6149
9	2100	1674	57.2963	1556	1792	1231	2117	426.0961
10	1800	1414	46.1705	1319	1509	976.1443	1852	386.1433
11	1220	1037	42.7547	948.4053	1125	600.4148	1473	183.3533
12	830.0000	779.7683	46.2953	684.2195	875.3171	341.9998	1218	50.2317
13	930.0000	915.7225	49.6776	813.1929	1018	476.3774	1355	14.2775
14	1150	1107	45.3572	1013	1200	669.3763	1544	43.2736
15	900.0000	1010	40.8862	925.2788	1094	574.1956	1445	-109.6638
16	600.0000	616.8546	60.1664	492.6772	741.0320	171.9593	1062	-16.8546
17	650.0000	818.9710	53.7946	707.9445	929.9976	377.5657	1260	-168.9710
18	600.0000	739.7591	54.9173	626.4154	853.1029	297.7653	1182	-139.7591
19	520.0000	646.4851	66.9576	508.2913	784.6789	197.4759	1095	-126.4851
20	320.0000	379.7000	93.5972	186.5249	572.8751	-89.1586	848.5586	-59.7000
21	400.0000	402.4048	67.0693	263.9805	540.8291	-46.6754	851.4850	-2.4048

22	400.0000	297.1052	88.3298	114.8013	479.4090	-167.3800	761.5903	102.8948
23	300.0000	249.8684	83.8210	76.8704	422.8665	-211.0438	710.7806	50.1316
24	220.0000	120.3014	79.4798	-43.7368	284.3395	-337.3232	577.9259	99.6986
25	170.0000	195.0799	62.0477	67.0197	323.1400	-250.9147	641.0744	-25.0799
26	165.0000	178.3657	69.2735	35.3921	321.3392	-272.1376	628.8689	-13.3657
27	160.0000	230.8272	63.2029	100.3828	361.2715	-215.8578	677.5121	-70.8272
28	.	214.2850	62.2028	85.9047	342.6653	-231.8016	660.3716	.
29	.	173.8682	66.5799	36.4540	311.2824	-274.9017	622.6381	.
30	.	168.8911	64.2049	36.3786	301.4036	-278.4022	616.1844	.
31	.	130.2298	68.4809	-11.1078	271.5675	-319.7569	580.2166	.
32	.	109.7090	69.3410	-33.4037	252.8217	-340.8384	560.2564	.
33	.	64.8651	77.2195	-94.5082	224.2383	-391.1081	520.8383	.

Sum of Residuals	0
Sum of Squared Residuals	1028313
Predicted Residual SS (PRESS)	1289276

Forecasting Values from Econometric Model for Corn

The REG Procedure
Model: MODEL1
Dependent Variable: MTA MTA

Output Statistics

Obs	Dep Var MTA	Predicted Value	Std Error Mean Predict	95% CL Mean		95% CL Predict		Residual
1	2300	2135	90.9014	1947	2324	1732	2538	164.9687
2	2240	2033	91.1805	1844	2222	1629	2436	207.2268
3	1700	1634	91.3865	1445	1824	1230	2038	65.8878
4	1670	1752	69.5828	1608	1896	1367	2137	-81.9997
5	1600	1504	86.3180	1325	1683	1105	1903	96.0267
6	1600	1560	70.2129	1414	1706	1175	1945	40.0386
7	900.0000	1037	90.0234	849.9750	1223	634.1958	1439	-136.6721

8	830.0000	1151	102.2818	938.8964	1363	736.1351	1566	-321.0158
9	1080	1109	55.4250	993.8594	1224	734.1792	1483	-28.8037
10	1080	1004	56.9742	885.8704	1122	628.4049	1380	75.9723
11	900.0000	1068	51.4008	961.7046	1175	696.1547	1440	-168.3034
12	680.0000	850.0525	65.5679	714.0730	986.0321	468.4483	1232	-170.0525
13	600.0000	706.1445	66.1043	569.0527	843.2364	324.1425	1088	-106.1445
14	610.0000	800.5714	52.8231	691.0231	910.1198	427.5672	1174	-190.5714
15	660.0000	689.3325	42.6216	600.9406	777.7243	321.9846	1057	-29.3325
16	600.0000	555.4185	55.4417	440.4393	670.3976	180.7833	930.0537	44.5815
17	750.0000	495.3447	49.4282	392.8370	597.8524	124.3471	866.3422	254.6553
18	650.0000	443.9133	49.4517	341.3567	546.4698	72.9022	814.9243	206.0867
19	600.0000	271.0373	71.5955	122.5573	419.5174	-115.1979	657.2726	328.9627
20	400.0000	505.2454	115.0293	266.6891	743.8016	76.2460	934.2447	-105.2454
21	580.0000	552.8928	60.5579	427.3035	678.4821	174.8663	930.9193	27.1072
22	500.0000	634.3061	72.2498	484.4691	784.1431	247.5472	1021	-134.3061
23	500.0000	603.0158	71.3272	455.0922	750.9395	216.9941	989.0375	-103.0158
24	350.0000	554.8292	76.9504	395.2439	714.4144	164.1902	945.4681	-204.8292
25	360.0000	279.1049	63.0307	148.3872	409.8226	-100.6561	658.8660	80.8951
26	265.0000	177.8712	89.0482	-6.8035	362.5459	-223.6709	579.4133	87.1288
27	340.0000	239.2461	81.9957	69.1973	409.2949	-155.7829	634.2751	100.7539
28	.	367.2400	130.0819	97.4666	637.0134	-79.8719	814.3519	.
29	.	318.7823	137.3447	33.9469	603.6177	-137.5756	775.1402	.
30	.	199.0936	141.8766	-95.1405	493.3276	-263.1888	661.3760	.
31	.	243.6247	143.1952	-53.3440	540.5934	-220.4031	707.6524	.
32	.	79.9300	154.5724	-240.6335	400.4936	-399.5408	559.4009	.
33	.	95.4454	157.2341	-230.6382	421.5291	-387.7335	578.6244	.

