Technical Efficiency in Water Usage:
An Analysis of Differences Among Farm Types and Sizes in Georgia

by

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(Under the direction of Rebecca Moore)

Abstract

The research presented in this paper is an examination of what factors affect the efficient/inefficient use of water among Georgia's farmers. Differences in intra-agriculture water usage are analyzed along two primary dimensions of interest: (1) farm type and (2) farm size. It is hypothesized that additional technical efficiency with water is accounted for by farms that adhere to culturally alternative agricultural practices, such as organic and conservation tillage, compared to conventional agricultural practices.

Index words: Agriculture, Data Envelopment Analysis, Georgia, Heckman Sample Selection Model, Subvector Irrigation Efficiency, Stochastic Production Frontier, Technical Efficiency, Tobit

TECHNICAL EFFICIENCY IN WATER USAGE:
AN ANALYSIS OF DIFFERENCES AMONG FARM TYPES AND SIZES IN GEORGIA

by

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DEDICATION

For the friends and family that make my life a pleasure to live.

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Chapter 1

Introduction

1.1 Motivation

The United Nations predicts that the earth's population will increase by nearly 50 percent over the next 40 years, reaching a level of 9.1 billion in 2050 from the current 6.8 billion (United Nations, Department of Economic and Social Affairs, Population Division, 2009). While population is by no means the sole determinant of water consumption, it does serve as a good proxy in understanding the relationship between current and future water demand. It is generally agreed that regardless of population changes, water consumption, by means of food consumption, will continue to increase through economic development, leading to increased affluence and subsequent demand for water-intensive protein sources. It is projected that irrigated agriculture will account for 72 percent of total water withdrawals from freshwater resources or reservoirs while accounting for 44 percent of total agricultural production in 2025 (Rosegrant, Cai, and Cline, 2002). Concern over these forces has resulted in increasing conservation efforts based on assessing of the water management potential in agriculture.

Prominent international organizations, including the United Nations's Water division (UN-Water), the Consultative Group on International Agricultural Research's International Water Management Institute (CGIAR-IWMI), the International Commission on Irrigation and Drainage (ICID), and the UN Food and Agriculture Organization (FAO) International Programme for Technology and Research in Irrigation and Drainage (IPTRID) Water Conservation and Use in Agriculture (WCA), place significant emphasis on the efficient use of water in agriculture. In an effort to promote this ideal, the IWMI and FAO have popularized the slogan “more crop per drop” with their recognition of the importance of water productivity and technical water use efficiency to address a relatively finite freshwater supply facing increasing demands for its use in agriculture.

In developed nations, gains from economic growth and a traditionally greater access to freshwater resources, has led to a high per capita use of water. In the United States, 11.6 percent of cropland is under some form of irrigation, with more than 60 percent of total water withdrawals being used for this purpose. During the ten year period from 1997 to 2007, there was a 31.2 percent increase in the total irrigated acreage in Georgia which now accounts for 22.7 percent of the 4.48 million acres of cropland (United States, National Agricultural Statistics Service, 2009a). While this trend in increasing levels of irrigated lands is leveling off rapidly, it does not appear to be decreasing. As a result, agriculture will likely serve as a continued, and dominant, user of water in the United States and Georgia specifically. Until recently, water quantity has not been of much concern in the Southeastern United States. However, after a recent drought induced a water deficit, the continued viability of the region’s current water sources has been called into question. Agricultural, environmental, and urban stakeholders seek continued and reliable access to the water resources that have been historically available. The purpose of the research presented in this thesis was to examine what factors affect the efficient use of water among Georgia’s farmers.

1.2 Statement of the Problem

Water is an economically complex resource with increasing scarcity, and in many settings is a common property resource. That is to say, it is a resource owned by a common (a group of people enjoying similar rights) and managed according to the adopted social institutions of the common (Griffin, 2006). The term “tragedy of the commons” as expressed by Hardin refers to the problem of open access resources (those resources in which there is an absence of management rules) and has been restated by economists as a situation in which individual users seek to maximize self-interest (Hardin, 1968). It is easy to imagine that if this behavior was fully realized by all individuals, decrement of the resource is a likely scenario. The socially efficient solution is when individuals equate marginal benefits to marginal costs, and in an open access situation, marginal net benefits are driven to zero by the individual decisions.

The United States' total internal renewable water resources are 9,332 cubic meter per capita, as compared to the worldwide average (not including Greenland) of 21,969 cubic meter per capita. (Food and Agriculture Organization, Water Resources Development and Management Service, 2008). Much of the international attention given to improved water management in agriculture has been directed towards developing nations, primarily because of an underdeveloped or nonexistent infrastructure for water resources in these countries. However, every nation in the world is faced with a finite quantity of internally renewable water resources. In addition, the vast majority of developed economies have an established, though often inundated, legal framework pertaining to water property rights that does not exist in the third world.

Within Georgia, agricultural production, and the subsequent use of irrigation, is focused in the southern half of the state. This heavily farmed area is characterized as a coastal plain, where elevation ranges from sea level to 225 meter. The water resources available are broadly divided as the Flint and Chattahoochee river basins in the Southwest, the Suwannee and Ochlocknee river basins in south central Georgia, and the coastal rivers in the Southeast. The average annual precipitation level within these river basins is 50 inches (Southeast Regional Climate Center, 2009), although evapotranspiration averages 70 percent of precipitation (Rasmussen, 2003). The Georgia Automated Environmental Monitoring Network, started in 1991, and other national weather monitoring systems maintain records of monthly precipitation dating as far back as 100 years for some weather stations. Seasonally, irrigation is concentrated during the later spring and summer months from May to August.

Estimates based on the 2008 University of Georgia Extension Irrigation Survey suggest 1.45 million acres of cropland are irrigated in Georgia, with the state crops, including corn, cotton, and peanut, accounting for 67 percent of the total irrigated acres (Harrison, 2009b). Regionally, these three crops and soybeans are primarily grown in the Southwestern and Eastern areas of the state, on the basis of total harvested acreage (United States, National Agricultural Statistics Service, 2009a). Vegetable production is concentrated in the Southern half of the state, while wheat and orchard crop production spans all regions of the state. Center pivot and linear move, travelling gun, and drip/trickle/mini/micro constitute the three primary classifications of irrigation equipment. These methods of irrigating have relatively high application efficiency potential and in most cases, given the particular crop and land conditions, the most efficient irrigation system that is available is currently in use (Evans et al., 1998). That is, while there often exists an irrigation system that is more efficient, it may not be applicable to the cropping conditions at a particular farm.

There is scope for efficiency gains in many aspects of the irrigation system and irrigation applications (Evans et al., 1998). In the same study Evans et al. (1998), suggested that the irrigation equipment itself could undergo repair and replacement for water conservation goals, such as ensuring the correct operation of an end gun shutoff in the case of center pivot systems or periodic maintenance of gaskets, pipes, hoses, and fittings on other water delivery systems. Additionally, their report concluded that more appropriate irrigation scheduling on orchard drip systems can also provide an average reduction in total water applied of 30 percent throughout a regular growing season. Currently, water use in agriculture has no cost and very limited restrictions (in the form of permitting) directly associated with its use. Extraction of water from surface and/or ground sources is the only variable cost associated with irrigation water. That is, the application of water through pumping costs the farmer the energy costs associated with the operation of the water pump. It is difficult for farmers to make socially optimal economic decisions concerning water allocation and conservation, when the current pricing of water does not make improving irrigation efficiency economically efficient in most situations. More precisely, water losses or inefficiencies are in fact at the optimal level unless the cost of preventing such losses is less than the value of the water saved (Griffin, 2006). In lieu of appropriate pricing incentives, public policy and regulation are essential to encourage the economically efficient development of water conservation methods within irrigated agriculture.

Because of the particularly exceptional 2007 drought in Georgia, policy makers have recognized the need for a water management plan. The growing scarcity of water in Georgia puts pressure on users of water, including irrigated agriculture, to increase the efficiency and productivity of water use in order to release water for other uses (Malano, Burton, and Makin, 2004). Many options have been discussed though few have attained statewide consensus. In developing such a plan, it is important to understand the current water use patterns of the economy at large, individuals' behavior towards the use of water, and to what policy incentives a given population will respond by altering behavior to achieve a more efficient solution. As a result of limited irrigation water monitoring, agricultural water use is perhaps the least understood.

1.3 Objectives of the Study

The primary goal of this research was to investigate the impact of farm-level management techniques and demographic characteristics on the technically efficient use of irrigation water. Technical efficiency in production assures that input levels are minimized for a given level of output, such that the amount of irrigation water applied cannot be reduced without also reducing the amount of output produced. The research will explore differences in water users along two primary dimensions of interest: (1)

large vs. small farms, and (2) alternative vs. conventional farm type. Specifically, this project seeks to:

1. Estimate and compare overall and input-specific technical efficiency measures.

2. Identify what factors affect technical water use efficiency.

Large and small farms often have different objectives and motivations when engaging in farming, and therefore their observance of water productivity is quite disparate when appropriate pricing and other policies are in place. Overall technical efficiency of farms larger than 20 acres has been shown to be greater than those under this threshold size (Reig-Martínez and Picazo-Tadeo, 2004). In terms of water usage measured on the basis of average number of hours irrigated per acre, large farms are more efficient while small farms tend to be less efficient (Skaggs and Samani, 2005). Furthermore, as farm size increases, excess water use decreases (Lilienfeld and Asmild, 2007). It should be noted that while organic farms typically are categorized within the small farm classification, they often emphasize a management methodology of sustainability which in theory may result in more efficient water usage that is generally observed on farms of that size. Little is known, however, about the degree to which water use on organic farms is efficient in practice.

Water used in Georgia agriculture currently has no cost and very limited restrictions (in the form of permitting) associated with its use. Thus, in Georgia, the price of irrigation water is equal to the cost of extraction, including pumping and diversion, storage, treatment, and delivery costs. According to one study, water scarcity is not a factor when farmers make decisions about irrigating and how much water to apply (Gonzalez-Alvarez, Keeler, and Mullen, 2006). Specifically in Georgia, little is known about water withdrawals by farmers because prior to 2003 these withdrawals were only monitored on a voluntary basis and are, therefore, limited in quantity of observations and geographic scope.

1.4 Organization of the Study

This thesis is comprised of five chapters. Chapter Two contains a review of the background literature, including relevant descriptive and technical information pertinent to analyzing water use and policy alternatives in Georgia agriculture. In Chapter Three, the methodologies for data collection and empirical analysis are detailed. Chapter Four presents the results of the analysis. Chapter Five concludes the thesis with a summary and discussion of the findings.

CHAPTER 2

LITERATURE REVIEW

2.1 REVIEW OF LITERATURE

Agricultural water use and demand has been studied extensively as a result of agriculture's role as the dominant water user in most regions of the world (Estes, Jensen, and Tinney, 1978; Cason and Uhlaner, 1991; Varela-Ortega et al., 1998; Renzetti, 2002; Banerjee et al., 2007; Hoekstra and Chapagain, 2007; Cai, Ringler, and You, 2008). Economists widely accept that financial incentives, whether it be water trading opportunities or increased water rates can be effective means of reducing water consumption in agriculture (Zilberman and Schoengold, 2005). Conversely, other studies have shown that there is no significant demand response to modest price changes, indicative of an inelastic demand, largely a result of those water delivery systems that are highly subsidized (Garrido, 2001; Jones, 2003). This subsidization, in most cases, rises when the price of water increases and mitigates the change of the real price of water. Georgia's farmers face a cost of water that includes no component of the inherent scarcity of water. By using pumping costs as a proxy for the price of water in Georgia, Gonzalez-Alvarez, Keeler, and Mullen (2006) found farmers decrease water use by 2.4 acre inches per $50 increase in pumping costs based on a mean pumping cost estimate of $21.54. Multiple authors have shown that the effect of an increase in the price of water on the adoption of water conserving irrigation technologies by farmers is positive (Caswell and Zilberman, 1985, 1986; Hayami and Ruttan, 1985; Kanazawa, 1992).

A number of demand side policy options exist on the issue of policy-led water management in agriculture. Broadly defined, these policies are price-rationing policies, quantity-rationing policies that set maximum quantities individuals and farms may extract, and demand-shifting policies which come in a variety of different structures (Griffin, 2006). There are fewer opportunities to increase the supply of water as the existence of ground water reservoirs are known (though not fully quantified) and the damming of rivers to create surface reservoirs has been plagued with unintended environmental consequences and high costs. While responses to these policies can be modeled according to economic theory (Weinberg, 2002), the presence of significant differences between farms with respect to their characteristics raises concern in regard to the accuracy of broadly modeled scenarios on specific groups of water users. For example, these models fail to explain how differences in a farm's business structure, such as family farm or corporation, affect policy responses.

One study that assessed this concern over intra-agriculture water use variability, found, through interviews and a comparison of hours irrigated per irrigation event, that the smallest farms lacked interest in improving their current, inefficient irrigation systems or methods in New Mexico (Skaggs and Samani, 2005). The findings were attributed to the prevailing characteristic of small farms–residential/lifestyle/retirement agriculture environment in which profit is not a discernable motivation for farming–such that irrigating is viewed as a cost of living/recreation as opposed to an operational business expense as realized by larger, commercial farms. Similarly, Zhou et al. (2008) found that larger farms in China were more likely to adopt water-saving technologies. Norman, McCann, and Al-Ghafri (2008) review that the factors which are external and internal to the farm and influence farmers' practices relating to water management are not well understood, particularly at the smallholder irrigation level within the context of agricultural development. Land tenure and livelihood strategies affect the performance of smallholder irrigation in Africa (Shah et al., 2002). Most recently, Speelman et al. (2008) reviewed the determinants of technical water use efficiency, concluding that farm size, land ownership, irrigation method, and crop choice were significant factors for smallholder farmers in South Africa. In Kansas, the level of excess water irrigation water used, or technical inefficiency in irrigation water use, is only weakly related to the type of irrigation system but is positively related to the age of the farmer (Lilienfeld and Asmild, 2007). Furthermore, Lilienfeld and Asmild (2007) found that farm size is negatively related to excess water use.

In both developed and developing countries, farm-level allocation of labor between agriculture and other economic pursuits is correlated with overall farm efficiency and irrigation efficiency. Chang and Wen (2008) found that full-time farmers were more efficient producers, overall, compared to those who were engaged in off-farm labor tasks. Similarly, according to Abernethy et al. (2000) and Skaggs and Samani (2005), there is a negative relationship between off-farm income and irrigation efficiency. Economic theory, specifically production theory, posits that this relationship is driven by the fixed amount of time an individual has at his/her disposal to allocate between various labor and leisure pursuits. If more of this time is spent in off-farm employment, it inherently reduces the amount of time available to carry out on-farm tasks.

The technical efficiency of farms has been estimated with two primary methods, Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA), in a number of studies. Overall technical efficiency of conventional and conservation tillage cultural farm practices in Georgia were estimated and compared, Ward et al. (2002) found that the number of efficient conservation tillage fields surpassed conventional tillage. However, using DEA, Ward et al. (2002) also found that when these production methods used crop varieties that were not transgenic, conventional tillage fields were, on average, more efficient that conservation tillage fields, and the technical efficiency of these two cultural farm practices was very low (56 percent for conservation tillage and 63 percent for conventional tillage) relative to fields with transgenic varieties. In a comparison of organic and conventional olive farms in Greece, Tzouvelekas, Pantzios, and Fotopoulos (2001) employed SFA to determine that organic producers were more technically efficiency relative to their own frontier. The results implied that conventional and organic olive farms, on average, could reduce the use of all inputs by 45.7 and 26.88 percent, respectively, without affecting output. Lansink, Pietola, and Backman (2002) found similar results in the case of conventional and organic crop farms in Finland with DEA estimates, but the degree of inefficiency among farms was significantly less. On average, conventional and organic farms could reduce the use of all inputs by 28 and 4 percent, respectively, holding output constant.

Environmental production conditions alter the results of farmers' production decisions, and otherwise identical producers employing the same technologies and with the same farming capabilities will produce different quantities of crop if faced with different rainfall or other environmental production conditions (Sherlund, Barrett, and Adesina, 2001). The inclusion of soil characteristics, slope, pest infestation, weed density and height, plant disease, and rainfall significantly affected the estimated technical efficiency scores for a sample of rice farmers in Côte d'Ivoire (Sherlund, Barrett, and Adesina, 2001). On average, these farmers were determined to be more than twice as technically efficient when accounting for environmental variables (76.56 percent) than without their inclusion (35.95 percent). Furthermore, the educational level of the farmer was not a statistically significant factor affecting technical efficiency without environmental variables, but had a positive and significant affect when environmental variables were taken into account (Sherlund, Barrett, and Adesina, 2001). In regard to irrigation, Kurukulasuriya and Mendelsohn (2007) went on to show that both temperature and precipitation affect the choice of irrigation and net farm revenue.

When referring to agriculture, Marlow (1999) defined technical water use efficiency as the mass of agricultural produce per unit of water consumed. The results of a DEA based study in Brazil found that farm-level technical efficiency was explained primarily by soil, climatic conditions, and the use of irrigation (Vicente, 2004). This suggests that the decision to irrigate positively affects the technically efficient use of all other inputs.

However, no conclusions were drawn concerning the relative technical water use efficiency of the farms in the study. One of the few studies to assess the technical water use efficiency found that the average water efficiency of small-scale irrigation schemes in South Africa was only 67 percent (Speelman et al., 2008). However, these same farms were 84 percent technically efficient overall, suggesting that while a farm may be relatively efficient in the use of all inputs, the same is not necessarily true for irrigation water. Finally, Lilienfeld and Asmild (2007) found that irrigating farms in Kansas used 280 m^3/ac more irrigation water than was necessary to produce the same output.

Through the lens of induced innovation, it is evident that occurrences of water shortage and, in turn, increasing values of water, has lead to new techniques, improved management practices and institutional reforms that are meant to increase water productivity (Barker, Dawe, and Inocencio, 2003). In Turkey, the Gediz basin was under drought conditions during the period of 1989 to 1994. This induced a change in the method of water allocation from demand to supply-based resulting in the development of groundwater resources and increased irrigation efficiency (General Directorate of Rural Services Turkey and International Water Management Institute, 2000). Within the Chao Phraya basin in Thailand, farmers responded to similar water shortages by diversifying crop production and improving dam management, gradually increasing irrigation efficiency (Molle, 2003). The Rio Lerma-Chapala basin in Mexico went through a set of circumstances similar to those being presently experienced in Georgia. In the 1980s, water shortages, aquifer depletion, and growth in agricultural water demand created an abrupt decline in the primary source of water for Guadalajara, Lake Chapala. Time has shown that the region's leaders established a water council, responsible for water allocation among users fostering improved water productivity (Scott et al., 2001). The implementation of a non-market based response was largely a function of the undeveloped legal system concerning water property rights. Scott et al. (2001) report that continued population pressures driving Guadalajara's increasing urban water demand have triggered a forced reallocation of more than 63 billion gallons of water away from irrigated agriculture.