B. Structural Time Series Analysis of Complete Data Set (STAMP Output)

Corn (STNS)

```
Method of estimation is Maximum likelihood
The present sample is: 1 to 27

MaxLik initialising...
it  1  f=  -4.00644 e0=   0.07737 step=   1.00000
it  2  f=  -3.98167 e0=   0.08693 step=   1.00000
it  3  f=  -3.97707 e0=   0.03896 step=   1.00000
it  4  f=  -3.97612 e0=   0.02306 step=   1.00000

MaxLik iterating...
it  4  f=  -3.97560 df=   0.00000 e1=   0.00001 e2=   0.05191 step
it  9  f=  -3.97558 df=   0.00000 e1=   0.00000 e2=   0.00000 step

Equation  2.

MTA = Trend + Expl vars + Irregular

Estimation report
Model with  3 parameters ( 2 restrictions).
Parameter estimation sample is    1. 1 -   27. 1. (T =   27).
Log-likelihood kernel is -3.975585.
Very strong convergence in   9 iterations.
( likelihood cvg 2.109576e-007
  gradient cvg   6.732392e-008
  parameter cvg  1.658021e-006 )

Eq  2 : Diagnostic summary report.

Estimation sample is    1. 1 -   27. 1. (T =   27, n =   25).
Log-Likelihood is -107.341 (-2 LogL = 214.682).
Prediction error variance is 17841.2

Summary statistics
                     MTA
 Std.Error        133.57
 Normality       0.23277
 H(  8)          0.54457
 r( 1)        -0.0048609
 r( 8)          0.017299
 DW               1.7109
 Q( 8, 6)         4.1493
 Rd^2            0.61432

Eq  2 : Estimated variances of disturbances.

Component           MTA (q-ratio)
Irr             0.00000 ( 0.0000)
Lvl              23823. ( 1.0000)
Slp              1311.4 ( 0.0550)

Eq  2 : Estimated coefficients of final state vector.

Variable      Coefficient      R.m.s.e.       t-value
Lvl               -162.38        521.29       -0.3115  [ 0.7580]
```

Slp	-10.497	83.430	-0.12581	[0.9009]

Eq 2 : Estimated coefficients of explanatory variables.

Variable	Coefficient	R.m.s.e.	t-value	
COV	164.82	337.35	0.48858	[0.6294]
MPro	5.2415	2.5215	2.0787	[0.0481]
MPV	-250.04	383.90	-0.65132	[0.5208]
SPRO	0.69755	3.7515	0.18594	[0.8540]
SPV	1.8389	67.408	0.027281	[0.9785]
TW	0.00090752	0.00079873	1.1362	[0.2666]
MLR	141.56	216.38	0.65422	[0.5189]
MDP	-143.23	71.127	-2.0137	[0.0549]
PCF	-267.32	251.29	-1.0638	[0.2976]

Eq 2 : Forecasts for F-MTA.

Period	Forecast	R.m.s.e.	- Rmse	+ Rmse
28. 1	326.04	173.51	152.53	499.55
29. 1	312.08	272.20	39.878	584.28
30. 1	298.12	366.85	-68.735	664.97
31. 1	284.16	462.81	-178.65	746.96
32. 1	270.19	561.74	-291.54	831.93
33. 1	256.23	664.29	-408.06	920.52
34. 1	242.27	770.72	-528.44	1013.0
35. 1	228.31	881.10	-652.79	1109.4
36. 1	214.35	995.45	-781.10	1209.8
37. 1	200.39	1113.7	-913.32	1314.1

Normality test for Residual MTA

Sample Size	25	
Mean	0.271339	
Std.Devn.	0.752579	
Skewness	0.123053	
Excess Kurtosis	-0.756995	
Minimum	-1.246540	
Maximum	1.666387	
Skewness Chi^2(1)	0.063092	[0.8017]
Kurtosis Chi^2(1)	0.59692	[0.4398]
Normal-BS Chi^2(2)	0.66001	[0.7189]
Normal-DH Chi^2(2)	0.23277	[0.8901]

Goodness-of-fit results for Residual MTA

Prediction error variance (p.e.v)		17841.176645
Prediction error mean deviation (m.d)		11686.154618
Ratio p.e.v. / m.d in squares		1.483829
Coefficient of determination	R2	0.943768
... based on differences	RD2	0.514321
Information criterion of Akaike	AIC	10.752227
... of Schwartz (Bayes)	BIC	11.376149

Serial correlation statistics for Residual MTA.
Durbin-Watson test is 1.7109.
Asymptotic deviation for correlation is 0.2.

Lag	dF	SerCorr	BoxLjung	ProbChi2(dF)
1	0	-0.0049		

```
  2    0    -0.1375
  3    0    -0.2876
  4    1     0.1142     3.5116    [ 0.0609]
  5    2    -0.0496     3.5945    [ 0.1658]
```