Modern applied welfare economics recognizes that water allocation decisions among sectors must increasingly include value judgments, as competition for these scarce water resources also increases, in order to best serve society (Castle and Lindeborg, 1960). By far the most critical water resource value judgments include those which ensure food security needs as well as sufficient, universal access to water while meeting basin level sustainability objectives. McKinney et al. (1999) review comprehensive optimization modeling frameworks that, at the basin level, integrate hydrologic, agronomic, and economic relationships. Others have suggested the use of specific water pricing policies, including pricing based on area irrigated, volumetric pricing according to water use or consumption, output or input pricing, fixed and variable rate pricing, or water markets (Tsur and Dinar, 1997; Perry, 2001). A thorough understanding of overall technical efficiency and technical water use efficiency is a necessary step towards discerning how resources can be more efficiently used.

2.2 Georgia Agriculture

In the state of Georgia, it is estimated that roughly 10.15 million acres, or 27 percent of the total land area, are owned as farmland. Of this land, 3.39 million acres were harvested cropland in 2007, with estimates of irrigated acreage ranging between one and 1.5 million acres according to the results of the 2007 Census of Agriculture and the 2008 Georgia Irrigation Survey, respectively (United States, National Agricultural Statistics Service, 2009a; Harrison, 2009b). Georgia ranks first in the nation in the production of broilers (young chickens weighing less than two and a half pounds), peanuts, pecans, and watermelons (USDA, NASS Georgia Field Office, 2009). In terms of value of production, broilers alone constitute the largest single agricultural product, accounting for 46.8 percent of total farm receipts (or approximately $3.2 billion), while cotton comes in second, contributing 7.9 percent of total farm receipts (or roughly $537 million) in 2007 (Parker, 2009). Agriculture is the most important sector of the economy, with food, fiber, and related industries accounting for 16 percent (or $56 billion) of Georgia's total economic output (nearly $353 billion). Furthermore, one in seven residents (15 percent) of Georgia works in agriculture, forestry, or a related field (Flatt, 2004).

Fourteen primary rivers basins lie within the political boundary of Georgia. The pressure on any particular basin from agriculture is directly related to the amount of irrigation within that basin. Figure 2.1 is a map depicting estimates of the total number of irrigated cropland acres that were harvested, as of the 2007 Census of Agriculture (United States, National Agricultural Statistics Service, 2009a). Aggregated at the county level, the total land that is under irrigated agricultural production is greatest in counties that are displayed as the lightest color, white. An overlay of the river basins is included to illustrate which of these face the largest pressures from agricultural users. It is apparent that regardless of the river basin, there are areas in each in the southeastern half of the state which have a significant amount of irrigated acreage. However, the Flint, Ochlockonee, and Suwannee river basins have areas with the greatest number of irrigated acres per county.

2.3 Characteristics of Irrigation

Agricultural water use in Georgia, and much of the southeast, is characterized by a multitude of distinguishing dimensions. In order to consider the "price" of water as a determinant in quantity demanded, it is essential to understand the benefits and fixed costs associated with the decision to initially implement an irrigation system and the variable costs associated with the continued application of water to cropland. The nature of irrigation in Georgia is largely supplementary, because Georgia is characterized by a hot, moist growing season with an average rainfall of 50 inches (Southeast Regional Climate Center, 2009). Most irrigation occurs between April and September and the

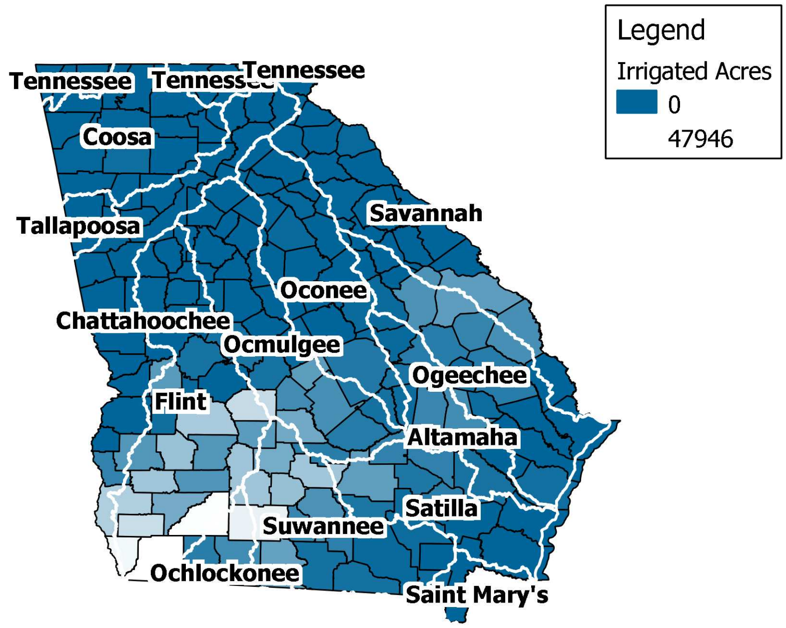


Figure 2.1: Irrigated Acreage by County and Basin (United States, National Agricultural Statistics Service, 2009a; McFadden, 2003)

amount of water applied differs based on the farmer, crops grown, and rainfall (Georgia Environmental Protection Division, 2009). The statewide averages of the inches of water per acre by crop in 2008, a severe drought year, are displayed in Table 2.1.

The average amount of irrigation water applied is equivalent to 12 inches of water per acre per growing season[1] (Cummings, Holt, and Laury, 2003; Evans et al., 1998). Given this average and the irrigation occurring through a center pivot system, the cost of water using a diesel pump and generator equates to $184.59 per acre-foot of water[2] (the amount of water needed to cover an acre of land with a foot of water), while the use of

[1]Cummings, Holt, and Laury (2003) reports that irrigation withdrawals in wet years (those years with above average precipitation) are as low as 4 inches per acre, or 1/3 acre-foot of water, 7 inches in average years, or 0.5833 acre-feet of water, and as high as 18 inches in years of severe drought, or 1.5 acre-feet of water.

[2]Diesel estimates based on 65.5 hours per acre-inch required for 60 horsepower pump and 25 horsepower generator with both generator and pump using 0.0746 gallons per horsepower per hour at a cost of $3.00 per gallon. Electric estimates based on 65.5 hours per acre-inch required for

Table 2.1: Average Irrigation Amounts in Georgia in 2008 by Crop (Georgia Environmental Protection Division, 2009)

Crop	Inches of Water per Acre
Cotton	10.0
Corn	14.0
Peanut	9.9
Soybean	6.7
Pecan (drip)	11.7
Sod production	17.9

an electric pump is equal to $24.61 per acre-foot[3] (Bullen and Benson, 2007). When factoring in the other costs often present in setting up an electric pump system, it may make sense for some farmers to choose a diesel pump regardless of the additional variable cost per acre-foot of water.

The majority of farmers that decide to irrigate in Georgia do so with center pivot, linear move, traveling gun, or drip/trickle/mini/micro irrigation systems. Approximately 67 percent of total irrigated acreage is done so with center pivot and linear move irrigation technology (Harrison, 2009b). The fixed costs associated with installing a center pivot irrigation system capable of delivering water to 81 acres (the full circle of a common, larger size, 1,000 foot sprinkler system plus end gun), are estimated

40 horsepower pump using 0.746 kilowatt hours per horsepower per hour at a cost of $0.085 per kilowatt hour.

[3]While the cost of electric water withdrawals are significantly lower, the logistical difficulties in getting electricity to a pump results in additional costs, such as line extension charges, monthly minimum (stand-by) charges, as well as the rate for the actual electricity. In addition, if more then 10 to 15 horsepower is required for the pump (simplistically, a function of the number of acres irrigated and the depth/distance the water much travel), a single-phase power source is not sufficient to supply the necessary electricity demand, and a more costly three-phase power source is a requisite (Harrison, 2009a).

at $104,243 and $125,243 in 2007 for an electric system and diesel system, respectively, assuming a new well must be drilled (Bullen and Benson, 2007). The yearly fixed costs associated with the interest, property tax, and insurance rate on an 81 acre center pivot irrigation system vary between $76.54 per acre for diesel systems and $63.70 per acre for electric systems (Bullen and Benson, 2007).

As was previously noted, the variable cost of irrigation is only a function of the extraction and application costs of water. In most cases, the most significant single cost is the fuel or electricity required to pump the water from a ground or surface water source. Smith and Ziehl (2008) estimated that, during 2008, corn farmers in South Georgia that did not irrigate could expect 85 bushels per acre at a total variable cost of $3.10 per bushel (or $263.33 per acre) as compared to 185 bushels per acre at a total variable cost of $3.34 per bushel (or $617.81 per acre) for irrigated corn when using diesel or $2.44 per bushel (or $451.03 per acre) for irrigated corn when using electricity[4]. Once a farmer has paid the initial fixed costs of installing an irrigation system, the benefits associated with the decision to irrigate lead to an output per acre that is more than double what could otherwise be achieved, while the total variable cost per bushel is an additional 7.7 percent in the case of diesel but 21.3 percent less in the case of electricity.

A key consideration for farmers is that corn prices have historically remained in the $3.00 per bushel range, yet the annual average price of corn in Georgia during 2008 was $4.60 per bushel (United States, National Agricultural Statistics Service, 2009b). This brings to light a few interesting points. First, farmers that do not irrigate will operate at a loss if corn prices either do not exceed $3.00 per bushel or if he cannot produce more than 85 bushels per acre. Second, a farmer that irrigated with diesel in 2008 did so with

[4]The variable costs per acre for seed, lime, fertilizer, weed control, insect control, pre-harvest and harvest machinery, labor, and crop insurance were assumed to be equal for non-irrigators and irrigators following the prices and application rates suggested by Smith and Ziehl (2008) in http://www.ces.uga.edu/Agriculture/agecon/budgets/excel/Corn%20Irrigated%202008.xls and with 12 inches of water applied per acre at a total price of $184.59 for diesel and $24.61 for electricity as suggested by Bullen and Benson (2007).

the expectation that he will either produce more than 185 bushels per acre or that the per bushel price he receives will be greater than \$3.34. Alternatively, a farmer with a diesel powered irrigation system in place may still decide to irrigate less in order to ensure a profit at \$3.00 per bushel. Finally, an irrigating farmer with an electrically operated irrigation system in place has profit potential even if the price of corn falls below \$3.00 per bushel, and room for significant profit potential relative to non-irrigators and farms employing diesel powered irrigation systems.

Different irrigation technologies have a variety of associated water application characteristics and efficiency potentials. The ratio of the average amount of irrigation water that infiltrates to the root zone and is available for plant use to the average amount of total irrigation water applied is called application efficiency (Evans, 2006). The potential application efficiencies of irrigation systems commonly installed in the Southeastern United States are detailed in Table 2.2 (Evans, 2006). A center pivot is the predominant irrigation system used for corn, cotton, peanut, soybean, sorghum, Vidalia onions, watermelons, and wheat. For tobacco, a traveler system is predominant, and for peaches the systems are divided between drip/trickle and traveler. Another characteristic, uniformity, refers to how consistently individual emitters or sprinklers apply water across the irrigated area. One possible conclusion to this information is that a transition to more efficient trickle systems, where applicable, could result in up to a 20 percent gain in application efficiency when replacing center pivot sprinklers, and, therefore, 20 percent less water is needed in order to achieve the same result. In contrast, Mollá (2000) and others have shown that after transitioning to drip irrigation technologies, irrigators have not reduced total irrigation water applied.

According to the USGS, estimated total agricultural water withdrawals for the year 2005 in Georgia was approximately 300 billion gallons of water (Fanning and Trent, 2009). This represents a decrease of 30 percent between 2000 and 2005 in the amount of water consumed by agriculture. A report on irrigation conservation practices found that,

Table 2.2: Potential Water Application Efficiency by Irrigation System

		Range (%)	Average (%)
Sprinklers	Solid Set	60 - 80	70
	Center Pivot	70 - 85	75
	Linear Move	60 - 70	65
	Big Gun	55 - 65	60
	Traveler	55 - 70	60
Drip/Trickle		80 - 98	90

at an average cost of $860 for each million gallons of water conserved, 11.6 billion gallons of water could be conserved through four widely achievable improvements in irrigation practices: (1) repair/installation of properly operating end gun shutoff, (2) repair of the water delivery system on travelling gun systems, (3) use of best-management practice irrigation scheduling techniques on orchard drip systems, and (4) replacement of old sprinkler packages on center pivot and linear move systems where uniformity is less than 80 percent(Evans et al., 1998). The amount of water saved is equivalent to nearly a four percent reduction in total irrigation withdrawals. For a farmer to conduct these repairs of his own volition, the cost of the water conserved must be less than the marginal cost of unnecessarily applying/pumping that water.

While there exists large variance in the amount of water consumed by agriculture as a result of the currently limited information regarding actual water withdrawals per permit, it has been consistently recognized that this sector's consumptive quantities make one of the largest consumers of water in the state; water consumption by thermo-electric power utilities is approximately equal to that of agriculture (Fanning and Trent, 2009). The growing scarcity of water in Georgia puts pressure on irrigated agriculture to increase the efficiency and productivity of water use in order to release water for other uses (Malano, Burton, and Makin, 2004). Figure 2.2 illustrates the distribution of irrigation permits, both surface and groundwater, throughout Georgia, noting again that not all allowable acreage is being irrigated necessarily. It is evident that most farm irrigation occurs below the Fall Line and a significant portion of the total permitted agricultural water withdrawals and irrigated acreage lie within the Flint, Ochlockonee, and Suwannee River basins (refer to Figure 2.1 on page 15).

2.4 Water Policy in Georgia

In 1988 Georgia enacted an agricultural water use permitting system, requiring those who, on a monthly average, withdrew 100,000 gallons per day or more to obtain a withdrawal permit from the Georgia Environmental Protection Division's Agricultural Permitting Unit (GA EPD-APU) of the Georgia Department of Natural Resources (DNR). As of 2008, these permits are free to farmers irrigating in any basin except the Flint River Basin and are generally approved to those that follow the proper application procedure. Those farmers that apply for an agricultural water permit within the Flint River Basin must pay a $250 application fee. Geologic and/or hydrologic evaluations of each agricultural water withdrawal permit are conducted in order to protect existing water users to the extent provided in Georgia law. According to the EPD's Agricultural Withdrawal Application (Georgia Environmental Protection Division, 2008), an application may be rejected on the basis that another user is too close or that the waters at the applicant's requested withdrawal location are already at capacity use.

Water rights are private property in Georgia that are characterized as a "system of riparian rights vested in landowners [in which] the courts have characterized the Georgia concept as natural flow subject to reasonable use" (Blount et al., 2002). This restricts legislator's ability to interfere with the lawful use of both groundwater and surface water resources, apart from nuisances, held within or adjacent to a landowner's property, thereby defining water as private property. As established by Riparian

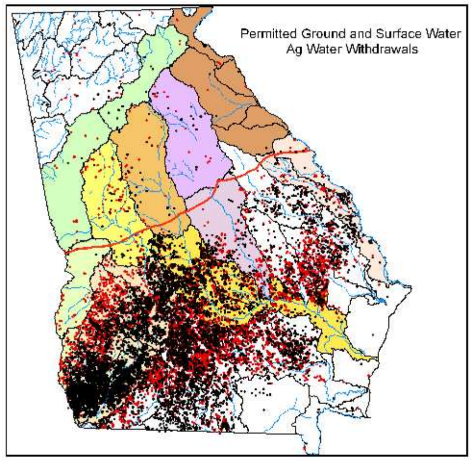


Figure 2.2: Irrigation Permits in Georgia (Georgia Environmental Protection Division, 2009)

common law, private use may not unreasonably impede Riparian uses, legally enabling the EPD to regulate, without assuming ownership, private and public use of surface and ground waters. This system is jointly referred to as a "Regulated Riparian." Currently, there are more than 21,500 permits for agricultural water withdrawals (Georgia Environmental Protection Division, 2009).

Prior to 2003, permit holders were not required to report their water use. As of June 2009, all new and existing permit holders will have water meters on all their wells and pumps. An estimate of the quantity withdrawn for irrigation purposes in 2005, provided by the USGS, is 486 million gallons per day from ground water and 265 million gallons per day from surface water sources, totaling nearly 761 million gallons per day[5] (Fanning and Trent, 2009). In relation to total statewide water withdrawals, agriculture ranks third, at 14.3 percent of total water withdrawals, to public supply (second) and

[5]Estimates do not take into account water withdrawn but not consumed, such as from runoff or faulty irrigation equipment. Thermo-electric is attributed with 50 percent of total withdrawals, though water consumed ranges from 1 to 100 percent depending on the type and age of the power operation.

thermo-electric uses (first). However, estimates typically regard agriculture and thermo-electric as approximately equal as the largest consumptive user of water in Georgia (Fanning and Trent, 2009).

Operating from 1998 to 2005, a monitoring program, AG WATER PUMPING (Agricultural Water: Potential Use and Management Program in Georgia), was established to provide reasonable, statistically valid estimates of agricultural water use within Georgia in response to uncertainty shrouding alternate estimates by the USDA, USGS, and other statewide organizations. The monthly program monitored, voluntarily, almost 800 fields with permitted irrigation withdrawals covering 38,330 acres. From these observations, the irrigation average for 2001 and 2002 (years with below average rainfall) was 6.65 and 7.49 acre inches, respectively (Thomas et al., 2003).

Due to heavy demands, low levels of precipitation and the record low flow levels of the Flint River in 1999, the Flint River Drought Protection Act (FRDPA) was enacted in 2001. The policy was intended to allow a buyback of surface and groundwater during EPD designated dry years by establishing a fund to compensate farmers in the Flint River Basin who voluntarily withheld from irrigating (Hollis, 2007). Put another way, the government paid farmers with valid agricultural water withdrawal permits to not exercise the use of the water they were permitted to use for the year in question, but allowing the farmers to retain their permit to be exercised in future years. In addition, the approval of all new ground water permit applications was suspended from the Floridian aquifer (new surface water permits in the Flint River basin were barred from 1998 to March 2006). According to Georgia law as of 2002, agricultural water withdrawal permits were explicitly granted transferability, or the authority for the water rights associated with an agricultural water withdrawal permit to be given/sold to another farm or non-farm uses (Blount et al., 2002). The FRDPA is the first, and only, policy of its kind in Georgia in which farmers currently holding valid permits have the option to sell their right to withdraw irrigation water in a sealed bid auction back to the state of

Georgia. As of 2009, the 2001 and 2002 growing seasons were the only two years that the EPD declared a severe drought for farmers in Georgia's Flint River Basin, thereby engaging the FRDPA. The auction structure differed in the two years in that the 2001 auction was a multiple round competitive auction, whereas in the 2002 auction, there was an EPD posted ceiling price of $150 per acre.