Corn (DTNS)

```
Method of estimation is Maximum likelihood
The present sample is: 1 to 27

Equation  3.
MTA = Trend + Expl vars + Irregular

Estimation report
Model with  1 parameters ( 1 restrictions).
Parameter estimation sample is    1. 1 -   27. 1. (T =   27).
Log-likelihood kernel is -3.975585.

Eq  3 : Diagnostic summary report.

Estimation sample is    1. 1 -   27. 1. (T =   27, n =   25).
Log-Likelihood is -110.054 (-2 LogL = 220.108).
Prediction error variance is 16481

Summary statistics
                     MTA
 Std.Error        128.38
 Normality       0.44418
 H(  8)           1.5702
 r( 1)         -0.030256
 r( 6)           0.12176
 DW               1.9098
 Q( 6, 6)         5.0612
 Rd^2            0.55135

Eq  3 : Estimated variances of disturbances.

Component            MTA (q-ratio)
Irr               26997. ( 1.0000)

Eq  3 : Estimated coefficients of final state vector.

Variable      Coefficient      R.m.s.e.       t-value
Lvl                410.14        362.03        1.1329  [ 0.2680]
Slp               -71.264        16.834       -4.2333  [ 0.0003]

Eq  3 : Estimated coefficients of explanatory variables.

Variable      Coefficient      R.m.s.e.       t-value
COV               -135.48        495.52      -0.27341  [ 0.7868]
MPro               8.7229        2.9921        2.9153  [ 0.0074]
MPV               -119.35        547.32      -0.21807  [ 0.8291]
SPRO              -9.9382        4.3347       -2.2927  [ 0.0306]
SPV                45.749        102.87       0.44473  [ 0.6603]
TW             5.3712e-005    0.00078874     0.068098  [ 0.9462]
MLR               -40.594        176.38      -0.23016  [ 0.8198]
MDP               -298.12        103.54       -2.8791  [ 0.0081]
```

PCF	-420.77	305.66	-1.3766	[0.1808]

Eq 3 : Forecasts for F-MTA.

Period	Forecast	R.m.s.e.	- Rmse	+ Rmse
28. 1	203.03	176.71	26.319	379.74
29. 1	122.07	178.06	-55.990	300.13
30. 1	41.107	179.49	-138.38	220.59
31. 1	-39.855	181.00	-220.85	141.14
32. 1	-120.82	182.58	-303.40	61.766
33. 1	-201.78	184.25	-386.02	-17.534
34. 1	-282.74	185.98	-468.72	-96.759
35. 1	-363.70	187.79	-551.49	-175.91
36. 1	-444.66	189.67	-634.33	-255.00
37. 1	-525.63	191.61	-717.24	-334.01

Normality test for Residual MTA

Sample Size	25	
Mean	0.133584	
Std.Devn.	0.788768	
Skewness	0.199103	
Excess Kurtosis	-0.288534	
Minimum	-1.255062	
Maximum	1.887891	
Skewness Chi^2(1)	0.16518	[0.6844]
Kurtosis Chi^2(1)	0.086721	[0.7684]
Normal-BS Chi^2(2)	0.2519	[0.8817]
Normal-DH Chi^2(2)	0.44418	[0.8008]

Goodness-of-fit results for Residual MTA

Prediction error variance (p.e.v)		16480.955393
Prediction error mean deviation (m.d)		10118.555221
Ratio p.e.v. / m.d in squares		1.688915
Coefficient of determination	R2	0.948055
... based on differences	RD2	0.51349
Information criterion of Akaike	AIC	11.534776
... of Schwartz (Bayes)	BIC	11.752709

Serial correlation statistics for Residual MTA.
Durbin-Watson test is 1.90976.
Asymptotic deviation for correlation is 0.2.

Lag	dF	SerCorr	BoxLjung	ProbChi2(dF)
1	0	-0.0303		
2	1	0.0077	0.0275	[0.8683]
3	2	-0.1524	0.7405	[0.6906]
4	3	0.0727	0.9102	[0.8230]
5	4	-0.3277	4.5345	[0.3385]

Corn (NTNS)

Method of estimation is Maximum likelihood
The present sample is: 1 to 27

Equation 4.
MTA = No level + Expl vars + Irregular

Estimation report

```
Model with  1 parameters ( 1 restrictions).
Parameter estimation sample is    1. 1 -   27. 1. (T =   27).
Log-likelihood kernel is -3.975585.

Eq  4 : Diagnostic summary report.

Estimation sample is    1. 1 -   27. 1. (T =   27, n =   27).
Log-Likelihood is -124.984 (-2 LogL = 249.968).
Prediction error variance is 35910.4

Summary statistics
                     MTA
 Std.Error        189.50
 Normality       0.99862
 H(  9)          0.62618
 r( 1)       -0.0013716
 r( 6)           0.21986
 DW               1.9550
 Q( 6, 6)         7.9209
 R^2             0.88682



Eq  4 : Estimated variances of disturbances.

Component           MTA (q-ratio)
Irr              53866. ( 1.0000)

Eq  4 : Estimated coefficients of final state vector.

Variable      Coefficient      R.m.s.e.       t-value

Eq  4 : Estimated coefficients of explanatory variables.

Variable      Coefficient      R.m.s.e.       t-value
COV               -1751.1        471.98         -3.71  [ 0.0009]
MPro               4.6273        3.8567        1.1998  [ 0.2406]
MPV                1486.1        569.49        2.6096  [ 0.0146]
SPRO              0.54805        4.9762       0.11013  [ 0.9131]
SPV                390.24        95.275        4.0959  [ 0.0003]
TW              0.0028976    0.00056337        5.1432  [ 0.0000]
MLR                18.220        158.94       0.11464  [ 0.9096]
MDP               -468.44        135.35       -3.4609  [ 0.0018]
PCF               -155.39        422.74      -0.36757  [ 0.7161]

Eq  4 : Forecasts for F-MTA.

Period     Forecast    R.m.s.e.      - Rmse      + Rmse
  28. 1      280.42      232.09      48.334      512.51
  29. 1      275.67      232.09      43.583      507.76
  30. 1      270.92      232.09      38.832      503.01
  31. 1      266.17      232.09      34.081      498.26
  32. 1      261.42      232.09      29.330      493.51
  33. 1      256.67      232.09      24.579      488.76
  34. 1      251.92      232.09      19.828      484.01
  35. 1      247.17      232.09      15.077      479.26
```

```
  36. 1      242.42      232.09      10.326      474.50
  37. 1      237.66      232.09      5.5747      469.75

Normality test for Residual MTA
Sample Size     27
Mean                    0.016838
Std.Devn.               0.816323
Skewness                0.403746
Excess Kurtosis        -0.252995
Minimum                -1.460424
Maximum                 2.072173
Skewness  Chi^2(1)       0.73355  [0.3917]
Kurtosis  Chi^2(1)      0.072008  [0.7884]
Normal-BS Chi^2(2)       0.80556  [0.6685]
Normal-DH Chi^2(2)       0.99862  [0.6070]

Goodness-of-fit results for Residual MTA
Prediction error variance (p.e.v)          35910.374259
Prediction error mean deviation (m.d)      23791.794196
Ratio p.e.v. / m.d in squares                  1.450326
Coefficient of determination       R2          0.886818
... based on differences           RD2         0.22434
Information criterion of Akaike    AIC        11.155448
... of Schwartz (Bayes)            BIC        11.587394

Serial correlation statistics for Residual MTA.
Durbin-Watson test is 1.95504.
Asymptotic deviation for correlation is 0.19245.

 Lag  dF    SerCorr   BoxLjung    ProbChi2(dF)
  1    0    -0.0014
  2    1     0.0034     0.0004    [ 0.9838]
  3    2    -0.1099     0.3947    [ 0.8209]
  4    3    -0.3402     4.3340    [ 0.2276]
  5    4    -0.2239     6.1185    [ 0.1905]
```