During the FRDPA auction, a $72 per acre floor price was the estimated value of agricultural water withdrawal permits in the Flint River Basin, and in turn the value of irrigation water, based on a price differential of $800 to $1000 between land with existing irrigation permits and that without (Cummings, Holt, and Laury, 2003). The average price paid per acre was $135.85 in 2001, totaling 208 permits or 33,101 acres, and $126.05 in 2002, totaling 272 permits or 40,386 acres. As noted by this study, a significant limitation to the findings is that as many as one-third of the options to not irrigate sold to the EPD might not have been exercised even if they had not been sold, resulting in a potential downward bias in the average price estimates. Another study utilizing a hedonic model of land value estimated the value of holding an irrigation permit after the Flint River Basin permitting suspensions at $913 per acre, with an associated marginal value of permitted pumping capacity equal to $7.26 per acre-inch per acre per day (Spurgeon and Mullen, 2005).

2.5 Alternative / Conservation Agriculture

The Green Revolution of the last 50 years has led to the industrialization of agriculture in developed and developing nations alike. This modernization has increased both agricultural production and the use of inputs. Prior to this shift in agricultural cultivation practices, crop yields depended on internal resources, recycling of organic matter, built-in biological control mechanisms, and rainfall patterns (Altieri, 1995). There are those that have questioned the long-term sustainability of a farming system that uses energy and natural resources with such intensity (Lynam and Herdt, 1989). In response to such questions, others have looked at alternative ways to retain modern yield improvements while reexamining the agroecological linkages, recognized throughout history, thereby reducing the need for such a prevalent rate of chemical input application. However, it is largely unknown if cultural farm type has an independent effect on irrigation water use.

As necessary throughout this research, the term 'alternative agriculture' will be used as a way to include all cultural farm systems that practice some form of agricultural method, contrary to the prevailing modern commercial techniques (Antle and Capalbo, 2002). It is virtually impossible to know each farmer who employs some degree of agricultural and natural resource management efforts unless they ascribe to a classifiable or specific alternative cultural farm practice. Some of these, which are categorized, have organizations and/or are listed publicly in Georgia include organic farming, conservation tillage, and grass-fed livestock. Survey gathered data are a useful mechanism for filling the information gap between organizational affiliation and on-farm implementation.

In the United States, organic farming is currently the only federally certifiable alternative agriculture technique. This unique categorization is largely due to the fact that organic farming employs zero synthetic inputs. These synthetic inputs are detectable in soils and on plant matter, which makes their presence measurable and the lack thereof certifiable. In order to turn out produce without such inputs, organic farmers must actively manage soil fertility, pests, and plant diseases. The extent and variety of these methods are beyond the scope of this research, though it is relevant to note that they are all characterized by managerial capabilities, as well as awareness and knowledge of agroecological interdependencies. As of 2005, USDA certified organic cropland and pastureland accounted for a very small percentage of the total harvested cropland, 1.3 percent (Greene, 2009). In Georgia, this figure shrinks to less than half of one percent, or 955 acres carrying such certification. Additionally, there are some farms that practice organic agricultural techniques, but, because of the cost of certification or previous land use management, they are not currently certified.

The acreage under grass-fed livestock, conservation agriculture, and uncertified organic farmland within Georgia is currently unavailable, though it will be a necessary component of this research to compile and estimate this amount in conjunction with certified organic acreage. Conservation agriculture's tenets include minimal soil disturbance, permanent soil cover, and crop rotations, though exercised with varying degrees of emphasis on an individual basis (Food and Agriculture Organization of the United Nations, Agriculture and Consumer Protection Department, Conservation Agriculture, 2008). Grass-fed livestock are not fed diets of grain, soy, and other supplements on feedlots but rather forage on pasture. Often times, these feeding practices also decrease the reliance and/or use of antibiotics, growth hormones, and other drugs, though the degree to which this occurs in practice is also variable based on an individual farm basis. When pastureland is managed according to this methodology in conjunction with cropland, the rotation between pasture and cropland can also yield improved soil fertility and quality. Again, it must be emphasized that these methods utilize active management of agricultural and natural resources. In Georgia, there are two primary organizations by which alternative agriculturalists are represented: (1) The Georgia Conservation Tillage Alliance (GCTA) and (2) Georgia Organics. Those raising livestock by feeding only grass are compiled by the American Grass-fed Association and Eatwild.com.

A large body of agronomic and soil science literature concludes that organic agriculture and conservation tillage can be effective management strategies for enhancing soil quality/health and thereby increasing soil water storage and water infiltration (Doran, 2002; Reeves et al., 2005; Triplett, Doren, and Schmidt, 1968). These characteristics translate into less irrigation water needing to be applied in order to achieve the same desired results. In regard to production, on average, organic farms are more efficient relative to their own technology, but use a less productive technology than conventional farms (Lansink, Pietola, and Backman, 2002). As such, our *a priori* expectation is that farms practicing such management techniques will be more efficient users of water than conventional farming; however, agricultural practices less sensitive to soil management may necessitate increased irrigation to maintain productivity on degraded soils (Tillman et al., 2002).

The ideal of increased irrigation efficiency implies a change in technology, management practices, or both (Skaggs and Samani, 2005). These changes can be manifest in additional cultural farm practices, such as deficit irrigation (applying less than full crop-consumptive requirements), shifting to alternative crops/varieties that require less water, or properly evaluating irrigation scheduling (Marlow, 1999). While the broader environmental concerns related to modern agriculture are of little analytical interest to this research, in consideration of water management, the effect of farm level compliance/adoption of conservational and environmental management techniques on water use behavior has yet to be studied.

2.6 Summary

Previous literature addressing the factors that affect water usage has not attributed, or considered, differences in agricultural practices between farms. Additionally, the body of water policy literature has focused its efforts on modeling homogenous groups of individuals/firms economic response to such policies. Among farmers, there is vast heterogeneity of which variation in water usage has yet to be credited. This research seeks to establish the presence, or absence, of variation in this outcome based on farm type (conventional vs. alternative) and farm size.

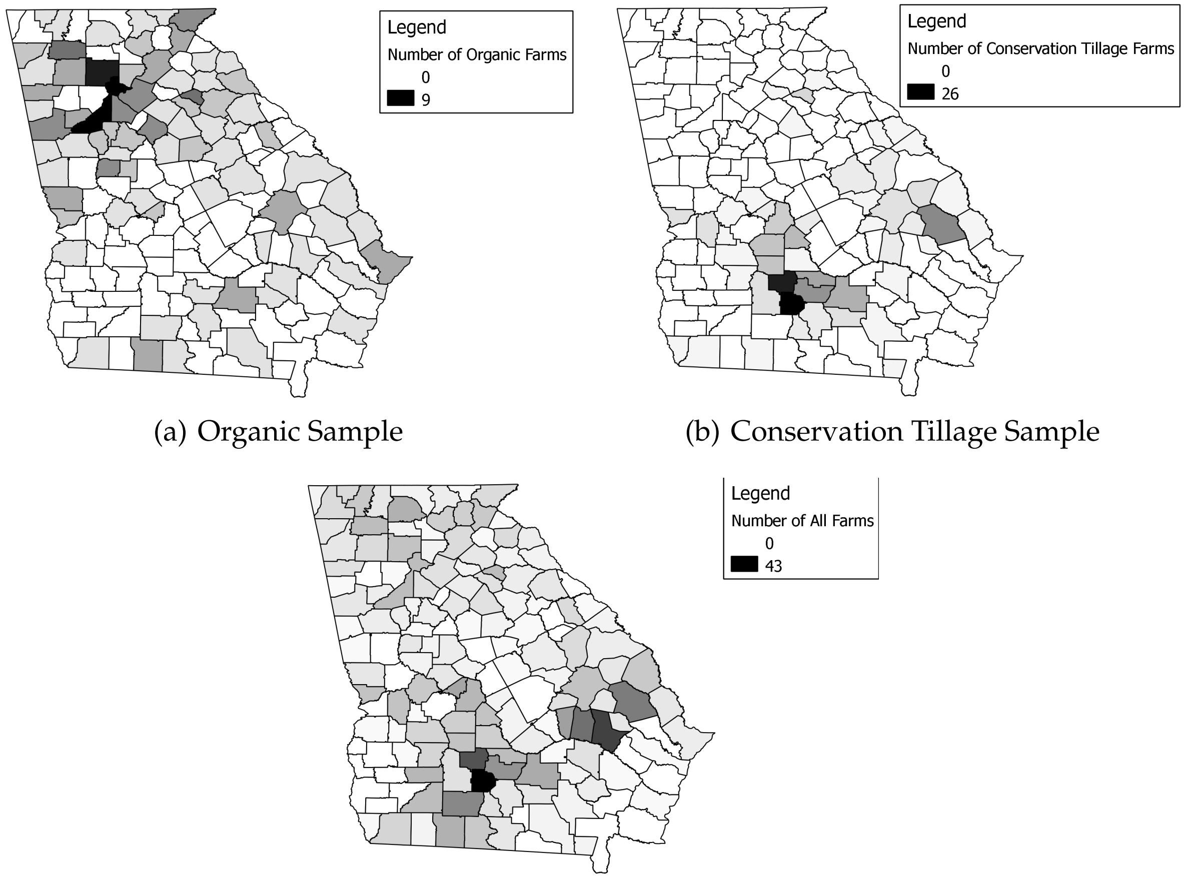
CHAPTER 3

METHODOLOGY

The overall goal of this research is to investigate how farm type and other farmer specific characteristics affect technical irrigation water use efficiency. Previous research has found significant statistical differences between large and small farms with regard to water use decisions because of farm-level characteristics, but research has not explored what, if any, of the variance in water usage can be attributed to differences in cultural farm practices. While agronomic literature concludes that agricultural techniques exist that can successfully increase physical characteristics, such as soil organic matter management and soil water capacity, the relationship between these techniques and technical efficiency of irrigation water use has not been thoroughly studied. Because of this gap in knowledge related to the factors which are external and internal to the farm and the subsequent effect of these factors on technical efficiency, this research will seek to quantify the internal factor's affect on technical efficiency in water usage. This information is important if future policy is to be effective in addressing water usage inefficiencies within the agricultural sector.

3.1 SURVEY DESIGN

This study utilizes researcher collected survey data from organic, conservation tillage, and conventional farms in order to investigate differences in technical water use efficiency between different farm types. Georgia has a relatively small number of farms employing alternative cultural strategies, of which all known affiliates were surveyed. As was mentioned in Chapter Two, these farms were identified based on their



(a) Organic Sample

(b) Conservation Tillage Sample

(c) Complete Survey Sample

Figure 3.1: Identified Survey Sample and Alternative Farms in Georgia

association with various alternative agriculture organizations throughout Georgia. These farmers are spread throughout the state with a large degree of variability in farm size, farm revenue, crops grown, and many other internal and external characteristics. The area of least representation is the Southern region, which is also the region that has the highest concentration of irrigation permits and farms (See Figure 3.1 and Figure 2.2).

A pilot survey was conducted in March 2009 with a small group of stakeholders, including key members of the organizations from which the sample was drawn, after which suggestions were taken into account and adjustments to the survey were applied.

Table 3.1: Survey Sample and Response Rates

Farm Type	Sample Size (%)	Undeliverable	Received	Response Rate
Total	769 (100)	84	157	22.9 %
Conventional	435 (56.6)	64	66	17.8 %
Conservation Tillage	173 (22.5)	13	45	28.1 %
Organic	161 (20.9)	7	46	29.9 %

After making these changes, an initial mailed survey was sent out in April 2009 to 769 farms. Non-respondents were mailed a second survey in May 2009. The unit of observation used in this study is the farm. Among these alternative farms, we expected an initial response rate in the order of 50 percent or greater due to the activist nature of many of these farms. Actual response rates are presented in Table 3.1.

Each survey participant was asked questions concerning farm demographics, production and water usage decisions (see Appendix A on page 114). This information included farm acreage, acres irrigated by crop, labor, average acre-inches of water applied, frequency of chemical use, and the degree to which various cultural farm practices were employed, such as conservation tillage, organic agriculture, cover cropping, green manure, etc.

The key farm-level characteristic is the type of cultural farm practices, coded as multiple dichotomous dummy variables equal to one for those who indicated they "frequently or regularly used" a particular cultural farm practice, and zero for those who farm without such method. Past research has not compared water usage between organic or conservation tillage and conventional farms. Production acreage is used as the primary measure of the effect of farm size on technical irrigation water use efficiency and refers to the quantity of total acreage with crops planted on it in 2008. In the DEA and SFA production frontier models, total acre inches applied is equal to the number of acres the farmer indicated were irrigated with surface water plus the number of acres irrigated with ground water multiplied by the respective average number of inches of water applied by source:

$$\begin{aligned}\text{Total Acre Inches} = {} & (\text{Irrigated Acreage}_{Ground} * \text{Average Inches per Acre}_{Ground}) \\ & + (\text{Irrigated Acreage}_{Surface} * \text{Average Inches per Acre}_{Surface})\end{aligned} \tag{3.1}$$

Figure 3.2 depicts a basic relationship seen in survey respondents between average inches of water applied per acre and total acreage in production drawn from the set of all survey respondents that were irrigators. The results illustrated in the figure are only slightly suggestive of what other authors have concluded: smaller farms use more water per unit of land. That is, the relationship is in essence horizontal and does not reflect that the amount of acreage under production is negatively related to the mean inches of water applied per acre.

Additional farm-level traits include business structure of the farm, labor employed, time spent farming, irrigation acreage allocation decisions, cropping pattern, crops grown, type of irrigation equipment used, years of farming experience, and motivation for farming. Business structure is a dummy variable coded as one for farms that are solely or family owned ,and zero for farms that are operated under a partnership or corporation. In regard to labor, the survey asked questions about the number of part-time and full-time laborers. Coelli et al. (2005) suggests that labor variables in a production are best measured as either the number of full-time laborers, labor days per season, or labor hours[1]. Given a 34 week growing season between the average first and last frost dates in Georgia, March 18th to November 15th, labor days was computed as (National Climatic Data Center, National Oceanic and Atmospheric Administration, U.S.

[1] All of these measures were tested for model performance. Labor days per season was determined to be the best measure of labor in this dataset.

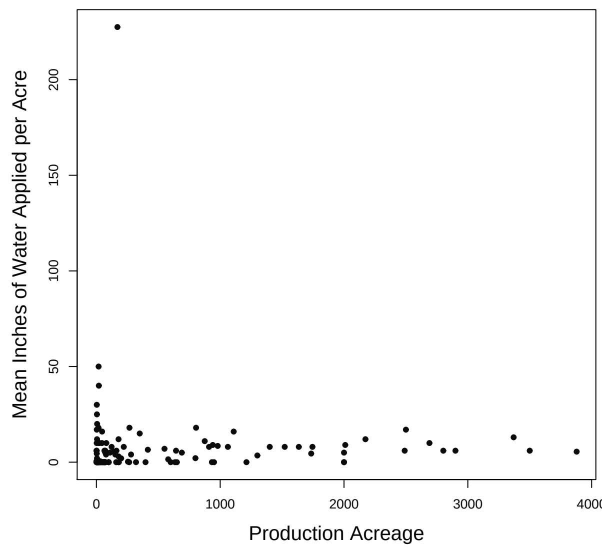


Figure 3.2: Scatter Plot of Average Inches of Water Applied per Acre and Production Acreage

Department of Commerce, 1988):

$$\text{Labor Days} = \left[\text{\# Full-time laborers} + \left(\text{\# Part-time laborers} * \frac{1}{2}\right)\right] * 5 \text{ Days per Week} * 34 \text{ Weeks per Season} \tag{3.2}$$

Two Herfindahl indexes, also known as Herfindahl-Hirschman Index (HHI), were computed to look at crop diversification with respect to the allocation of acreage and irrigated acreage. It assumes that an infinite number of alternative production choices are available to the farmer and can also be used as an effective indicator of farm manager skill (Chand, 1997). Herfindahl measures are bound between 0 and 1 and are inversely related to crop diversification such that a Herfindahl index value of one implies complete specialization/concentration in one crop while a value of zero implies absolute diversification. These indexes were calculated such that:

$$HHI^A = \sum_{i=1}^{N} (\% \; acreage_i)^2 \tag{3.3}$$

where $\%\ acreage_i$ is equal to the percentage of total production acreage that is used in the production of crop type i. The categories of crops were broken up into (1) field crops, (2) vegetables and melons, (3) fruit and orchard crops, (4) hay and forage crops, and (5) pasture or grazing land. The irrigation HHI is different in that $HHI^I = \sum_{i=1}^{N}(\%\ Irrigated\ Acreage_i)^2$ where $\%\ Irrigated\ Acreage_i$ is the percentage of total irrigated production acreage that is used in the production of crop type i[2].

In considering water usage, various crops have different water needs and are useful control variables as data permits. Similarly, variability in irrigation technology application rates requires a control for what kind of irrigation equipment is used when the data is sufficient for inclusion. The variables of business structure and motivation for farming are particularly useful for analyzing the relationship between factors that are internal and endogenous to the farm with water usage. Demographic variables include age, gender, years of education, and the percent of household income from farming. Percentage of income from off-farm employment is another measure that has been thoroughly researched and shown to be highly correlated with farm behavior, serving to capture some unmeasured characteristics associated with a farmer's capabilities as well as time away from farm-related activities.

While the total sample size equals 156 observations, only 112 of those observations were complete data points for the methods described in the following sections. Those observations that were unusable were missing data on either farm revenue, irrigated acreage, average inches of water applied per acre, or the number of laborers. Table 3.2 displays the means for the variables of interest of selected farm types and groups. Mean farm revenue is similar between farm types with the exception of large farms (Prod. Ac > 100) and small farms (Prod. Ac < 100). Large farms have a greater mean total acreage, production acreage, and irrigated production acreage, and it can be inferred that the reason this group of farmers has the highest mean farm revenue, 1.575 million dollars, is

[2]The division of the crops into categories is the same for both HHI measures.

Table 3.2: Variable Means by Farm Type

	Overall	**Organic**	**Cons. Tillage**	**Conventional**
Variable Mean	$(N = 112)$	$(N = 28)$	$(N = 56)$	$(N = 42)$
Farm Revenue ($)	904420	87857	924688	1168810
Total acreage (ac)	736.30	146.57	978.12	630.97
Total irrigation water (ac in)	3866.39	54.81	3034.85	6237.98
Total labor employed (days)	2264.64	549.46	1449.55	3934.29
Organic (1 = yes)	0.25	1	0.25	0
Conservation Tillage (1 = yes)	0.5	0.5	1	0
Business structure (1 = sole/family)	0.527	0.786	0.554	0.405
Full-time farmer (1 = yes)	0.642	0.444	0.764	0.550
Production acreage (ac)	698.05	136.47	947.57	588.17
Age (years)	56.70	54.46	58.71	54.49
Education (years)	15.41	16.21	15.21	15.32
Farming experience (years)	26.63	17.39	28.91	26.45
Income from farming (%)	0.492	0.335	0.608	0.416
Acreage Herfindahl [0,1]	0.761	0.710	0.798	0.720
Irrigation acreage Herfindahl [0,1]	0.587	0.572	0.661	0.458
Irrigated production acreage (ac)	388.17	14.92	465.97	412.13
Irrigator (1 = yes)	0.66	0.68	0.73	0.55

Table 3.3: Variable Means by Irrigators and Farm Size

	Overall	**Irrigators**	**Prod. Ac<100**	**Prod. Ac>100**
Variable Mean	$(N = 112)$	$(N = 74)$	$(N = 50)$	$(N = 62)$
Farm Revenue ($)	904420	1312027	102550	1576516
Total acreage (ac)	736.30	936.22	50.70	1308.71
Total irrigation water (ac in)	3866.39	5851.83	78.47	7034.63
Total labor employed (days)	2264.64	3234.60	572.90	3687.05
Organic (1 = yes)	0.25	0.26	0.44	0.01
Conservation Tillage (1 = yes)	0.5	0.55	0.36	0.62
Business structure (1 = sole/family)	0.53	0.54	0.66	0.43
Full-time farmer (1 = yes)	0.64	0.76	0.45	0.81
Production acreage (ac)	698.05	905.83	30.12	1264.63
Age (years)	56.7	56.0	55.9	57.6
Education (years)	15.41	15.41	15.74	15.12
Farming experience (years)	26.6	27.1	20.2	32.0
Income from farming (%)	0.49	0.58	0.32	0.64
Acreage Herfindahl [0,1]	0.76	0.80	0.76	0.77
Irrigation acreage Herfindahl [0,1]	0.587	0.875	0.463	0.699
Irrigated production acreage (ac)	388.17	576.85	10.00	703.48
Irrigator (1 = yes)	0.66	1	0.54	0.77

directly attributable to these characteristics. Within organic farms, 78.6 percent are solely/family owned and the farmers practicing these cultural practices are among the youngest, most educated, but least experienced of any other group. Additionally, while organic farms are similar in many respects to smaller farmers (Prod. Ac < 100), such as irrigated production acreage, total irrigation water applied, labor days, and percentage of household income from farming, they differ greatly on the basis of farm revenue and production acreage. Smaller farms produce less farm revenue on average and do so on the smallest mean production acreage of any other group. Farms that did not indicate that the cultural practices of conservation tillage or organic agriculture were frequently employed on-farm, thereby dubbed conventional, have the smallest percentage of solely/family owned farms relative to other groups.

In looking at the effect of farm type on the technically efficient use of irrigation water, the summary of potential determinants and the inputs in the production process by farm type/group helps to point out clear differences that exist among these groups. That is, while smaller and organic farms use the least total irrigation water, they also irrigate the fewest acres of land. Yet, almost 70 percent of organic farms irrigate, implying that while irrigation is prevalent among this farm type, it is small scale in nature. *A priori*, this stands to reason: organic farms have fewer available inputs that can be used as agricultural risk management tools. Irrigation water is not a restricted input for organic agriculture, whether certified through the United States Department of Agriculture or as an independent cultural farm practice, and it is expected that farms make the best use of the resources at their disposal as both risk management tools and additional inputs in the production process. This could have the effect of farmers on organic farms being able to more carefully micro-manage the use of water. Conversely, these farmers dampened experience farming could translate into a more haphazard and/or overabundant application of irrigation water. Alternatively to organic farms, a smaller proportion of conventional farmers irrigate, though they irrigate much more land. Large and

Table 3.4: Comparison of Sample to Georgia Farm Characteristics

Variable	**Georgia (2007)**[†]	**Survey Sample**
Average age (years)	57.8	56.3
Family or individually owned (%)	94.8	50.6
Full-time farmers (%)	42.0	63.8

[†] United States, National Agricultural Statistics Service (2009a)

conservation tillage farms have the highest proportion of irrigators but are the most experienced relative to the other identified farm types, on average.

In comparison to statewide averages as of the 2007 Census of Agriculture, our sample was similar to that of the state. Table 3.4 illustrates that the average farmer age in the sample was nearly identical. While approximately 95 percent of Georgia's farms are solely or family owned, half of Georgia's farms have no cropland in production. Most of the farms not in production are in this category, though direct statistics are not readily available. Approximately 50 percent of survey respondents indicated that they were family or solely owned, which seems to be a good comparison to the rest of cropland farms in Georgia. Finally, for seemingly obvious reasons, our sample included a far greater proportion of irrigators, and that fact is likely a contributing factor to the increased proportion of full-time farmers relative to the state average. That is, we would expect that full-time farmers are more likely to irrigate than part-time farmers. Figure 3.3 illustrates that on the basis of farm size, our sample has a lower percentage of farms in the 10 to 179 acre range relative to the rest of the state and a higher percentage of farms larger than 500 acres. There are pros and cons to this distribution; ideally, a sample of the population reflects the population, but since acreage is a key variable of interest, it is useful to see an even distribution at the different farm sizes.

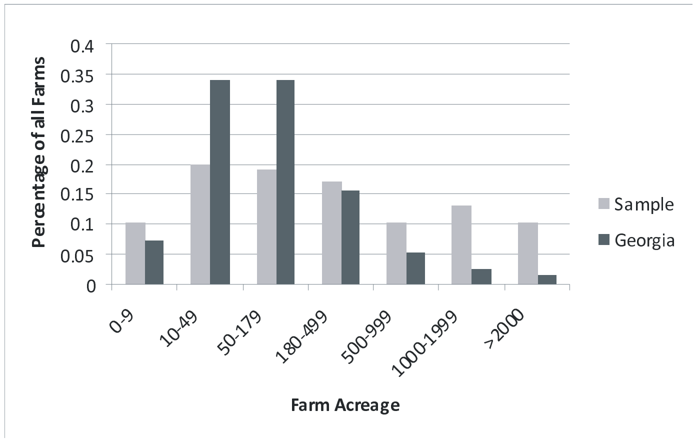


Figure 3.3: Farms by Size

Table 3.5 shows the observed characteristics and their correlation with total irrigated water applied. In Chapter Four, the analysis of this data goes beyond the effect of demographic and management characteristics on *quantity* of water used. All of these observed correlations are very weak with the exception of production acreage and total water applied, but this is only logical. That is, as production acreage increases, irrigators use more total irrigation water even if the average inches of water per acre remains constant.

3.2 Methodological Framework

The analysis of this research focuses on one primary aspect of efficiency: technical efficiency. More specifically, our analysis seeks to determine farm-level, input-specific technical measures for agricultural water use and then to ascertain the factors that determine whether a farmer/producer is a technically efficient user of water or a technically inefficient user of water. In general, input-specific technical efficiency

Table 3.5: Pearson Correlations Between Farm Characteristics and Water Use

	Correlation	
Variable	*Average Water/Acre*	*Total Water Applied*
Age	-0.0931	-0.1065
Gender	-0.2172*	-0.0200
Education	0.0485	0.0035
Years farming	-0.0702	0.0547
Full-time farmer	0.1318	0.2085*
Solely owned	-0.0675	-0.2258*
Production acreage	0.0179	0.6513*
Percentage of land owned	0.0806	-0.1561
Organic agriculture	-0.0134	-0.1583
Conservation Tillage	-0.0446	-0.0853

* indicates 95% significance level

indicates the ratio of minimum potential input required to produce the given output (Lovell, 1993).

Two primary techniques have been used in the literature to estimate input-specific technical efficiency: (1) Data Envelopment Analysis and (2) Stochastic Frontier Analysis. Both of these methods yield farm-specific overall technical efficiency scores, and the estimates of the respective models can be used to derive input-specific technical efficiency scores. In order to analyze the determinants of technical water use efficiency/inefficiency, a second step is employed in which these technical efficiency scores, estimated using Data Envelopment Analysis and Stochastic Frontier Analysis, are used as the independent variable in a Tobit regression model. In the case of stochastic production frontier efficiency measure, a Heckman sample selection model is also applied to address non-irrigators.

3.3 Estimating Technical Efficiency

> Efficiency measurement involves a comparison of actual performance with optimal performance located on the relevant frontier. Since the true frontier is unknown, an empirical approximation is needed. The approximation is frequently dubbed a 'best-practice' frontier.
>
> —Fried, Lovell, and Schmidt (2008)

A producer is an economic agent that takes a set of inputs and transforms them into a set of outputs Thanassoulis, Portela, and Despic (2008). Economic efficiency has technical and allocative components, where the technical component refers to the ability to avoid waste in the production process (Fried, Lovell, and Schmidt, 2008). Waste arises either by (1) producing less output than technology and input usage allow or (2) by using more inputs than are required by technology and output production. These two ways of viewing waste, or the technical component of economic efficiency, mean that the analysis of technical efficiency can be approached from an output-oriented or input-oriented frame of reference depending on the respective objective of the firm. In the case of agriculture, it is most reasonable to assume that producers (farmers) are more interested in making the best possible use of their inputs (i.e. input-oriented), rather than to maximize output at any cost to the quantity of inputs (i.e. output-oriented). That is, while it may be possible for producers to increase production by increasing the amount of inputs, the cost of doing so often makes this mindset an irrational objective. Since no input or output prices are used in this research, the notion of output-oriented technical efficiency will not be further addressed.

This study is restricted to the estimation of technical efficiency and the measures originally proposed by Farrell (1957). The measure of technical efficiency he developed is

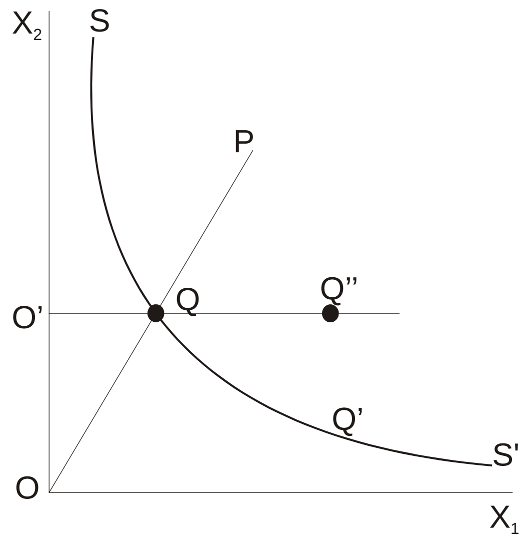


Figure 3.4: Input Technical and Subvector Efficiency

defined as the maximum radial reduction in all inputs that is feasible with given technology and outputs (input-conserving orientation). As shown in Figure 3.4, the isoquant SS' represents the proportions and quantities of the two inputs, X_1 and X_2, that can be used to produce a single unit of some output. The points Q and P represent the point of operation of two firms, where Q is the efficiently operating firm using the same ratio of inputs as the firm operating at point P. As Farrell (1957) noted, it can be seen that the firm operating at point Q uses only the fraction OQ/OP as much of each input to produce that same output as at P. Therefore, this fraction $\theta = OQ/OP$ is the technical efficiency of firm P, implying that firm P could reduce all inputs by $1 - \theta$ to produce the same quantity of output; firms producing beyond the SS' isoquant frontier are referred to as technically inefficient. In a similar way, the notion of subvector efficiency, proposed by Färe, Grosskopf, and Lovell (1994), is used to create technical efficiency measures for a subset of inputs based on a reduction of a single input (or a subset of inputs) while holding all other inputs and output fixed. Referring again to Figure 3.4, when compared to the firm operating at Q'' the firm operating at Q is producing the same amount of output with the same quantity of X_2 but a smaller amount of X_1. Therefore, a firm operating at Q'' could reduce input X_1 by $1 - \theta^w$, where $\theta^w = O'Q/O'Q''$ (the subvector efficiency).

3.3.1 Data Envelopment Analysis

Data envelopment analysis (DEA) is a nonparametric programming approach to calculating the technical efficiency score for a specific firm relative to the most efficient frontier. DEA uses mathematical programming to construct a piecewise linear isoquant to envelop the data and construct the frontier (Zhengfei and Lansink, 2003). Charnes, Cooper, and Rhodes (1978) proposed this relative efficiency measure based on linking inputs to outputs via an efficiency frontier under constant returns to scale. The variable returns to scale model was later introduced by Banker, Charnes, and Cooper (1984) and has been applied by Lansink, Pietola, and Backman (2002) and others, given by[3]:

$$\begin{aligned} \underset{\theta_i,\lambda}{Min}\, \theta_i \; subject\ to \\ -y_i + Y\lambda \geq 0 \\ \theta_i x_i^v - X^v\lambda \geq 0 \\ \theta_i x_i^f - X^f\lambda = 0 \\ N1'\lambda = 1 \\ \lambda \geq 0 \end{aligned} \tag{3.4}$$

where θ_i is a scalar representing the overall technical efficiency score ($\theta_i \in (0, 1]$) for the i^{th} firm, $N1$ is a vector of ones, and λ is a vector of constraints containing intensity variables/firm weights. When $\theta_i = 1$, the firm is technically efficient and lies on the frontier; $1 - \theta_i$ represents the maximum proportional reduction of all inputs, holding output fixed. The observed output and inputs are given by Y the vector of observed

[3]For consistency of notation in model comparison, the models as they are more traditionally represented may be adjusted.

output, X^v is the matrix of observed variable inputs, and X^f is the vector of the observed fixed input in which the observed output and inputs for the i^{th} firm (y_i, x_i^v, x_i^f) is the i^{th} row of Y, X^v, and X^f. The constraints imposed in this mathematical programming model ensure (from top to bottom) that (1) the firm producing output y_i does not produce more than on the frontier, (2) and (3) the proportional decrease in input use does not exceed that achieved when the best technology is observed, and (4) creates a variable returns to scale (VRS) specification.

Implicit in constraints (2) and (3) are the notions of strong and weak disposability of inputs, respectively. According to Färe, Grosskopf, and Lovell (1994), strong disposability refers to the ability of a producer to dispose of an unwanted input at no private cost; weak disposability must be disposed with additional, positive private costs by the producer. The DEA model applied in this research follows in the assumption that all the observed inputs used in agricultural production are freely disposable (strong disposability). While labor congestion can be observed in rare cases, this is not a standard scenario faced by agricultural producers. Similarly, returns to scale refers to the output that is produced for a proportional increase in all inputs. The VRS constraint relaxes the long run economic assumption that firms operate in the constant returns to scale (CRS) region of their production surface. For example, if a farm were to double all inputs and observe double output, the farm would be operating under CRS; however, if the inputs were doubled and output increased by more or less than double, the farm would be operating under VRS. The VRS assumption allows for the reality that some farms use levels of inputs that, when doubled are transformed into less, equal to, or more than double output.

In addition to overall technical efficiency scores, DEA techniques can be used to estimate a technical efficiency score for a single input rather than for entire vector of inputs. Input-specific technical efficiency, or subvector technical efficiency as it is most commonly referred to, can be computed following Färe, Grosskopf, and Lovell (1994). In the case of irrigation water use, this subvector, input-specific technical efficiency score is interpretable as a measure of excess water use (Lilienfeld and Asmild, 2007). Subvector technical efficiency is given by:

$$\begin{aligned} \underset{\theta_i^w,\lambda}{Min}\, \theta_i^w \, subject\, to \\ -y_i + Y\lambda \geq 0 \\ x_i^{v-w} - X^{v-w}\lambda \geq 0 \\ \theta_i^w x_i^w - X^w\lambda \geq 0 \\ x_i^f - X^f\lambda = 0 \\ N1'\lambda = 1 \\ \lambda \geq 0 \end{aligned} \tag{3.5}$$

where θ_i^w is the input x^w subvector technical irrigation efficiency score for firm i. This subvector efficiency score, θ_i^w, represents the maximum reduction in input x^w holding outputs and all other inputs fixed. The terms x_i^{v-w} and X^{v-w} represents the matrix of variable inputs where the column including the variable input total acre inches of water applied, x^w, is removed. In this form of the mathematical programming model, constraint (2) and (4) are no longer interacted with θ_i as we are now interested in the maximum proportional reduction in irrigation water only, $1 - \theta_i^w$. The estimation of subvector efficiency via DEA requires that non-irrigators be excluded from the frontier construction.

DEA lends itself well to calculating input-specific, or subvector, technical efficiency measures and is more appropriate for smaller samples as opposed to econometric methods such as stochastic frontier analysis (Färe, Grosskopf, and Lovell, 1994). However, DEA is deterministic and sensitive to measurement error and other noise in the data. The use of Data Envelopment Analysis has become popular in the banking/finance literature because of its ability to rank a small number of firms relative to each other based on some output of interest without degrees of freedom concerns. In industries such as banking and semiconductors, firms have considerable or complete control over their physical production environment (Sherlund, Barrett, and Adesina, 2001). In the case of agricultural production, any number of issues can arise when trying to apply this particular method, such as the aforementioned measurement error or environmental conditions that vary across geographic regions; the use of survey data in this research exacerbates this potential. When environmental production conditions, such as rainfall, can be incorporated in a DEA production frontier, this inclusion implies that they are inputs in the production process. This assumption may not always be valid as the farmer has no choice as to what level of rainfall he applies. Further, while support for small samples exists because of the nonparametric nature, the application of DEA to less than ideal data often leads to undesirable or inaccurate conclusions regardless of sample size. The survey data we employ is limited in this regard in that many of the typical inputs used in agricultural DEA applications is not in a quantified form, but rather is only indicated by the respondents on the basis of frequency. The incorporation of a statistical error term, via stochastic production frontier, is seen as the preferable method in the presence of data limitations, when sample size permits.

Following a variable returns to scale, input-oriented specification in which strong disposability of the fixed input (land) and strong disposability of all other variable inputs (labor, water, fertilizer, insecticide, and compost) and output (farm revenue) is assumed. While DEA is capable of handling ordinal data (Lotfi, Firozja, and Erfani, 2009), such as the fertilizer, insecticide, and compost measures derived from the survey responses, the lack of standard parameter estimates makes it difficult to assure the 'marginal effects' of these inputs are not unrealistic. As such, their inclusion in Chapter Four is only for comparative purposes.