B.2 Structural Time Series Analysis (STAMP 6.0 Output) Soybeans

SOYBEAN (STNS)

```
Method of estimation is Maximum likelihood
The present sample is: 1 to 27

 MaxLik initialising...
it  1  f=  -4.22181 e0=   0.49782 step=   1.00000
it  2  f=  -4.17424 e0=   1.47126 step=   1.00000
it  3  f=  -4.11886 e0=   0.04413 step=   0.07188
it  4  f=  -4.11819 e0=   0.02050 step=   1.00000

 MaxLik iterating...
it  4  f=  -4.11803 df=   0.00000 e1=   0.00000 e2=   0.00014 step=   1.00000
it  5  f=  -4.11803 df=   0.00000 e1=   0.00000 e2=   0.00000 step=   0.00000

Equation  1.

STA = Trend + Expl vars + Irregular

Estimation report
Model with  3 parameters ( 1 restrictions).
Parameter estimation sample is    1. 1 -   27. 1. (T =   27).
Log-likelihood kernel is -4.118029.

Eq  1 : Diagnostic summary report.

Estimation sample is    1. 1 -   27. 1. (T =   27, n =   25).
Log-Likelihood is -111.187 (-2 LogL = 222.374).
Prediction error variance is 15951.3

Summary statistics
                     STA
 Std.Error        126.30
 Normality       0.35490
 H(  8)          0.17512
 r( 1)          0.027267
 r( 8)          -0.11786
 DW               1.8399
 Q( 8, 6)         1.7164
 Rd^2            0.71840

Eq  1 : Estimated variances of disturbances.

Component           STA (q-ratio)
Irr              2961.9 ( 0.3649)
Lvl              8116.9 ( 1.0000)
Slp              4287.0 ( 0.5282)

Eq  1 : Estimated standard deviations of disturbances.

Component           STA (q-ratio)
Irr              54.424 ( 0.6041)
Lvl              90.094 ( 1.0000)
Slp              65.475 ( 0.7267)

Eq  1 : Estimated coefficients of final state vector.
```

Variable	Coefficient	R.m.s.e.	t-value	
Lvl	-126.52	218.83	-0.57818	[0.5683]
Slp	-68.357	104.13	-0.65646	[0.5175]

Eq 1 : Estimated coefficients of explanatory variables.

Variable	Coefficient	R.m.s.e.	t-value	
COV	-146.75	278.59	-0.52675	[0.6030]
SPRO	-2.8477	3.3248	-0.8565	[0.3999]
SPV	22.129	53.527	0.41342	[0.6828]
MPro	-0.042286	2.2295	-0.018966	[0.9850]
MPV	-39.360	322.22	-0.12215	[0.9038]
TW	0.0029406	0.00073364	4.0083	[0.0005]
PCF	-120.35	216.56	-0.5557	[0.5834]
SDP	-23.445	76.307	-0.30725	[0.7612]

Eq 1 : Forecasts for F-STA.

Period	Forecast	R.m.s.e.	- Rmse	+ Rmse
28. 1	95.893	159.17	-63.274	255.06
29. 1	24.430	260.35	-235.92	284.78
30. 1	-47.033	376.17	-423.20	329.13
31. 1	-118.50	505.03	-623.53	386.54
32. 1	-189.96	645.78	-835.74	455.82
33. 1	-261.42	797.49	-1058.9	536.07
34. 1	-332.89	959.44	-1292.3	626.55
35. 1	-404.35	1131.0	-1535.4	726.66
36. 1	-475.81	1311.7	-1787.5	835.89
37. 1	-547.27	1501.1	-2048.3	953.79

Normality test for Residual STA

Sample Size	25	
Mean	-0.189769	
Std.Devn.	0.802488	
Skewness	0.080022	
Excess Kurtosis	-0.284779	
Minimum	-1.957514	
Maximum	1.605662	
Skewness Chi^2(1)	0.026681	[0.8702]
Kurtosis Chi^2(1)	0.084478	[0.7713]
Normal-BS Chi^2(2)	0.11116	[0.9459]
Normal-DH Chi^2(2)	0.3549	[0.8374]

Goodness-of-fit results for Residual STA

Prediction error variance (p.e.v)		15951.274869
Prediction error mean deviation (m.d)		10589.007369
Ratio p.e.v. / m.d in squares		1.444643
Coefficient of determination	R2	0.970859
... based on differences	RD2	0.418396
Information criterion of Akaike	AIC	10.566183
... of Schwartz (Bayes)	BIC	11.142110

Serial correlation statistics for Residual STA.
Durbin-Watson test is 1.83994.
Asymptotic deviation for correlation is 0.2.