3.3.2 Stochastic Frontier Analysis

The econometrically based Stochastic Frontier Analysis (SFA) approach, as suggested independently by Aigner, Lovell, and Schmidt (1977) and Meeusen and Broeck (1977), incorporates the statistical noise of conventional econometric analysis. For a producer i using inputs x_{ji} to produce output y_i with a given technology:

$$y_i = f(x_{ji}; \alpha) \exp\{\varepsilon_i \equiv v_i - u_i\} \tag{3.6}$$

where α is a parameter vector characterizing the structure of production technology, $f(x_{ji}; \alpha)$ is the deterministic production frontier, and ε_i is the error term. Given a parameter vector α, $f(\cdot)$ is a function that reflects the expected output level y_i for a farm with characteristics x_{ji}. Implicitly assumed in any production function is that firms attempt to maximize the observed output produced by inputs. In the context of frontier estimation $f(x_{ji}; \alpha)$ is the frontier, or what observed output should be. Typically observed output is less than the frontier because of inefficiency and other reasons. As is reflected in the general form of a stochastic production frontier, the error term, ε_i, is comprised of v_i, the random disturbance term and u_i, the technical inefficiency component of the error term. Figure 3.5 illustrates the basic features of stochastic production frontier analysis. The pictured production function exhibits decreasing returns to scale, though this assumption is not necessary for the estimation of a frontier. Inputs are displayed on the horizontal axis and output on the vertical axis. The usual, symmetric, mean zero random error term, v_i, captures all idiosyncratic errors for farmer i and is assumed to be distributed $N(0, \sigma_v^2)$. A second, non-negative, error term component, u_i, represents unmeasured variation in the production of y_i that is attributable to technical inefficiency and follows either a half-normal or an exponential distribution. These two error components, v_i and u_i are assumed to be independent. In Chapter Four, the normal-exponential model is applied such that the probability density

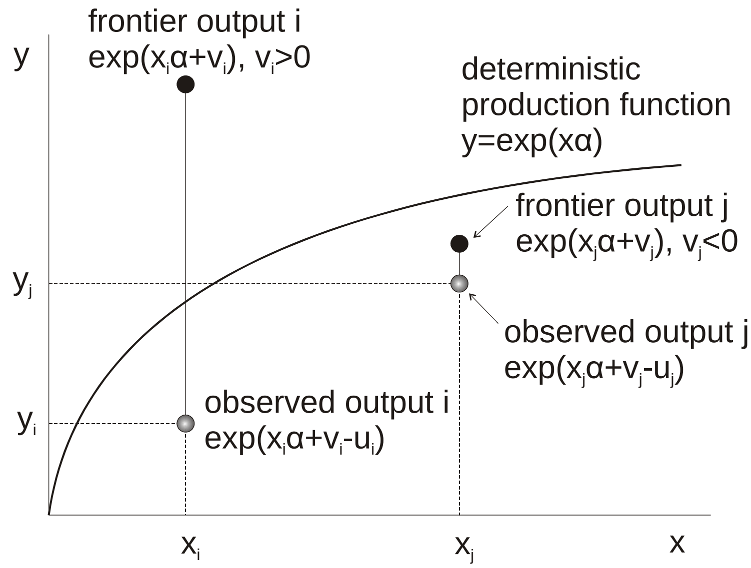


Figure 3.5: Stochastic Production Frontier

function (pdf), ϕ, is given by:

$$f(u_i;\kappa) = \begin{cases} \kappa e^{-\kappa u_i} & : u_i \geq 0 \\ 0 & : u_i < 0 \end{cases} \tag{3.7}$$

In the exponential model, $\sigma_u = 1/\kappa$. Because of the random sampling assumption, the joint distribution is simply the product of the densities. The maximum likelihood principle says that out of all the possible values for κ, the value that makes the likelihood of the observed data largest should be chosen (Wooldridge, 2002). Maximum likelihood estimation (MLE) is performed to find estimates of the structural parameters in the model. With these assumptions,

$$\ln L(\alpha, \sigma_v, \sigma_u) = \sum_{i=1}^{N} \left[-\ln \sigma_u + \frac{1}{2}\left(\frac{\sigma_v}{\sigma_u}\right)^2 + \ln \Phi\left(\frac{-(\varepsilon_i + \sigma_v^2/\sigma_u)}{\sigma_v}\right) + \frac{\varepsilon}{\sigma_u}\right] \tag{3.8}$$

where Φ is the standard normal cumulative distribution function (cdf), such that,

$$\Phi(z_i) = \int_{-\infty}^{z} \phi(t)dt, \quad \text{where } \phi(z) = \frac{1}{\sqrt{2\pi}} e^{-z^2/2} \tag{3.9}$$

and

$$z_i = \frac{-(\varepsilon_i + \sigma_v^2/\sigma_u)}{\sigma_v} \tag{3.10}$$

A further expansion of the general form is helpful for the development of input-specific technical efficiency scores derived from the econometric estimation of the stochastic production frontier:

$$y_i = f(x_{ji}, w_i; \alpha)\exp\{\varepsilon_i \equiv v_i - u_i\} \tag{3.11}$$

in which w_i is the single input, irrigation water, and x_{ji} is all other inputs (land and labor) used in the production of y_i (farm revenue). When applied to a translog production function, the technology is described by:

$$\begin{aligned}\ln(y_i) = \alpha_0 + \sum_{j=1}^{J}\alpha_j \ln(x_{ji}) + \frac{1}{2}\left(\sum_{j=1}^{J}\sum_{k=1}^{J}\alpha_{jk}\ln(x_{ji})\ln(x_{ki})\right) \\ + \alpha_w \ln(w_i) + \frac{1}{2}\left(\alpha_{ww}\ln(w_i^2) + \sum_{j=1}^{J}\alpha_{jw}\ln(x_{ji})\ln(w_i)\right) + v_i - u_i\end{aligned} \tag{3.12}$$

The variables α_j represent the first-order coefficients on acreage and labor while α_w is the estimated parameter on total acre inches of irrigation water, and the components α_{jj} and α_{ww} are the squared terms for these inputs, respectively. Finally, α_{jk} represents the interaction terms between land and labor while the α_{jw} variables is the coefficient on the interaction terms between water and the other inputs of production, land and labor.

Kumbhakar (1988) first noted that the technical efficiency measures of Aigner, Lovell, and Schmidt (1977) and Meeusen and Broeck (1977) were aggregate measures that comprised the inefficiency of all inputs jointly, and were, therefore, ineffectual measures of input-specific inefficiency. Following Reinhard, Lovell, and Thijssen (1999, 2000), input-oriented, single factor, technical irrigation water efficiency is derived by:

$$\theta_i^w = exp\left[\frac{-\zeta_i \pm \sqrt{\zeta_i^2 - 2\alpha_{ww}u_i}}{\alpha_{ww}}\right] \tag{3.13}$$

where,

$$\zeta_i = \frac{\partial \ln(y_i)}{\partial \ln(w_i)} = \alpha_w + \sum_{j=1}^{J}\alpha_{jw}\ln(x_{ji}) + \alpha_{ww}\ln(w_i) \tag{3.14}$$

It should be noted that with a Cobb-Douglas production function given by,

$$y_i = \prod_{j=1}^{J} x_{ji}^{\alpha_j} \tag{3.15}$$

the single factor, input-specific efficiency calculation reduces down to $\theta_i^w = e^{-u_i/\alpha_w}$ which provides the same ranking as the technical efficiency scores where $\theta_i = e^{-u_i}$ and, therefore, no additional information. As such, we will constrain the use of SFA for our purposes to the translog specification. However, a Cobb-Douglas will be used to verify the validity of the translog functional form. Using SFA, a standard Cobb-Douglas production function, $\ln(y_i) = \alpha_0 + \sum_{j=1}^{J} \alpha_j \ln(x_{ji})$, is estimated as a linear relationship in the same way as a translog specification. Such a production function has certain benefits over a translog specification in that it requires fewer explanatory variables to estimate, (no interaction or squared terms) requiring fewer degrees of freedom. Second, the coefficients in a Cobb-Douglas production function, α_j are directly interpretable as elasticities. A good check of model performance and uniformity across production functions is to compare the estimated elasticities.

Up until now, the models presented have maintained the assumption that the variance of the error term, $\sigma^2 = \sigma_v^2 + \sigma_u^2$ is homoscedastic such that, $sigma_v^2 = \exp\{\psi_0\}$, a constant. SFA further allows for the specification of the form of heteroskedasticity in σ_v^2, and/or σ_u^2. Since we are not interested in modeling the inefficiency error component in this stage, our modeling framework focuses on the idiosyncratic error term component. This random disturbance includes factors exogenous to the farmer and farm, including most notably weather. When modeling over a large geographic area, as is the case with the state of Georgia, weather patterns can differ greatly across regions, thereby affecting agricultural output. Precipitation is one such weather factor that can identify different climatic patterns or regions over a particular area. As such, the following error model is explored, where p_i is average total county precipitation in 2008.

$$\sigma_v^2 = \exp\{\psi_0 + \psi_1 p_i\} \tag{3.16}$$

Accounting for the effect of local precipitation patterns enables all observations, irrigators and non-irrigators, to be estimated with the same deterministic frontier equation. Referring again to Figure 3.5, each farms frontier output differs according to the magnitude and direction of v_i. Under the heteroskedastic assumption of v_i, each farm faces different idiosyncratic events. If local precipitation patterns are a positive factor in the production of farm revenue, frontier output exceeds the deterministic production function and vice versa if negative. Whereas DEA is limited in its ability to account for stochastic weather events, thereby preventing the full ranking of all farmers, the incorporation of precipitation can explain why non-irrigators are able to produce output along the same frontier as farms that irrigate.

3.4 Determinants of Technical Irrigation Water Use Efficiency

The next step is to identify the determinants of inefficiency using DEA and SFA calculated efficiency measures, censored between 0 and 1. A common approach is the estimation of a second-step relationship between the efficiency measures and suspected correlates of efficiency. Two applicable models to this research and the dependent variable, subvector technical efficiency scores for irrigation water use are the Tobit and Heckman models.

3.4.1 The Tobit Model

Using technical irrigation water use efficiency as the dependent variable, a Tobit model is employed to determine the relationship between farm type, size, and other farm-level characteristics because of the censored nature of technical efficiency ($\theta_i \in (0, 1]$). The Tobit model, originally proposed by Tobin (1958), is one designed to handle a limited dependent variable that is roughly continuous over strictly positive values, but is zero for a nontrivial fraction of the population. For example, in the population of farmers in Georgia, the variable θ_i^w, technical irrigation water use efficiency, can take on an infinite range of values. Within the population, not all of the farmers are efficient irrigators, and therefore, there will be a nontrivial number of farmers that have an irrigation efficiency score of zero[4]. Thus, because the dependent variable is not always observed, it is latent.

The general Tobit model is given by:

$$\theta_i^{w*} = \beta_0 + \beta_1 d_{1i} + \ldots + \beta_j d_{ji} + \epsilon_i = \mathbf{d}\beta + \epsilon_i$$
$$\theta_i^{w} = \begin{cases} \theta_i^{w*} : 0 < \theta_i^{w*} < 1 \\ 0 \quad : \quad \theta_i^{w*} < 0 \\ 1 \quad : \quad \theta_i^{w*} > 1 \end{cases} \tag{3.17}$$

where θ_i^w is the DEA subvector efficiency index for water or the SFA computed input-specific efficiency score. The matrix of independent variables $\mathbf{d}$, is composed of each d_{ji} including dummy variables for farm type, family/sole ownership, and whether the farm manager is employed fulltime or part-time. The continuous variables included in $\mathbf{d}$ include production acreage, age, years of education, years of farming experience, the percentage of household income from farming, acreage allocation Herfindahl index, and irrigation acreage allocation Herfindahl index. The subvector irrigation efficiency score is distributed Normal with a mean of zero and variance σ^2 such that $\theta_i^w \sim N(0, \sigma^2)$.

Following Wooldridge (2002) and Greene (2002), the density function of θ_i^w given $\mathbf{d}$ is the same as the density of θ_i^{w*} given $\mathbf{d}$ such that,

$$\begin{aligned} P(\theta_i^w = 0 \mid \mathbf{d}) &= P(\theta_i^{w*} < 0 \mid \mathbf{d}) = P(\epsilon < -\mathbf{d}\beta) \\ &= P\left(\frac{\epsilon}{\sigma} < -\frac{\mathbf{d}\beta}{\sigma}\right) = \Phi\left(-\frac{\mathbf{d}\beta}{\sigma}\right) = 1 - \Phi\left(\frac{\mathbf{d}\beta}{\sigma}\right) \end{aligned} \tag{3.18}$$

[4]SFA computed efficiencies approach zero, while DEA scores equal zero.

from which the log-likelihood function can be derived as:

$$\begin{aligned}\ln L(\beta,\sigma) = &-\frac{1}{2}\overbrace{\sum_{0>\theta_i^w>1}\left[\left(\frac{\theta_i^w-\mathbf{d}\beta}{\sigma}\right)^2+\ln 2\pi\sigma^2\right]}^{\text{non-censored observations}} \\ &+\underbrace{\sum_{\theta_i^w=0}\ln\Phi\left(\frac{\theta_i^w-\mathbf{d}\beta}{\sigma}\right)}_{\text{left censored observations}}+\underbrace{\sum_{\theta_i^w=1}\ln\left[1-\Phi\left(\frac{\theta_i^w-\mathbf{d}\beta}{\sigma}\right)\right]}_{\text{right censored observations}}\end{aligned} \tag{3.19}$$

As is reflected in Equation 3.19, the log-likelihood function is merely the sum of the log-likelihoods of the censored and non-censored observations. After estimating a Tobit model, the expected, unconditional value of the realized variable, θ_i^w is computed as,

$$E(\theta_i^w \mid \mathbf{d_i}) = \Phi_i\left(\mathbf{d_i}\beta+\sigma\frac{\phi_i}{\Phi_i}\right)+(1-\Phi_i)C \tag{3.20}$$

where C is the value at which θ_i^w is censored, 0 or 1. Tobit parameter estimates are interpreted as the marginal effect of d_j on θ_i^w.

3.4.2 The Heckman Sample Selection Model

In the case of irrigation efficiency estimates derived from parameter estimates of the stochastic production frontier, scores cannot be computed for the entire sample. The reason for this in our case is at least twofold. First, the model must be a good fit for the data, and second, the farmer must irrigate in order to have an irrigation efficiency score. In the case of SFA, input-specific efficiency scores are not always observed via computation; this is an issue of incidental truncation, rather than censoring. That is, the rule determining whether we observe θ_i^w does not directly depend on the the outcome of θ_i^w (Wooldridge, 2002). If the farmer was actually irrigating at the time of the survey, then we observe the irrigation efficiency score because we assume it is the computed irrigation efficiency score. But, for farmers choosing not to irrigate, we cannot observe their irrigation water use. Therefore, the truncation of θ_i^w is incidental because it depends on another variable, namely, irrigation participation. Finally, observations on θ_i^w are recorded/computed only when another variable, z_i (see Equation 3.21), takes on values above 0, the sample is called sample selected.

The Heckman sample selection model, or Heckit model as it is also referred to, was originally proposed by Heckman (1976) to address the violation of the Gauss-Markov assumption of zero correlation between the independent variables and the error term. The two-stage estimation approach of Heckman is, in the first-stage a probit model estimated on the probability of observing an outcome and in the second-stage, an ordinary least squares (OLS) estimation with the inverse Mills' ratio as an additional explanatory variable. The inverse Mills' ratio, estimated from the first-stage probit model, can correct for possible selection bias in OLS.

The general form of handling incidental truncation is to add an explicit selection equation (Wooldridge, 2002):

$$\begin{aligned} \theta_i^{w*} &= \beta_0 + \beta_1 d_{1i} + \ldots + \beta_j d_{ji} + \epsilon_i = \mathbf{d}\beta + \epsilon_i \\ \theta_i^{w} &= \begin{cases} \theta_i^{w*} & : z_i = 1 \\ \text{not observed} & : z_i = 0 \end{cases} \\ z_i^* &= \delta_0 + \delta_1 s_{1i} + \ldots + \delta_k s_{ki} + e_i = \mathbf{s_i}\delta + e_i \\ z_i &= \begin{cases} 0 : z_i^* \leq 0 \\ 1 : z_i^* > 0 \end{cases} \end{aligned} \tag{3.21}$$

where $\theta_i^{w*} = \mathbf{d}\beta + \epsilon_i$ is the outcome equation used in the Tobit model (see Equation 3.17 on page 50) and $z_i^* = \mathrm{s}\delta + e_i$ is the selection equation. Furthermore, $\mathbf{d} \subset \mathrm{s}$ such that any d_j is also an element of s and there are some elements of s that are not also in $\mathbf{d}$. That is, there must be additional variables that affect participation in irrigation, but not subvector irrigation efficiency. The error terms (ϵ_i, e_i) are assumed to come from a bivariate Normal distribution with parameters σ_ϵ^2, σ_e^2, and ρ such that,

$$\begin{aligned}
\epsilon_i &\sim N(0, \sigma) \\
e_i &\sim N(0, 1) \\
corr(\epsilon_i, e_i) &= \rho
\end{aligned} \tag{3.22}$$

Breen (1996) and Wooldridge (2002) go on to show that if ϵ_i and e_i are jointly normal with zero mean, then $E(\epsilon_i \mid e_i) = \rho e_i$ for some parameter ρ, implying that,

$$E(\theta_i^w \mid s_i, e_i) = \mathbf{d}\beta + \rho e_i \tag{3.23}$$

Finally, because z_i and e_i are related by Equation 3.21,

$$E(\theta_i^w \mid s_i, z_i = 1) = \mathbf{d}\beta + \rho\lambda(\mathbf{s}\delta) \tag{3.24}$$

where λ is the inverse Mills' ratio when $s = 1$.

Heckman's model is equivalent to the combination of a OLS regression for the outcome and a Probit model for participation where the Probit equation is given by,

$$P(z = 1 \mid \mathbf{s}) = \Phi(\mathbf{s}\delta) \tag{3.25}$$

The full log-likelihood function is then:

$$\begin{aligned}
\ln L = -\frac{1}{2} & \overbrace{\sum_{0 \le \theta_i^w \le 1} \left[\ln\left(2\pi\sigma_\epsilon^2\right)\right] + \left[\frac{\theta_i^w - \mathbf{d}\beta}{\sigma_\epsilon}\right]^2}^{\text{OLS}} \\
& \underbrace{+ \sum_{z_i = 0} \ln(1 - \Phi_i) + \sum_{z_i = 1} \ln \Phi \left[\frac{\mathbf{s}\delta + \rho\left(\frac{\theta_i^w - \mathbf{d}\beta}{\sigma_\epsilon}\right)}{\sqrt{1 - \rho^2}}\right]}_{\text{Probit}}
\end{aligned} \tag{3.26}$$

The interpretation of coefficients in a Heckman model are less intuitive than the parameter estimates in other standard regression models or even the marginal effects associated with Tobit models. The presence of the same variables in both the outcome and selection equation makes this direct evaluation not feasible; however Sigelman and

Zeng (1999) proposed the marginal effects of d_{ji} on the conditional expectation of θ_i^w could be computed by:

$$\frac{\partial E(\theta_i^w \mid z^* > 0, \mathbf{d})}{\partial d_j} = \beta_j - \delta_j \rho \sigma_\epsilon \omega(\mathbf{s}\delta) \tag{3.27}$$

where $\omega = \lambda(\mathbf{s}\delta)[\lambda(\mathbf{s}\delta) + \mathbf{s}\delta]$ and the inverse Mills ratio $\lambda(\mathbf{s}\delta) = \phi(\mathbf{s}\delta)/(1 - \Phi(\mathbf{s}\delta))$.

3.4.3 Robust Standard Errors using Sampling Weights

As with most econometric models, an underlying assumption is that the observations are independent, and identically distributed ($i.i.d.$). The assumption of independent and identically-distributed random variables asserts that each random variables has the same probability distribution and they are all mutually independent. Estimation with robust standard errors, via stratification and sampling weights, is an effective corrective measure when dealing with data from surveys that are often designed in such a way that observations are not $i.i.d.$ (Deaton, 1997). That is, farmers were sampled based on their known affiliation to specialized farmer organizations in order to obtain enough observations of organic farmers and those employing conservation tillage for the desired statistical analysis. Therefore, by construction, observations from different strata belong to at least partly different populations; this means that they are not $i.i.d.$ Stratification typically reduces standard errors, especially in small samples. In correcting for known stratification, the implementation of 'inflation factors' imposes weights on each observation to represent a certain share of the population. Broadly speaking,

$$Weight = \frac{1}{\text{Prob. of Selection}} = \frac{\text{Sub-group Population}}{\text{\# of Observations in Sub-group}} \tag{3.28}$$

One of three stratum was assigned to each observation for the purpose of robust standard error estimation based on the farmers survey responses: (1) organic farm, (2) conservation tillage, and (3) conventional farm type. The observations in each strata were then given a weight to reflect their sub-groups population. Sampling weights are assigned according to the total number of farms in the particular stratified group. In the

Table 3.6: Assumed Cropland Farm Sub-group Populations

Group	**Population**
Total cropland farms	31,924
Conventional	20,650
Conservation tillage	11,119
Organic	154

case of organic farms, the sum of all acreage owned or rented by farms indicating they are an organic farm is greater than the total amount of certified organic acreage in Georgia. Therefore, we can assume that the sample frame was the full population and base weights on the total number sampled. In the case of conservation tillage farms, the population is more uncertain. Estimates for the amount of acreage under conservation tillage in Georgia differ based on crop and source, ranging from a conservative 20 percent to a generous 50 percent (Hollis, 2007; Culpepper et al., 2009). For our purposes, the population of farms practicing conservation tillage techniques was assumed to be the mean of this minimum and maximum at 35 percent of the total number of farms with cropland in Georgia. The remainder of farms were assumed to be the population of conventional farms shown in Table 3.6.

3.5 Summary

This chapter has provided an outline of the methodological approach to data collection, sample selection, and data analysis that was utilized in this research. Some of the pertinent limitations were introduced, while attention was paid to the importance of more concretely understanding water usage decisions among agriculturalists. In Chapter Four, the results of this analysis will be presented.

CHAPTER 4

RESULTS

In this chapter, the farm-level Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) models are used to examine technical efficiency in water usage. Secondly, the relationship between technical irrigation water use efficiency and farm characteristics, cultural farm types, and demographic traits of the farmer are then estimated with Tobit and Heckman models.

To facilitate the discussion, the chapter is organized in three primary sections. The first section describes the results of the technical efficiency estimates produced through Data Envelopment Analysis and Stochastic Frontier Analysis. This section concludes with a brief summary of the functional differences between DEA and SFA approaches, and the results of each modeling technique are compared. In section two of the chapter, Tobit and Heckman models are applied to the DEA and SFA technical efficiency estimates followed by an analysis of the relationships that are illustrated; a comparison of the Tobit results concludes this section.

4.1 TECHNICAL EFFICIENCY ESTIMATES

Overall technical efficiency and input-specific, technical efficiency of irrigation water use estimates were produced using DEA and SFA modeling techniques. The DEA results were computed with the software package OnFront (Economic Measurement and Quality, 2000), and the SFA results were estimated using Stata StataCorp (2007). While DEA is non-stochastic and therefore susceptible to statistical noise, SFA is parametric and therefore susceptible to misspecification of the functional form.

In developing these models, we draw on conventional economic production theory to select inputs most relevant to the production process. The three common divisions in production inputs are land, labor, and capital. An underlying assumption of such models is homogeneity of the firms in the technology employed and outputs produced. That is, each farm is assumed to produce outputs that are identical to consumers. Similarly, land, labor, and capital inputs are assumed to be equally productive for every farm, implying that production technology is the same across farms. Given sufficient sample size, when these assumptions do not hold true across different subgroups of firms or farms, subgroups can be modeled separate from one another and then compared based on relationships of computed relative efficiency scores. Conceptually, organic and conventional farms both produce agricultural goods. However, if consumers view these products as distinctly different or if the factors of production vary between organic and conventional on the basis of productivity, than these two subgroups of farms are not homogeneous. Lansink, Pietola, and Backman (2002) found that organic farms are more efficient in production relative to their own technology but use a less productive technology by estimating organic and conventional farms on unique DEA frontiers. Depending on the research question, this approach may be preferable when the observed output is measured in terms of quantity and not gross revenue. That is, if unique frontiers are constructed for each subgroup of the farmer population, all variation between subgroups is already accounted for. Given that this research is primarily interested in accounting for differences in efficiency between all farmers rather than differences within subgroups, we employ a production model through DEA and SFA with all farm types such that:

$$y_i = f(Acreage, Labor, Irrigation\,Water) \tag{4.1}$$

where *Acreage* is total farm acreage, *Irrigation Water* is total number of inches of water applied, and *Labor* is the number of labor days in 2008 as computed in Equation 3.2 on page 31. Because of the ability of DEA to support ordinal measures, we expand the production model in Equation 4.1 to include additional levels of input use:

$$y_i = f(Acreage, Labor, Irrigation\ Water, Fertilizer, Insecticide, Compost) \qquad (4.2)$$

The variables *Fertilizer*, *Insecticide*, and *Compost* are discrete measures of the frequency of application/use and are bounded on the interval $[0, 1]$. Table 4.1 summarizes these variables. In order to be included in the usable sample, the observations had to have complete information for farm revenue and the number of part-time and full-time laborers. The second exclusion restriction was that those farms that irrigated in 2008 had to include an estimate of average inches of irrigation water per acre and total number of acres irrigated or they were excluded from the usable sample. Of the original sample ($n = 156$), 14 observations were missing data on farm revenue, 2 on the number of laborers, and 22 failed to report an estimate of average per acre water use. Further, in order to be in the usable sample for the expanded DEA production function, given by Equation 4.2, the observations also must have data about the frequency of fertilizer, insecticide, and compost available; 6 observations were missing information on these additional inputs. After accounting for surveys with incomplete data, the total sample of irrigators and non-irrigators is $n = 112$.

4.1.1 Data Envelopment Analysis Efficiency Estimates

As discussed in Chapter Three, DEA is a linear programming model in which decision-making units (DMUs) are compared to one another on the basis of their output given an observed quantity of inputs. According to economic production theory, firms have two frameworks in which to transform inputs into output. Essentially, a firm is either input-oriented or output-oriented depending on the objectives of the firm. An input-oriented model was chosen to reflect firms decisions to minimize the use of inputs in the production of a given level of output as opposed to an output-oriented model that assesses the maximum output for a given levels of input.

Table 4.1: Summary Statistics for Variables Included in the Data Envelopment Analysis & Stochastic Frontier Analysis Models

Variable	**Mean**	**Standard Deviation**	**Min**	**Max**
Farm revenue ($)	904,419.6	2,184,443	0	12,500,000
Total acreage (ac)	736.3	1,296.2	0	10,000
Total irrigation water (ac in)	3,866.4	13,041.6	0	114,300
Laborers	13.3	60.3	0	615
Fertilizer frequency (%)	0.640	0.436	0	1
Insecticide frequency (%)	0.494	0.410	0	1
Compost frequency (%)	0.262	0.406	0	1

$n = 112$

When using DEA, the envelopment surface will differ depending on the scale assumptions: constant, decreasing, or increasing returns to scale. A variable returns to scale (VRS) model was selected to encompass production technology that may exhibit increasing, constant, and/or decreasing returns to scale. Our *a priori* expectations follow the VRS reasoning in the case of agriculture. For example, it is unreasonable to assume that at all levels of irrigation water use, an additional unit of water can be applied with the same affect on output as the first unit. Said another way, at some point we expect that the excess water application could lead to water logged soils, erosion, and crop failure.

As stated previously, two DEA models with two functional forms per model were estimated. The first model has only the continuous variables, *Acreage, Irrigation Water,* and *Labor*, denoted Linear DEA_{AWL} and Log-Linear DEA_{AWL}. The second model, denoted Linear DEA_{FIC} and Log-Linear DEA_{FIC} to reflect the additional inclusion of *Fertilizer, Insecticide,* and *Compost* frequency measures. In our DEA model we assume strong disposability of variable inputs and the output (*Irrigation Water, Labor, Fertilizer,*

Table 4.2: Data Envelopment Analysis Estimates of Overall and Irrigation Water Use Subvector Efficiencies

	Subvector θ^w				**Overall θ**			
	Linear		*Log-Linear*		*Linear*		*Log-Linear*	
Efficiency (%)	DEA_{AWL}	DEA_{FIC}	DEA_{AWL}	DEA_{FIC}	DEA_{AWL}	DEA_{FIC}	DEA_{AWL}	DEA_{FIC}
$0 \leq \theta \leq 20$	49	38	11	1	48	6	0	0
$20 < \theta \leq 30$	6	3	7	5	16	19	0	0
$3 < \theta \leq 40$	1	3	3	3	11	15	0	0
$40 < \theta \leq 50$	1	2	9	5	7	15	11	0
$50 < \theta \leq 60$	1	0	10	8	3	8	12	0
$60 < \theta \leq 70$	0	0	8	8	2	7	14	4
$70 < \theta \leq 80$	1	0	7	11	4	4	20	18
$80 < \theta \leq 90$	1	1	6	6	3	8	26	35
$90 < \theta \leq 100$	11	24	10	24	18	30	29	55
N (irrigators)	71	71	71	71	112 (71)	112 (71)	112 (71)	112 (71)
Mean (irrigators)	24.75 (·)	42.73 (·)	54.70 (·)	72.51 (·)	37.67 (36.87)	59.29 (55.89)	77.93 (73.07)	88.90 (87.90)

Insecticide, *Compost*, and *Income*, respectively) and strong disposability in the fixed input (*Acreage*). The estimation of subvector efficiency follows the procedure detailed in Section 3.3.1 on page 41 wherein non-irrigators are excluded from the frontier estimation of subvector irrigation water use technical efficiency. The estimated overall technical efficiency and subvector irrigation water efficiency scores are presented in Table 4.2.

What is observed in these results is a clustering around 0 - 20% and 90% - 100% in the subvector efficiency estimates from the linear models. In the case of the log-linear models, the clustering is less apparent at the 0 - 20% range, and the distribution of subvector efficiency scores is more evenly spread out among the specified ranges between 0 and 100%. The clustering of efficiency estimates near the minimum and maximum values is problematic in that it provides little information other than categorically delineating the most and least efficient farms into two groups. Limited variation in the estimates will also likely lead to Tobit and Heckman models that perform poorly and inaccurately reflect the true effect of farm type and size on technical water use efficiency. Furthermore, for each functional form and efficiency score, the inclusion of the ordinal input measures, fertilizer, insecticide, and compost, leads to a mean efficiency score greater in magnitude relative to the acreage, irrigation water, and labor only models. These ordinal input measures are not directly comparable between observations. The "frequent or regular use" likely translates to different quantities of input applied for each farmer. That is, one farmer may use fertilizer regularly but only apply a small amount, while another farmer may apply fertilizer less frequently but at higher levels of concentration. Furthermore, the additional input measures carry three values, 0, $\frac{1}{3}$, $\frac{2}{3}$, and 1, indicating a minimal amount of variation in this input. Thus, these reasons suggest that farms are being ranked as more similar, and with a greater efficiency score. For the purpose of further analysis, we will focus on the Log-Linear DEA_{AWL} model.

To assess the assumption that all farms are homogeneous in outputs and inputs, organic farms are estimated on a unique frontier to assess if differences are significant when they are not ranked relative to non-organic farms. Table 4.3 summarizes the DEA efficiencies for organic farms that irrigate when their frontier is estimated as part of all (*All*) farms versus estimated on their own frontier (*Unique*). These results show that (1) there are only 19 organic farms that irrigate in this sample and (2) the unique frontier solutions produce distinctly different results. The computed DEA efficiency scores indicate that, when compared against other organic farms only, organic farms are more technically efficient overall and in irrigation water use than if evaluated with

Table 4.3: Overall and Subvector Data Envelopment Analysis Efficiencies of Organic Irrigators

	Mean		**Std. Dev.**	
Log-Linear DEA$_{\mathbf{AWL}}$	*All*	*Unique*	*All*	*Unique*
Subvector θ^w	0.452	0.588	0.340	0.422
Overall θ	0.728	0.901	0.186	0.117

$n = 18$

non-organic farms as well. Thus, organic farms are more technically efficient relative to their own technology. However, while mean subvector efficiency for organic farms is greater, it is also more highly dispersed suggesting increased variation within organic farms. In analyzing the affect of farm type on technical efficiency in irrigation water use, these results imply that, on average, the cultural farm practice of organic agriculture is negatively related to the efficient use of irrigation water.

4.1.2 Stochastic Production Frontier Efficiency Estimates

Whereas DEA is a linear programming model, and therefore incapable of accounting for statistical noise, stochastic production frontier analysis is econometrically based via Maximum Likelihood Estimation (MLE), thereby including an error term. As previously stated, a translog production function was assumed due to the added nature of derived input-specific efficiency scores over Cobb-Douglas counterparts. The measures for fertilizer, insecticide, and compost are ordinal and therefore not appropriate for a translog production specification[1]. As such, these must be removed to ensure validity of the production function. For continuity and comparison sake, the same inputs were used

[1]A stochastic production frontier could not be fit for the formal translog specification, whereby the variables for fertilizer, insecticide, and compost are logged.

in the initial stochastic production frontier estimation; however, because of the data limitations in relation to the chemical inputs, a frontier could not be fit. The survey questionnaire included questions pertaining to the use of various inorganic and organic inputs, but only in regard to frequency of use, rather than quantity. When a semilogarithmic production function was estimated, similar results were observed. Furthermore, when a translog production function was estimated using just acreage, irrigation water, and labor, the estimated first-order coefficients were within the rational range of zero and one, but not statistically significant.

Playing on the benefits of the separation of the error term in SFA into two components, statistical noise and inefficiency, the model can be improved by modeling the heteroskedasticity of the idiosyncratic error component. The first homoscedastic frontier model was estimated to determine whether an asymmetric error component does in fact exist. A likelihood ratio test rejected the null hypothesis of zero variance for the asymmetric error at the $\alpha = .05$ significance level ($\chi_1^2 = 4.67$). Following this result, average county precipitation in 2008, derived using Geographical Information System (GIS) software, was incorporated into the model as a factor defining the heteroskedasticity of the idiosyncratic, asymmetric erorr component. To do so, total precipitation data for 2008 was gathered from 62 weather stations in Georgia (Hoogenboom, 2009). This data was then spatially interpolated using ESRI ArcGIS software to estimate precipitation at any location in Georgia (ESRI, 2008). Taking the average of this generated precipitation surface by county yields a single mean precipitation value for each county in Georgia (see Appendix E). Finally, the cumulative, 2008 average county precipitation estimates were associated to the sample according to the primary county in which the farmers fields are located.

These results are presented in Table 4.4. In a translog stochastic production frontier, the first-order parameters should carry a magnitude between zero and one. The first-order parameters are within this range and in the expected direction, and are significant at the 99 percent level with the exception of acreage. The fact that acreage does not carry the expected sign or significance is not a total surprise, given the sample; i.e., there were observations that included farms with up to 300 acres but 'produced' no income. It is important that modeling procedures are based on theoretical assumptions and not guided by sample specifics[2]. Furthermore, when a Cobb-Douglas production function was assumed, the coefficient on acreage was both positive and significant (Table 4.6).

Turning to the idiosyncratic error component, the coefficient on precipitation is negative. While not immediately apparent, this is an expected result and suggests that as the observed average county precipitation increases, the variance, σ_v^2, approaches zero, and γ approaches one[3]. When $\gamma = 1$, deviations from the frontier are due entirely to inefficiency. Evaluated at the minimum and maximum precipitation levels, 29.91 and 41.04 inches, $0.516 < \gamma < \sim 1$, respectively, suggesting large differences in the production of farm revenue based on the levels of precipitation. Furthermore, the Wald test statistic for the model of $\chi_9^2 = 93815$ strongly rejects the null hypothesis that all coefficients in the model equal zero, supporting the validity of model parameters and derived efficiency measures.

An additional check of model reliability lies in elasticities. While the coefficients in a Cobb-Douglas production function can be interpreted as elasticities, the coefficients in a translog functional specification are not as transparent. Shown in Table 4.5, these computed elasticities are positive, as expected, and fall within a reasonable range. Similarly, the observed elasticities in the Cobb-Douglas model are directly comparable to those computed from translog parameter estimates. Furthermore, the SFA elasticities confirm the VRS assumption of the DEA models with a total elasticity equal to 1.27, implying that if all inputs are increased by 1 percent, farm revenue increases by 1.27

[2]As confirmation of this interpretation, when a frontier was estimated with only farms whose income was greater than zero, the sign on acreage was positive.

[3]$\gamma = \sigma_u^2/\sigma^2$

Table 4.4: Parameter Estimates of the Translog Stochastic Production Frontier

Parameter	**Estimate**	**Parameter**	**Estimate**
Constant	5.302	$\ln \sigma_v^2$	
Total acreage (ac)	-0.105**	Constant	46.382*
Total labor days	0.636**	Precipitation	-1.483*
Total irrigation water (ac in)	0.973**		
$(\text{Acreage})^2$	0.267**	$\ln \sigma_u^2$	
$(\text{Labor days})^2$	0.098*	Constant	2.091**
$(\text{Irrigation water})^2$	0.044**		
(Acreage) $*$ (Labor days)	-0.081**	N	105
(Acreage) $*$ (Irrigation water)	-0.091**	Wald $\chi^2(9)$	93815**
(Labor days) $*$ (Irrigation water)	-0.060*	Log-likelihood	-223.030

* $\alpha = .05$, ** $\alpha = .01$

percent. The minimum and maximum values of the total elasticity indicates that some farms are operating at decreasing returns to scale while other are operating at increasing returns to scale. The productive elasticity of irrigation water is 0.319 implying that there are decreasing returns to scale with respect to irrigation water use. Additionally, the range of values for irrigation water elasticity suggests that all farms are operating at a point where, for any level of acreage and labor, if the amount of irrigation water applied increases by 1 percent, farm revenue increases by less than 0.86 percent. This is an interesting result because it means that farms at using more irrigation water than long-run constant returns to scale assumptions suggest. Irrigation water is the only elasticity with a maximum value less than 1, and it may be indicative of the depressed price of this input in Georgia.