Lag	dF	SerCorr	BoxLjung	ProbChi2(dF)
1	0	0.0273		
2	0	0.0456		
3	0	-0.0397		
4	1	-0.0038	0.1307	[0.7177]
5	2	-0.0753	0.3223	[0.8512]

Soybeans (DTNS)

Method of estimation is Maximum likelihood
The present sample is: 1 to 27

Equation 3.

STA = Trend + Expl vars + Irregular

Estimation report
Model with 1 parameters (1 restrictions).
Parameter estimation sample is 1. 1 - 27. 1. (T = 27).
Log-likelihood kernel is -4.118029.

Eq 3 : Diagnostic summary report.

Estimation sample is 1. 1 - 27. 1. (T = 27, n = 25).
Log-Likelihood is -119.085 (-2 LogL = 238.171).
Prediction error variance is 28012.6

Summary statistics

	STA
Std.Error	167.37
Normality	1.5540
H(8)	0.30348
r(1)	0.31354
r(6)	-0.11026
DW	1.2714
Q(6, 6)	7.9424
Rd^2	0.80547

Eq 3 : Estimated variances of disturbances.

Component	STA (q-ratio)
Irr	43187. (1.0000)

Eq 3 : Estimated coefficients of final state vector.

Variable	Coefficient	R.m.s.e.	t-value	
Lvl	-471.37	290.95	-1.6201	[0.1178]
Slp	23.122	19.294	1.1984	[0.2420]

Eq 3 : Estimated coefficients of explanatory variables.

Variable	Coefficient	R.m.s.e.	t-value	
COV	-647.70	602.95	-1.0742	[0.2930]
SPRO	8.5091	5.1149	1.6636	[0.1087]
SPV	38.873	124.52	0.31219	[0.7575]
MPro	-8.9629	3.4823	-2.5738	[0.0164]

MPV	854.89	658.58	1.2981	[0.2061]
TW	0.0052767	0.00088114	5.9885	[0.0000]
Crate	564.90	355.11	1.5908	[0.1242]
SDP	179.69	147.16	1.2211	[0.2334]

Eq 3 : Forecasts for F-STA.

Period	Forecast	R.m.s.e.	- Rmse	+ Rmse
28. 1	227.41	223.50	3.9072	450.92
29. 1	260.44	225.21	35.228	485.64
30. 1	293.46	227.02	66.445	520.48
31. 1	326.48	228.92	97.561	555.41
32. 1	359.51	230.93	128.58	590.44
33. 1	392.53	233.03	159.50	625.57
34. 1	425.56	235.23	190.33	660.79
35. 1	458.58	237.52	221.07	696.10
36. 1	491.61	239.89	251.72	731.50
37. 1	524.63	242.35	282.28	766.98

lity test for Residual STA

Sample Size	25	
Mean	-0.212804	
Std.Devn.	0.796690	
Skewness	0.405168	
Excess Kurtosis	0.114095	
Minimum	-1.880697	
Maximum	1.793874	
Skewness Chi^2(1)	0.684	[0.4082]
Kurtosis Chi^2(1)	0.01356	[0.9073]
Normal-BS Chi^2(2)	0.69756	[0.7055]
Normal-DH Chi^2(2)	1.554	[0.4598]

Goodness-of-fit results for Residual STA

Prediction error variance (p.e.v)		28012.583584
Prediction error mean deviation (m.d)		18873.892118
Ratio p.e.v. / m.d in squares		1.402373
Coefficient of determination	R2	0.948825
... based on differences	RD2	0.505466
Information criterion of Akaike	AIC	10.081150
... of Schwartz (Bayes)	BIC	11.061089

Serial correlation statistics for Residual STA.
Durbin-Watson test is 1.27145.
Asymptotic deviation for correlation is 0.2.

Lag	dF	SerCorr	BoxLjung	ProbChi2(dF)
1	0	0.3135		
2	1	0.2285	4.2967	[0.0382]
3	2	0.0947	4.5716	[0.1017]
4	3	0.0252	4.5920	[0.2042]
5	4	-0.2941	7.5105	[0.1112]

Soybeans (NTNS)

Method of estimation is Maximum likelihood
The present sample is: 1 to 27

Equation 4.

STA = No level + Expl vars + Irregular

Estimation report
Model with 1 parameters (1 restrictions).
Parameter estimation sample is 1. 1 - 27. 1. (T = 27).
Log-likelihood kernel is -4.118029.

Eq 4 : Diagnostic summary report.

Estimation sample is 1. 1 - 27. 1. (T = 27, n = 27).
Log-Likelihood is -128.36 (-2 LogL = 256.72).
Prediction error variance is 32596.2

Summary statistics

	STA
Std.Error	180.54
Normality	6.8410
H(9)	0.44778
r(1)	0.35442
r(6)	-0.27759
DW	1.2318
Q(6, 6)	14.111
R^2	0.94045

Eq 4 : Estimated variances of disturbances.

Component	STA (q-ratio)
Irr	46321. (1.0000)

Eq 4 : Estimated coefficients of final state vector.

Variable	Coefficient	R.m.s.e.	t-value

Eq 4 : Estimated coefficients of explanatory variables.

Variable	Coefficient	R.m.s.e.	t-value	
COV	10.306	430.64	0.023931	[0.9811]
SPRO	1.5124	3.4130	0.44314	[0.6612]
SPV	-107.88	88.537	-1.2184	[0.2336]
MPro	-6.8079	3.3599	-2.0262	[0.0527]
MPV	148.34	501.91	0.29555	[0.7698]
TW	0.0039356	0.00027089	14.528	[0.0000]
Crate	277.52	312.98	0.8867	[0.3831]
SDP	151.50	150.11	1.0092	[0.3218]

Eq 4 : Forecasts for F-STA.