Table 4.5: Translog Production Function Elasticities

Variable	**Elasticity**	**Std. Dev.**	**Min**	**Max**
Total	1.274	0.357	0.442	1.958
Acreage	0.366	0.458	-0.676	1.417
Irrigation Water	0.319	0.189	-0.199	0.856
Labor	0.589	0.298	-0.063	1.154

Table 4.6: Parameter Estimates of the Cobb-Douglas Stochastic Production Frontier

Parameter	**Estimate**	**Parameter**	**Estimate**
Constant	6.975**	$\ln \sigma_v^2$	
Total acreage (ac)	0.3985**	Constant	12.183*
Total labor days	0.474**	Precipitation	-0.367*
Total irrigation water (ac in)	0.236***		
		$\ln \sigma_u^2$	
N	105	Constant	2.197**
Wald $\chi^2(3)$	144**		
Log-Likelihood	-241.140		

* $\alpha = .10$, ** $\alpha = .05$, *** $\alpha = .01$

Following the frontier estimation, overall technical efficiency scores and input-specific irrigation use efficiency scores were computed, as is illustrated in Table 4.7. The incorporation of precipitation further limited the sample to $n = 105$, a loss of 7 observations over the DEA counterpart. The SFA efficiency estimates appear to be distributed most similarly to the Linear DEA_{AWL} estimates. Less than half of the irrigators are more than 20% technically efficient in water usage, although a comparison of the subvector efficiency means between irrigators and all farms suggests that irrigators are, on average, less technically efficient than non-irrigators. Furthermore, because of computational data requirements in the derivation of input-specific efficiency scores following SFA, only $n = 42$ irrigation efficiency scores could be computed. This is a significant limitation as we move to estimate the effect of factors internal to the farm on irrigation efficiency in the next section and may reflect greater concern over the validity of the SFA computed efficiency scores. That is, the better the SFA model describes the data, the more irrigation efficiency scores that can be computed, and the more likely that are estimates are the true subvector efficiency score for irrigation water use.

With a second modeling technique, we can test the hypothesis that organic farms should be estimated on their own frontier. Using a Chow test, we can test whether the independent variables have different impacts on different subgroups of the population. The null hypothesis is that all the coefficients are equal between the two groups. Under both the translog and Cobb-Douglas functional specification, we reject the null hypothesis at the 99 percent level[4]. This implies that the "best-practice" frontier for organic farms is different from the frontier of conventional farms. A simple way to estimate two frontiers in the same maximum likelihood estimation (MLE) procedure is with a dummy for the particular group of interest that acts as an intercept shifter. This only marginally changed the results of the SFA, with a 98 percent agreement between the efficiency scores in the previous section. This dummy was positive and significant,

[4] $\chi^2(10) = 2.110^9$ for the translog functional specification and $\chi^2(4) = 6.410^9$ with a Cobb-Douglas production function.

Table 4.7: Stochastic Frontier Analysis Estimates of Overall and Irrigation Water Use Subvector Efficiencies

Efficiency (%)	**Subvector** θ^w	**Overall** θ
$0 \leq \theta \leq 20$	27	45
$20 < \theta \leq 30$	0	16
$30 < \theta \leq 40$	1	14
$40 < \theta \leq 50$	1	8
$50 < \theta \leq 60$	2	1
$60 < \theta \leq 70$	1	6
$70 < \theta \leq 80$	2	3
$80 < \theta \leq 90$	4	5
$90 < \theta \leq 100$	4	7
N (irrigators)	42 (34)	105 (71)
Mean (irrigators)	29.82 (26.72)	31.76 (33.48)

indicating that being organic has a positive affect on the production of income. As a final note, since our primary interest lies in analyzing the effect of cultural farm types, such as organic farming, on technical irrigation water use efficiency, the estimation of this group on a second, unique frontier, would effectively remove the possibility of identifying this relationship in the following Tobit analysis.

4.1.3 Comparison of DEA and SFA Efficiency Scores

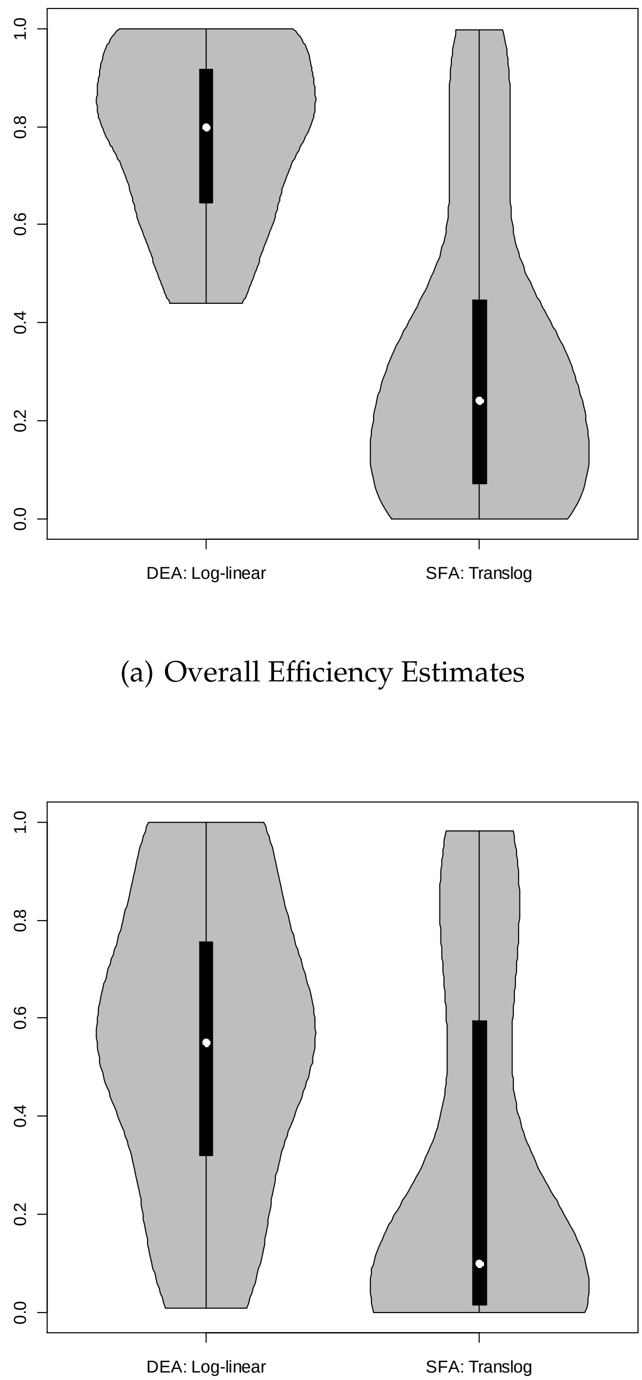
Before moving onto the second step of the analysis, wherein we try to establish the causal effect of farm type and size on technical efficiency of irrigation water use, it is imperative that the efficiency estimates are valid and representative of reality. Additionally, as the analysis progresses in the next section, the interpretation of the

Table 4.8: Summary Statistics of Data Envelopment Analysis and Stochastic Frontier Analysis Efficiency Scores

Efficiency Score		**N**	**Mean**	**Std. Dev.**
Overall θ	*Log-Linear* DEA_{AWL}	112	0.779	0.174
	Translog SFA	105	0.318	0.298
Subvector θ^w	*Log-Linear* DEA_{AWL}	71	0.547	0.299
	Translog SFA	42	0.298	0.364

results and conclusions must stem from the modeled efficiency scores that are the most reliable. Table 4.8 summarizes the number of observations with computed scores for the Log-Linear DEA_{AWL} and Translog SFA, average efficiency scores, and the distribution of scores. In each case, the mean irrigation efficiency score is smaller in magnitude and more dispersed then their overall efficiency score counterparts.

Figures 4.1(a) and 4.1(b) visually show the differences in the distribution and means of the overall technical efficiency and input-specific scores, respectively, computed via the two methods using a violin plot. The violin plot illustrates that the models are similar in terms of maximums, but the 75th percentile of the SFA overall technical efficiency scores is the minimum for the DEA efficiency scores. Similarly, the log-linear DEA model appears to condense the distribution and shift the mean of scores up relative to the SFA model. The shape of the violin plot represents kernel density, and the DEA and SFA overall technical efficiency estimates are essentially inverse of one another in this regard. That is, the DEA overall efficiency measures are negatively skewed while the SFA estimates are positively skewed. With respect to input-specific efficiency scores for irrigation water use, the distribution for the DEA measures is not comparable to those of overall technical efficiency. Within the computed measures, the two estimates share minimums and maximums, but the SFA estimates are positively skewed in the same



(a) Overall Efficiency Estimates

(b) Subvector Irrigation Efficiency Estimates

Figure 4.1: Violin Plots of Data Envelopment Analysis and Stochastic Frontier Analysis Efficiency Estimates

Table 4.9: Pearson Correlations Between Efficiency Measures

		Overall θ		**Subvector** θ^w	
		DEA	*SFA*	*DEA*	*SFA*
θ	*DEA*	1			
	SFA	0.5869*	1		
θ^w	*DEA*	0.8375*	0.8617*	1	
	SFA	0.4465*	0.9149*	0.7352*	1

* indicates a 99% significance level

way as with the overall efficiency scores. Contrary, however, to the overall technical efficiency scores, the log-linear DEA model input-specific technical efficiency scores have the most widely dispersed distribution and appears not to be skewed.

Table 4.9 shows the Pearson correlations between each of the computed technical efficiency scores. As expected, we see more than 90 percent correlation between the overall and subvector SFA technical efficiency scores, indicating that these two models rank the sample of farmers nearly identically. Of greater interest is the weaker correlation between SFA and the log-linear DEA overall technical efficiency measures, equating to only 59 percent. However, at the input-level, this relationship is much greater with 73 percent correlation between the DEA and SFA subvector efficiency estimates.

A better measure of comparison between DEA and SFA efficiency measures with respect to the ranking of farms is the Kendall's Tau ranking correlation coefficients. In Table 4.10, these correlation coefficients are computed at the different levels of sample restriction carried out in the following section. When computing the Kendall's Tau ranking correlation coefficients between two variables, the observations can only be compared on a one-to-one basis. For example, the row indicated as $n = 105$ indicates that one of the variables (in this case the SFA overall technical efficiency scores) only has 105 observations and the computation is, therefore, restricted to the minimum set of shared observations. Kendall's Tau tests the strength of association between two ordinal variables, i.e., the similarity of rank. The strength of this relationship between the DEA irrigation water efficiency score and the DEA overall technical efficiency scores falls within the range of 0.6364 and 0.6541, respectively. Farms with the highest and lowest irrigation efficiency scores tend to exhibit relatively high and low technical efficiency scores, and the slight majority of relatively technically efficient farms are not water wasting. That is, a positive correlation indicates that the ranks of both variables increase together (Crichton, 2001). Conversely, the SFA model yields a rank coefficient within the range of 0.7669 and 0.7917 between the same efficiency scores, reflecting the same conclusion.

These comparisons of the technical efficiency scores estimated by DEA and SFA provide a useful basis for understanding the data as the analysis moves forward. For those readers who desire a detailed comparison of each score, Appendix D on page 132 provides a row-by-row comparison of each farm's overall and water use technical efficiency scores.

4.2 Factors Affecting the Technically Efficient Use of Irrigation Water

In the second step of the analysis presented in this paper, Tobit and Heckman models are estimated with the computed DEA and SFA irrigation efficiency scores as the dependent variable. One specification is used across all estimates and procedures. Stratification and sampling weights are then introduced as a comparative measure to generalize the results more broadly.

The variables used in the Tobit estimation are summarized in Table 4.11. The acreage and irrigation Herfindahl indexes are on the interval $[0, 1]$ and are measures that capture the farmer's management capabilities regarding crop diversification and irrigation acreage allocation decisions, respectively. As a Herfindahl index approaches one,

Table 4.10: Kendall's Tau Ranking Correlation Coefficients Between Efficiency Measures

			Overall θ		**Subvector** θ^w	
			DEA	*SFA*	*DEA*	*SFA*
$n = 105$	θ	*DEA*	0.9740			
		SFA	0.4179*	1		
$n = 68$	θ	*DEA*	0.9737			
		SFA	0.6418*	1		
	θ^w	*DEA*	0.6541*	0.7669*	0.9697	
		SFA	-	-	-	-
$n = 42$	θ	*DEA*	0.9164			
		SFA	0.3937*	1		
	θ^w	*DEA*	-	-		-
		SFA	0.4239*	0.7909*	-	1
$n = 33$	θ	*DEA*	0.9527			
		SFA	0.4943*	1		
	θ^w	*DEA*	0.6364*	0.7424*	0.9508	
		SFA	0.5663*	0.7917*	0.6326*	1

* indicates a 99% significance

Table 4.11: Summary Statistics of Independent Variables in Tobit and Heckman Regressions

Variable	**N**	**Mean**	**Std. Dev**
Organic (1 = yes)	112	0.250	0.435
Conservation tillage (1 = yes)	112	0.500	0.5022
Business structure (1 = solely/family owned)	112	0.527	0.502
Full-time farmer (1 = yes)	109	0.642	0.482
Production acreage (ac)	111	698.1	1182
Age of farmer (years)	110	56.70	11.73
Education of farmer (years)	111	15.41	2.060
Farming experience (years)	110	26.63	15.79
Household income from farming (%)	112	0.492	0.332
Acreage allocation Herfindahl index [0,1]	112	0.761	0.258
Irrigation allocation Herfindahl index [0,1]	112	0.587	0.450

diversification decreases. Percent of household income from farming, education, age, a dummy for full-time or part-time (equals 1 if fulltime, 0 otherwise), years farming, and a dummy for farm ownership (equals 1 if family/solely owned, 0 otherwise) are used to control for farm demographics.

4.2.1 Tobit Model Estimates

In the next two subsections, the results of the Tobit estimation when the DEA estimates and SFA estimates are the dependent, or left-hand side variables are presented. Each is run on the usable sample in which efficiency scores were computed validly and all information regarding the independent variables is present ($n = 68$ for DEA, $n = 39$ for SFA). In the third modeling approach, the DEA-Tobit and SFA-Tobit models are

Table 4.12: Summary Statistics of Variables in Tobit Regressions
(Restricted to Stochastic Frontier Analysis $\theta^w \neq \emptyset$)

Variable	**N**	**Mean**	**Std. Dev.**
Organic (1 = yes)	42	0.381	0.492
Conservation tillage (1 = yes)	42	0.524	0.505
Business structure (1 = solely/family owned)	42	0.667	0.477
Full-time farmer (1 = yes)	39	0.667	0.478
Production acreage (ac)	41	476.7	800.4
Age of farmer (years)	41	54.34	10.95
Education of farmer (years)	41	15.39	2.11
Farming experience (years)	41	24.22	14.59
Household income from farming (%)	42	0.535	0.326
Acreage allocation Herfindahl index [0,1]	42	0.774	0.260
Irrigation allocation Herfindahl index [0,1]	42	0.657	0.395

restricted to only the observations estimated irrigation efficiency scores were computed by both the DEA and SFA models.

The summary statistics for the observations with computed irrigation efficiency scores from the stochastic production frontier estimation are detailed in Table 4.12. Mean education, age, acreage Herfindahl index, years farming, and percent of household income from farming remain remarkably similar to those of the larger DEA observation pool, though mean production acreage drops by nearly 225 acres, or 46 percent. Similarly, the percentages of full-time farmers and practitioners of conservation tillage are relatively unchanged, although the percentages of organic farmers and solely/family owned farms increase from 25 to 38 percent and from 53 to 67 percent, respectively.

Table 4.13 presents the results of the Tobit estimation in which all usable sample observations were included. In the DEA-Tobit model, sole/family ownership, age, and the irrigation Herfindahl index are negative and insignificant; education, years of farming experience, full-time farmer, conservation tillage, and organic farming are positive and insignificant. The percentage of household income from farming is positive in the DEA-Tobit model while the SFA-Tobit estimate of the effect of household income from farming on subvector efficiency is negative, larger in magnitude, and significant. Herein lies the first direct contradiction in the relationship between an explanatory variable and subvector efficiency. If the DEA-Tobit estimate for household income from farming is the true effect of more on-farm labor allocation on technical irrigation water use efficiency, then we interpret that farmers who earns all of his personal household income from farming is a more efficient user of water, by a factor of 0.33. Alternatively, if the SFA-Tobit estimate is the true effect, then a farmer who earns all his household income from farming is a less efficient user of water, by a factor of 0.45.

Production acreage is positive and significant in the DEA and SFA model The irrigation acreage allocation and acreage allocation Herfindahl indexes are negative and significant in the SFA model, suggesting that, as both total acreage and irrigated acreage is allocated to fewer crops, irrigation efficiency decreases. That is, a lack of crop diversification as negatively related to irrigation efficiency, and as cropping decisions for irrigated acreage become more concentrated, farm-level water use is more technically inefficient.

As expected, the business structure of solely/family owned is negative and significant at the 99 percent level in the SFA model, indicating that farms under this business model are less technically efficient in water use than corporations or partnerships. In addition, as hypothesized, production acreage is significant and positively related to irrigation efficiency in both the DEA and SFA models, implying that as production acreage increases so too does the technically efficient use of irrigation water. Although the number of observations is reduced by more than half, the SFA-Tobit model performs surprisingly well. All variables, except full-time farmer and conservation tillage, are significant at the $\alpha = .05$ level; however, even these two measures are significant at the 90 percent level. Notably, the key variables of interest are all in the hypothesized direction.

As noted in the discussion of the estimation of efficiency scores, computational requirements and data availability restricted the number of input-specific technical efficiency scores that could be computed using SFA. Also, some of the observations for which a SFA efficiency estimate was computed did not have valid DEA efficiency scores. In order to look more closely at the differences between these models, and therefore to make inferences into the results they suggest, we produce the estimates for the DEA-Tobit and SFA-Tobit that is restricted to those observations where SFA and DEA efficiency scores were non-missing. Table 4.14 shows that when the DEA-Tobit is run on the restricted sample, the estimated coefficients are quite different in both direction and significance as compared to the unrestricted sample. The parameter estimates on conservation tillage, production acreage, acreage allocation Herfindahl index, and age are more than three times larger in magnitude and significant at the 99 percent level. Education and experience farming are again positive, but are now significant at the $\alpha = .05$ level.

Regarding the SFA-Tobit restricted model, the effect of organic agriculture and full-time farming on subvector efficiency are not statistically different from zero, while the effect of sole/family ownership is negative, larger in magnitude, and significant at the $\alpha = .01$ level. The parameter estimates on age, education, and years farming are comparable to the unrestricted sample in terms of magnitude, direction, and significance. Alternatively, the independent effect of household income from farming and acreage allocation and irrigation acreage allocation Herfindahl indexes are again negative and significant, but larger in magnitude.