Period	Forecast	R.m.s.e.	- Rmse	+ Rmse
28. 1	280.66	215.22	65.434	495.88
29. 1	285.40	215.22	70.179	500.63
30. 1	290.15	215.22	74.924	505.37
31. 1	294.89	215.22	79.669	510.12
32. 1	299.64	215.22	84.414	514.86

```
  33. 1      304.38      215.22      89.159      519.61
  34. 1      309.13      215.22      93.904      524.35
  35. 1      313.87      215.22      98.649      529.10
  36. 1      318.62      215.22      103.39      533.84
  37. 1      323.36      215.22      108.14      538.59

Normality test for Residual STA
Sample Size     27
Mean                  -0.036466
Std.Devn.              0.838078
Skewness               0.865812
Excess Kurtosis       -0.144031
Minimum               -0.962458
Maximum                1.952864
Skewness  Chi^2(1)       3.3733  [0.0663]
Kurtosis  Chi^2(1)     0.023338  [0.8786]
Normal-BS Chi^2(2)       3.3967  [0.1830]
Normal-DH Chi^2(2)        6.841  [0.0327]

Goodness-of-fit results for Residual STA
Prediction error variance (p.e.v)          32596.242010
Prediction error mean deviation (m.d)      22653.388125
Ratio p.e.v. / m.d in squares                  1.318102
Coefficient of determination       R2          0.940451
... based on differences           RD2         0.424546
Information criterion of Akaike    AIC        10.984545
... of Schwartz (Bayes)            BIC        11.368497

Serial correlation statistics for Residual STA.
Durbin-Watson test is 1.23183.
Asymptotic deviation for correlation is 0.19245.

 Lag  dF    SerCorr   BoxLjung    ProbChi2(dF)
  1    0     0.3544
  2    1     0.2034     5.0791    [ 0.0242]
  3    2     0.1942     6.3101    [ 0.0426]
  4    3     0.0192     6.3226    [ 0.0969]
  5    4    -0.3716    11.2382    [ 0.0240]
```

C : Univariate Time Series Analysis of Complete Date Set (SAS output)

Output for Soybeans ARIMA (3, 2, 0)

Minimum Information Criterion

Lags	MA 0	MA 1	MA 2	MA 3	MA 4	MA 5
AR 0	3.485709	3.23418	3.258447	3.310908	3.308814	3.351643
AR 1	3.405397	3.281533	3.308405	3.354883	3.352171	3.399219
AR 2	3.300624	3.272447	3.328263	3.194788	3.246513	3.270968
AR 3	3.176244	3.229657	3.284949	3.245159	3.2982	3.316606
AR 4	3.227692	3.283393	3.338964	3.290264	3.339054	3.372176
AR 5	3.27107	3.326767	3.382621	3.323892	3.376036	3.425171

Error series model: AR(6)
Minimum Table Value: BIC(3,0) = 3.176244

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
AR1,1	-0.62797	0.10494	-5.98	<.0001	1
AR1,2	-0.56643	0.10891	-5.20	<.0001	2
AR1,3	-0.39662	0.10523	-3.77	0.0002	3

Variance Estimate	21.80243
Std Error Estimate	4.669307
AIC	465.6411
SBC	472.7112
Number of Residuals	78

Correlations of Parameter Estimates

Parameter	AR1,1	AR1,2	AR1,3
AR1,1	1.000	0.463	0.388
AR1,2	0.463	1.000	0.462
AR1,3	0.388	0.462	1.000

Autocorrelation Check of Residuals

```
   To        Chi-            Pr >
  Lag       Square      DF     ChiSq    --------------------Autocorrelations---
------------          6        3.53      3    0.3167    -0.031    -0.041    -
0.107    -0.085     0.015
12          7.23       9     0.6135      0.074     -0.019     -0.138     -0.005
0.122         18        10.63      15     0.7781     -0.098      0.102      0.067
-0.030      0.087        24         21.27      21     0.4425     -0.015     -0.307
-0.039     0.000     0.015
```

```
 Autocorrelation Plot of Residuals

  Lag    Covariance    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8
9 1      Std Error

    0              21.802429                            1.00000             |
|********************|
    1      -0.667549          -.03062     |                    .    *|      .
|
    2      -0.886567          -.04066     |                    .    *|      .
|0.113334
    3      -2.334701          -.10708     |                    .   **|      .
|0.113521
    4      -1.849855          -.08485     |                    .   **|      .
|0.114808
    5       0.335661          0.01540     |                    .     |      .
|0.115610
    6      -3.087894          -.14163     |                    .  ***|      .
|0.115636
    7       1.622644          0.07442     |                    .     |*     .
|0.117839
    8      -0.409631          -.01879     |                    .     |      .
|0.118440
    9      -3.006727          -.13791     |                    .  ***|      .
|0.118478
   10      -0.107627          -.00494     |                    .     |      .
|0.120519
   11       2.661362          0.12207     |                    .     |**    .
|0.120521
   12      -0.580131          -.02661     |                    .    *|      .
|0.122096
   13      -2.136477          -.09799     |                    .   **|      .
|0.122170
   14       2.218085          0.10174     |                    .     |**    .
|0.123174
   15       1.462893          0.06710     |                    .     |*     .
|0.124246
   16      -0.654380          -.03001     |                    .    *|      .
|0.124710
   17       1.904137          0.08734     |                    .     |**    .
|0.124803
   18      -0.851752          -.03907     |                    .    *|      .
|0.125584
```

```
   19       -0.336252          -.01542     |                    .      |      .
|0.125739

                                   "." marks two standard errors
```

Inverse Autocorrelations

```
                Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8
9 1

                  1        -0.00693      |                    .      |      .
|
                  2        -0.04020      |                    .     *|      .
|
                  3         0.31321      |                    .      |******
|
                  4         0.08937      |                    .      |**    .
|
                  5        -0.09737      |                    .    **|      .
|
                  6         0.27967      |                    .      |******
|
                  7         0.01222      |                    .      |      .
|
                  8        -0.08701      |                    .    **|      .
|
                  9         0.20790      |                    .      |****.
|
                 10         0.07872      |                    .      |**    .
|
                 11        -0.18048      |                    .****|        .
|
                 12         0.11369      |                    .      |**    .
|
                 13         0.09561      |                    .      |**    .
|
                 14        -0.13632      |                    .  ***|       .
|
                 15         0.00755      |                    .      |      .
|
                 16         0.06592      |                    .      |*     .
|
                 17        -0.12037      |                    .    **|      .
|
                 18         0.04651      |                    .      |*     .
|
                 19         0.04878      |                    .      |*     .
|

The ARIMA Procedure

                                     Partial Autocorrelations

                Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8
9 1
```

```
                  1         -0.03062     |                       .    *|      .
|
                  2         -0.04164     |                       .    *|      .
|
                  3         -0.10995     |                       .   **|      .
|
                  4         -0.09536     |                       .   **|      .
|
                  5         -0.00145     |                       .     |      .
|
                  6         -0.16511     |                       .  ***|      .
|
                  7          0.04315     |                       .     |*     .
|
                  8         -0.03938     |                       .    *|      .
|
                  9         -0.17761     |                       .****|      .
|
                 10         -0.03835     |                       .    *|      .
|
                 11          0.11466     |                       .     |**    .
|
                 12         -0.09895     |                       .   **|      .
|
                 13         -0.12009     |                       .   **|      .
|
                 14          0.12017     |                       .     |**    .
|
                 15          0.02897     |                       .     |*     .
|
                 16         -0.06504     |                       .    *|      .
|
                 17          0.15693     |                       .     |***   .
|
                 18         -0.05669     |                       .    *|      .
|
                 19         -0.06182     |                       .    *|      .
|

                              Model for variable diff2_sqrty

                                No mean term in this model.


                                  Autoregressive Factors

                 Factor 1:   1 + 0.62797 B**(1) + 0.56643 B**(2) + 0.39662
B**(3)

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                                  Obs    original    ARIMAvalue

                                    1       40          1.000
                                    2       49         39.347
                                    3       36         50.524
                                    4       51         31.853
```

5	37	54.940
6	36	32.446
7	56	35.367
8	74	61.131
9	46	77.070
10	47	38.157
11	50	47.022
12	50	49.784
13	75	48.889
14	75	81.152
15	98	72.646
16	105	102.736
17	100	103.979
18	120	96.309
19	96	123.349
20	103	87.328
21	80	103.409
22	60	72.340
23	55	54.276
24	54	53.024
25	57	52.749
26	63	56.684
27	78	63.291
28	90	80.542
29	90	91.031
30	96	87.729
31	94	95.619
32	85	91.274
33	101	80.856
34	111	103.728
35	102	110.927
36	98	97.135
37	106	95.055
38	112	106.078
39	119	111.014
40	146	118.196
41	212	150.455
42	233	226.509
43	324	231.584
44	540	343.495
45	460	592.634
46	440	422.623
47	490	426.691
48	620	493.584
49	720	642.392
50	920	727.904
51	950	954.411
52	1190	930.29
53	890	1231.87
54	1250	789.10
55	1750	1339.89
56	2000	1847.30
57	2200	2008.19
58	2300	2197.33
59	2400	2268.10
60	2050	2368.71
61	2100	1908.62

62	1800	2074.33
63	1220	1678.70
64	830	1058.91
65	930	728.66
66	1150	947.54
67	900	1184.37
68	600	810.63
69	650	519.79
70	600	657.10
71	520	571.57
72	320	488.48
73	400	268.06
74	400	420.09
75	300	388.56
76	220	268.38
77	170	197.49
78	165	155.44
79	160	161.30
80	180	155.26
81	.	181.86
82	.	177.76
83	.	172.67
84	.	167.60
85	.	162.66
86	.	157.88
87	.	153.25
88	.	148.76
89	.	144.41
90	.	140.19

Output for Corn (ARIMA MODEL):

The SAS System
The ARIMA Procedure

Minimum Information Criterion

Lags	MA 0	MA 1	MA 2	MA 3	MA 4	MA 5
AR 0	5.822939	5.864675	5.847204	5.86613	5.904516	5.956155
AR 1	5.874405	5.900868	5.87823	5.905276	5.935775	5.981498
AR 2	5.861954	5.878786	5.93464	5.96145	5.992025	6.036725
AR 3	5.886308	5.915097	5.970878	6.011794	6.041529	6.084767
AR 4	5.912665	5.931087	5.9839	6.028899	6.076908	6.126671
AR 5	5.960213	5.980292	6.036054	6.081642	6.130748	6.180337

Error series model: AR(10)
Minimum Table Value: BIC(0,0) = 5.822939

Preliminary Estimation
Initial Autoregressive Estimates

	Estimate
1	-0.00220

Constant Term Estimate -4.61234
White Noise Variance Est 399.0421

Conditional Least Squares Estimation

Iteration	SSE	MU	AR1,1	Constant	Lambda	R Crit
0	30726	-4.60222	-0.00220	-4.61234	0.00001	1
1	30726	-4.60260	-0.00221	-4.61275	1E-6	0.00002

The ARIMA Procedure

ARIMA Estimation Optimization Summary

Iterations 1

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	-4.60222	2.29141	-2.01	0.0446	0

Constant Estimate	-4.60222
Variance Estimate	404.2946
Std Error Estimate	20.10708
AIC	681.6751
SBC	684.0189
Number of Residuals	77

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	4.89	6	0.5584	-0.002	-0.073	-0.046	0.207	0.032	
12	9.54	12	0.6559	-0.077	-0.008	-0.062	-0.176	-0.063	
18	14.29	18	0.7099	-0.023	-0.094	-0.099	0.031	0.155	
24	16.30	24	0.8769	0.098	-0.029	0.034	0.054	-0.005	

Autocorrelation Plot of Residuals

```
  Lag    Covariance    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8
9 1      Std
    0                   404.295                        1.00000           |
|********************|
    1      -0.888898          -.00220     |                    .      |      .
|
    2     -29.578695          -.07316     |                    .     *|      .
|
    3     -18.516489          -.04580     |                    .     *|      .
|
    4      83.683160           0.20699     |                    .      |****.
|
    5      12.949663          0.03203     |                    .      |*     .
|
    6     -34.479114          -.08528     |                    .   **|      .
|
    7     -31.025250          -.07674     |                    .   **|      .
|
    8      -3.191306          -.00789     |                    .      |      .
|
    9     -25.170441          -.06226     |                    .     *|      .
|
```

```
   10      -71.007488         -.17563     |                     .****|      .
|
   11      -25.633988         -.06340     |                     .    *|      .
|
   12      -32.955288         -.08151     |                     .   **|      .
|
   13       -9.334699         -.02309     |                     .      |      .
|
   14      -37.856068         -.09363     |                     .   **|      .
|
   15      -40.094043         -.09917     |                     .   **|      .
|
   16       12.491342         0.03090     |                     .      |*     .
|
   17       62.508398         0.15461     |                     .      |***   .
|
   18       24.121950         0.05966     |                     .      |*     .
|
   19       39.789030         0.09842     |                     .      |**    .
|

                          "." marks two standard errors
```

Inverse Autocorrelations

```
               Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8
9 1

                 1         0.12049     |                     .      |**    .
|
                 2         0.10644     |                     .      |**    .
|
                 3         0.06512     |                     .      |*     .
|
                 4        -0.17853     |                     .****|        .
|
                 5        -0.05377     |                     .    *|       .
|
                 6        -0.00745     |                     .      |      .
|
                 7        -0.00613     |                     .      |      .
|
                 8         0.00255     |                     .      |      .
|
                 9         0.03848     |                     .      |*     .
|
                10         0.10783     |                     .      |**    .
|
                11         0.01806     |                     .      |      .
|
                12         0.12569     |                     .      |***   .
|
                13         0.08743     |                     .      |**    .
|
                14         0.06874     |                     .      |*     .
|
```

```
          15          0.10566     |                        .      |**    .
|
          16         -0.05690     |                        .     *|      .
|
          17         -0.13879     |                        .  ***|      .
|
          18         -0.07143     |                        .     *|      .
|
          19         -0.12330     |                        .    **|      .
|
```

Partial Autocorrelations

```
         Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8
9 1

           1         -0.00220     |                        .      |      .
|
           2         -0.07317     |                        .     *|      .
|
           3         -0.04638     |                        .     *|      .
|
           4          0.20278     |                        .      |****.
|
           5          0.02704     |                        .      |*     .
|
           6         -0.06361     |                        .     *|      .
|
           7         -0.05783     |                        .     *|      .
|
           8         -0.05829     |                        .     *|      .
|
           9         -0.09292     |                        .    **|      .
|
```

Partial Autocorrelations

```
Lag     Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

 10         -0.16764     |                    .  ***|       .   |
 11         -0.05325     |                    .    *|       .   |
 12         -0.10738     |                    .   **|       .   |
 13         -0.03121     |                    .    *|       .   |
 14         -0.05688     |                    .    *|       .   |
 15         -0.11132     |                    .   **|       .   |
 16          0.01588     |                    .     |       .   |
 17          0.12695     |                    .     |***    .   |
 18          0.06418     |                    .     |*      .   |
 19          0.14429     |                    .     |***    .   |
```

The SAS System

Obs	original	ARIMAvalue
1	3637	.
2	3624	3583.27
3	3400	3570.33
4	3450	3347.35
5	3620	3397.12
6	3980	3566.35
7	4190	3924.79
8	4120	4133.93
9	4490	4064.21
10	4710	4432.75
11	4340	4651.91
12	4240	4283.33
13	4687	4183.73
14	4480	4629.00
15	4246	4422.78
16	4003	4189.70
17	3515	3947.69
18	3698	3461.82
19	3443	3644.00
20	3378	3390.15
21	3246	3325.45
22	3075	3194.08
23	3044	3023.92
24	3135	2993.08
25	3295	3083.62
26	3134	3242.85
27	3225	3082.63
28	2947	3173.18

29	3044	2896.57
30	2820	2993.08
31	2736	2770.24
32	2741	2686.69
33	2624	2691.66
34	2682	2575.31
35	2304	2632.99
36	2048	2257.19
37	1911	2002.82
38	1886	1866.76
39	1737	1841.93
40	1650	1694.02
41	1646	1607.68
42	1794	1603.71
43	1758	1750.60
44	1767	1714.86
45	1750	1723.80
46	1800	1706.92
47	1620	1756.55
48	1840	1577.92
49	2000	1796.26
50	2020	1955.15
51	2300	1975.01
52	2240	2253.21
53	1700	2193.58
54	1670	1657.30
55	1600	1627.53
56	1600	1558.07
57	900	1558.07
58	830	864.79
59	1080	795.65
60	1080	1042.78
61	900	1042.78
62	680	864.79
63	600	647.67
64	610	568.88
65	660	578.73
66	600	627.97
67	750	568.88
68	650	716.69
69	600	618.11
70	400	568.88
71	580	372.52
72	500	549.21
73	500	470.57
74	350	470.57
75	360	323.63
76	265	333.40
77	340	240.80
78	370	313.86
79	.	343.17
80	.	316.96
81	.	291.38
82	.	266.46
83	.	242.22
84	.	218.69
85	.	195.89

86	.	173.87
87	.	152.65
88	.	132.28