Table 4.13: Tobit Estimates of the Determinants of Technical Irrigation Water Use Efficiency

	DEA θ^w		**SFA θ^w**	
Independent Variable	$\hat{\beta}$	$\hat{\sigma}_\beta$	$\hat{\beta}$	$\hat{\sigma}_\beta$
Constant	0.5634*	0.3335	0.8480**	0.3543
Organic (1 = yes)	0.1392	0.0955	0.2646***	0.0913
Conservation tillage (1 = yes)	0.0816	0.0692	0.1530*	0.0761
Business structure (1 = solely/family owned)	-0.1143	0.0734	-0.2773***	0.0861
Full-time farmer (1 = yes)	0.0297	0.0991	0.2466*	0.1263
Production acreage (ac)	$0.46{\times}10^{-4}$*	$0.27{\times}10^{-4}$	$1.79{\times}10^{-4}$***	$0.55{\times}10^{-4}$
Age of farmer (years)	-0.0059	0.0039	0.0218***	0.0052
Education of farmer (years)	0.0082	0.0161	0.0534**	0.0200
Farming experience (years)	0.0032	0.0033	0.0149***	0.0043
Household income from farming (%)	0.3233**	0.1623	-0.4507**	0.1903
Acreage allocation Herfindahl index [0,1]	0.0245	0.1761	-0.4659***	0.1524
Irrigation allocation Herfindahl index [0,1]	-0.2241	0.1845	-0.3011***	0.0960
σ_ϵ	0.2520***	0.0238	0.1979***	0.0224
PsuedoR^2	0.568		1.501	
Log-Likelihood	-11.71		7.85	
LR $\chi^2_{(11)}$	30.77***		47.00***	
N	68		39	

* $\alpha = .10$, ** $\alpha = .05$, *** $\alpha = .01$

Table 4.14: Tobit Estimates of the Determinants of Technical Irrigation Water Use Efficiency (Restricted to Stochastic Frontier Analysis $\theta^w \neq \emptyset$ and Data Envelopment Analysis $\theta^w \neq \emptyset$)

	DEA θ^w		**SFA θ^w**	
Independent Variable	$\hat{\beta}$	$\hat{\sigma}_\beta$	$\hat{\beta}$	$\hat{\sigma}_\beta$
Constant	1.5587***	0.3152	0.7648**	0.3410
Organic (1 = yes)	0.0008	0.0989	0.1611	0.1081
Conservation tillage (1 = yes)	0.2713***	0.0672	0.1468**	0.0719
Business structure (1 = solely/family owned)	-0.1021	0.0840	-0.4085***	0.0820
Full-time farmer (1 = yes)	-0.0212	0.1858	0.1345	0.1979
Production acreage (ac)	2.50×10^{-4}***	0.77×10^{-4}	2.42×10^{-4}***	0.52×10^{-4}
Age of farmer (years)	-0.0279***	0.0058	-0.0179***	0.0053
Education of farmer (years)	0.0508**	0.0205	0.0818***	0.0196
Farming experience (years)	0.0121**	0.0048	0.0096*	0.0052
Household income from farming (%)	-0.2981	0.2854	-0.5544*	0.3004
Acreage allocation Herfindahl index [0,1]	-0.4735***	0.1825	-0.6298***	0.1773
Irrigation allocation Herfindahl index [0,1]	-0.1482	0.1534	-0.3873**	0.1628
σ_ϵ	0.1460***	0.0218	0.1652***	0.0213
PsuedoR^2	1.647		1.996	
Log-Likelihood	8.09		11.44	
LR $\chi^2_{(11)}$	41.17***		45.85***	
N	30		30	

* $\alpha = .10$, ** $\alpha = .05$, *** $\alpha = .01$

4.2.2 Tobit Model Estimates with Robust Standard Errors

As described in Chapter Three, survey data observations are susceptible to being not independently and identically distributed ($i.i.d.$) because of the nature of the sampling methodology. This is certainly a concern in the case of the data gathered as part of this research. In order to estimate the effect of farm type on technical irrigation water use efficiency, variation in farm type must exist. Thus, farmers were sampled based on their affiliation with farm type specific grower's associations. This was done to ensure a sample frame that encompassed three primary cultural farm types: (1) conventional agriculture, (2) conservation tillage, and (3) organic agriculture. Therefore, by construction, observations from different strata belong to at least partly different populations, meaning that they are not identically distributed (Deaton, 1997).

When stratification exists, it typically leads to reduced standard errors, particularly in small samples. Additionally, the number sampled from each group is not necessarily reflective of an equal proportion of the population for each group. That is, the total number of organically certified acreage in Georgia dwarfs that under non-organic management. Defining the stratums and the associated sampling weight can be an effective way to ensure that standard errors are robust. The weights employed, as detailed in Section 3.4.3, are based on the total number of cropland farms in Georgia, and stratification is defined on the basis of the three primary farm types of interest.

Under the robust standard error estimation procedure, presented in Table 4.15 the DEA model performed poorly and with results similar to those observed in the initial Tobit models. F-statistics of 4.46 in the DEA model and 12.36 for the SFA model, indicate that we reject the null hypothesis of the Wald test that the coefficients equal zero. In this estimation procedure, the effect of production acreage is not statistically different from zero. However, the dummy variable for business structure is negative and significant, and the coefficient on full-time farmer is positive and significant. Contrary to the DEA-Tobit estimates of the previous two models, this suggests that full-time farmers that operate a farm as a non-family partnership or corporation, are more technically efficient users of irrigation water, relative to part-time farmers and/or solely/family owned farms.

For the stochastic production frontier efficiency scores, the robust standard error estimation procedure yields results analogous to the initial model. While the acreage Herfindahl effect increases by more than 50 percent, the effect of irrigation acreage diversification is no longer statistically different from zero. Most notably, the constant is nearly twice as large in magnitude, compared to the initial Tobit model; however, the magnitude of the standard deviation of the error term is nearly 8 times larger in than the initial model. This observation coupled with the similarity of the other parameter estimates implies that, when correcting for sample stratification and the probability of being selected as a survey participant, the random variability in subvector efficiency is exacerbated.

A final estimation is run on the DEA and SFA efficiency estimates, wherein the robust standard errors are again applied, but with the number of observations restricted to those with jointly non-missing DEA and SFA efficiency scores. The F-statistics for both the DEA log-linear specification and the SFA translog specification indicate that we reject the null hypothesis. Under this econometric approach, production acreage and education are positive and statistically significant at the 99 percent level with both DEA and SFA efficiency measures as the dependent variable. In the SFA-Tobit model, the effect of business structure on the dependent variable is of the same magnitude as in the initial Tobit model. Alternatively, the coefficient representing the effect of household income from farming is double in magnitude that of the initial parameter estimate, -0.9772 and -0.4507, respectively. Production acreage is statistically significant, positive, and 2.68×10^{-4} in magnitude, comparable to previous estimates.

Table 4.15: Tobit Estimates of the Determinants of Technical Irrigation Water Use Efficiency (Robust Standard Errors)

	DEA θ^w		**SFA θ^w**	
Independent Variable	$\hat{\beta}$	$\hat{\sigma}_\beta$	$\hat{\beta}$	$\hat{\sigma}_\beta$
Constant	0.7963**	0.3819	1.5503***	0.4827
Organic (1 = yes)	0.1275	0.1168	0.2093**	0.0981
Conservation tillage (1 = yes)	-0.0683	0.0639	0.2342*	0.1251
Business structure (1 = solely/family owned)	-0.2451***	0.0807	-0.2690***	0.0791
Full-time farmer (1 = yes)	0.2937**	0.1307	0.2651	0.1658
Production acreage (ac)	$0.34{\times}10^{-4}$	$0.26{\times}10^{-4}$	$1.52{\times}10^{-4}$***	$0.50{\times}10^{-4}$
Age of farmer (years)	-0.0027	0.0045	-0.0329***	0.0099
Education of farmer (years)	-0.0044	0.0176	0.0531***	0.0166
Farming experience (years)	0.0010	0.0025	0.0177**	0.0074
Household income from farming (%)	-0.0006	0.1946	-0.6466***	0.1708
Acreage allocation Herfindahl index [0,1]	0.0024	0.1781	-0.7267***	0.1566
Irrigation allocation Herfindahl index [0,1]	-0.1949	0.1933	-0.1311	0.1584
σ_ϵ	0.2162***	0.0238	1.5503***	0.4827
$F_{(11,[(N-3)-(11+1)])}$	4.46***		12.36***	
N	68		39	
Population size	29949		29333	

* $\alpha = .10$, ** $\alpha = .05$, *** $\alpha = .01$

Table 4.16: Tobit Estimates of the Determinants of Technical Irrigation Water Use Efficiency (Robust Standard Errors, Restricted to Stochastic Frontier Analysis $\theta^w \neq \emptyset$ and Data Envelopment Analysis $\theta^w \neq \emptyset$)

	DEA θ^w		**SFA θ^w**	
Independent Variable	$\hat{\beta}$	$\hat{\sigma}_\beta$	$\hat{\beta}$	$\hat{\sigma}_\beta$
Constant	1.0241***	0.3050	1.0353**	0.4072
Organic (1 = yes)	0.0903	0.1765	-0.1336	0.1882
Conservation tillage (1 = yes)	0.0498	0.0581	0.1422	0.1379
Business structure (1 = solely/family owned)	-0.0777	0.0855	-0.2805***	0.0966
Full-time farmer (1 = yes)	0.2518	0.2014	0.1003	0.1722
Production acreage (ac)	2.50×10^{-4}***	0.61×10^{-4}	2.68×10^{-4}***	0.56×10^{-4}
Age of farmer (years)	-0.0179**	0.0083	-0.0168	0.0106
Education of farmer (years)	0.0452***	0.0159	0.0701***	0.0215
Farming experience (years)	0.0086	0.0071	0.0036	0.0098
Household income from farming (%)	-0.4710	0.3377	-0.9772***	0.3683
Acreage allocation Herfindahl index [0,1]	0.2450	0.3715	-0.3575	0.4167
Irrigation allocation Herfindahl index [0,1]	-0.6786*	0.3662	-0.2792	0.3825
σ_ϵ	0.1151***	0.0252	0.1796***	0.0345
$F_{(11,[(N-3)-(11+1)])}$	20.49***		46.75***	
N	30		30	
Population size	28734		28734	

* $\alpha = .10$, ** $\alpha = .05$, *** $\alpha = .01$

4.2.3 Heckman Sample Selection Model Estimates

In the case of irrigation efficiency estimates derived from parameter estimates of the stochastic production frontier, scores cannot be computed for the entire sample. The reason for this in our case is at least twofold. First, the model must be a good fit for the data, and second, the farmer must irrigate in order to have an irrigation efficiency score. In the case of SFA, input-specific efficiency scores are not always observed via computation. Regarding DEA subvector efficiency measures, the linear programming problem, given by Equation 3.5, must be solved with non-irrigators excluded from the envelopment procedure. As such, an estimate of technical irrigation water use efficiency is not observed. A Heckman, Heckit model as it is also referred, can produce consistent and unbiased estimates when correlation exists between the error terms of the outcome and selection equation. Applied to this research, if the unobservables associated with the decision to irrigate are statistically related to the unobserved characteristics of technical irrigation water use efficiency, OLS estimates are biased.

Outlined in Section 3.4.2, the Heckman approach is a two-stage probit/OLS model to correct for selection bias and endogeneity bias. The correction approach requires the selection of instrumental variables that are related to the participation in irrigation, but not to subvector efficiency. The research constructed survey included questions on the motivations why he/she farms such as for tax breaks, profit, hobby, and conservation. It is not immediately obvious that these reasons for farming have any independent affect on the observed subvector efficiency. In particular, having hobby as your reason for farming might well determine whether or not you choose to invest in irrigation equipment or are worried about risk management. Additionally, a personal motivation for conservation is likely more a factor in the decision process than in the outcome process. The survey also included questions concerning additional agricultural practices employed on-farm, including crop rotation, green manure, compost, integrated pest management, and rotational grazing. If the implementation of any singular or

Table 4.17: Summary Statistics of Instrumental Variables Included in Heckman Model

Variable	**Mean**	**Std. Dev.**	**N**
Motivation hobby [0,1]	0.407	0.332	110
Motivation conservation [0,1]	0.86	0.23	111
Crop rotation [0,1]	0.583	0.477	112
Green manure [0,1]	0.28	0.416	112
Compost [0,1]	0.262	0.406	112

combination of these techniques is sufficient for risk management and plant/soil water requirements, farmers may choose not to irrigate. Crop rotation, green manure, and compost were selected as three additional instrumental variables included in the selection equation but not the outcome equation.

Tables 4.17 and 4.18 present the summary statistics of the instrumental variables used in the Heckman model and results from the first stage probit model where the dependent variable is the probability of participating in irrigation. While not directly relevant to the research objectives of this thesis, these results do illustrate the statistical predictive power of the instruments and the other independent variables on the decision to irrigate. The variables for motivation hobby and conservation, crop rotation, green manure, and compost are all ordinal variables, coded between 0 and 1, representing levels of importance in the case of motivations and frequency of application in the case of the agricultural practices. If the farmer indicated that hobby/recreation was 'very important', motivation was coded as 1. Each step of the scale was given a value that can be thought of as the percentage of time the farmer makes farm related decisions as a result of his/her motivations for farming[5]. Frequency of application of a particular

[5] $1 = 0, 2 = 0.25, 3 = 0.5, 4 = 0.75, 5 = 1$

farming technique were coded in a similar way[6]. The results of the probit model indicate that the motivations of hobby and conservation are statistically significant in both the DEA-Probit and SFA-Probit models. Additionally, crop rotation, green manure, and compost are statistically significant at the $\alpha \leq .05$.

The full results of the Heckman model when the Data Envelopment Analysis subvector efficiency scores are the dependent variable in the outcome equation are presented in Table 4.19. The parameter estimates themselves cannot be directly interpreted without a formal computation of marginal effects that takes into account the parameter estimates of both the outcome and selection equation. However, the important parameter of interest is ρ, the correlation of the error terms between the outcome and selection equation. In the DEA-Heckman model, ρ is not statistically different from zero, and, therefore, OLS estimates are not biased and the Tobit model is the correct model, given these instruments.

Similarly, the full results of the Heckman model with the technical irrigation water use efficiency estimates from the stochastic production frontier model as the dependent variable in the outcome equation are detailed in Table 4.20. Again, the parameter estimates are of little interest in this format, but ρ is statistically different from zero at the 95 percent level. This nonzero value of ρ as well does not have a meaningful interpretation other than to say that, when negative, any unobserved factor that makes participation in irrigation more likely, also makes the observed subvector efficiency score, θ^w, smaller in magnitude. The SFA-Heckman model appears to be a good model on the grounds that all of the independent variables used in the Tobit models are statistically significant at the $\alpha \leq .10$ level. Furthermore, the likelihood-ratio test statistic is 52.13 as compared to 47.00 in the initial Tobit model, meaning that we reject the null hypothesis that the restricted model is a better predictor of θ^w than the unrestricted model.

[6] $Never = 0, Rarely\ or\ as\ last\ resort = 0.33, On\ occasion = 0.66, Frequently\ or\ regularly = 1$

Table 4.18: Probit Results for Technical Irrigation Water Use Efficiency at Farm

	DEA θ^w		**SFA θ^w**	
Independent Variable	$\hat{\beta}$	$\hat{\sigma}_\beta$	$\hat{\beta}$	$\hat{\sigma}_\beta$
Constant	-1.8874	4.0150	-0.7569	1.7468
Organic (1 = yes)	0.5582	0.7985	0.2172	0.4706
Conservation tillage (1 = yes)	0.8229	0.8646	-0.2859	0.3822
Business structure (1 = solely/family owned)	0.2576	0.6937	0.7153**	0.3485
Full-time farmer (1 = yes)	-0.9819	1.0233	-0.6823	0.5225
Production acreage (ac)	0.0001	0.0003	-0.0004**	0.0002
Age of farmer (years)	-0.1026***	0.0541	-0.0661***	0.0223
Education of farmer (years)	0.0661	0.2061	0.0201	0.0788
Farming experience (years)	0.0013	0.0376	0.0116	0.0162
Household income from farming (%)	1.4429	1.6552	1.3374	0.8320
Acreage allocation Herfindahl index [0,1]	1.3496	1.9429	2.1337**	0.9085
Irrigation allocation Herfindahl index [0,1]	4.3952***	1.2263	-0.4628	0.4634
Motivation hobby [0,1]	-3.7129**	1.5051	-1.7862***	0.6332
Motivation conservation [0,1]	4.3324*	2.2112	1.9312*	0.9929
Crop rotation [0,1]	1.1820	0.8799	1.0981**	0.4877
Green manure [0,1]	-0.6127	1.2046	-1.2137**	0.5658
Compost [0,1]	0.5306	0.8843	2.0518***	0.6098
PsuedoR^2	0.788		0.333	
Log-Likelihood	-14.88		-46.82	
LR $\chi^2_{(16)}$	110.61***		46.73***	
N	107		107	

* $\alpha = .10$, ** $\alpha = .05$, *** $\alpha = .01$

Table 4.19: Heckman Estimates of the Determinants of Technical Irrigation Water Use Efficiency (Data Envelopment Analysis θ^w as Dependent Variable)

	DEA θ^w Outcome		DEA θ^w Selection	
Independent Variable	$\hat{\beta}$	$\hat{\sigma}_\beta$	$\hat{\beta}$	$\hat{\sigma}_\beta$
Constant	0.5259*	0.2995	-2.7411	3.9337
Organic (1 = yes)	0.1425*	0.0858	0.5470	0.8251
Conservation tillage (1 = yes)	0.0673	0.0623	0.6001	0.9054
Business structure (1 = solely/family owned)	-0.1099*	0.0658	0.3232	0.6995
Full-time farmer (1 = yes)	0.0344	0.0894	-1.0316	1.0696
Production acreage (ac) 1,0,3,2	$.40\times10^{-4}$*	0.24×10^{-4}	1.41×10^{-4}	3.73×10^{-4}
Age of farmer (years)	-0.0043	0.0035	-0.1075**	0.0544
Education of farmer (years)	0.0099	0.0146	0.0917	0.1983
Farming experience (years)	0.0033	0.0030	0.0052	0.0365
Household income from farming (%)	0.2946**	0.1490	1.3347	1.6744
Acreage allocation Herfindahl index [0,1]	0.0832	0.1749	1.8757	2.0369
Irrigation allocation Herfindahl index [0,1]	-0.3427	0.2395	4.2903***	1.2091
Motivation hobby [0,1]			-3.8800**	1.5282
Motivation conservation [0,1]			5.1148**	2.5148
Crop rotation [0,1]			0.8738	0.9741
Green manure [0,1]			-0.4175	1.1851
Compost [0,1]			0.3485	0.8570
ρ	-0.4070	0.5751		
σ	0.2278***	0.0201		
λ	-0.0927	0.1332		
Log-Likelihood	-10.20			
LR $\chi^2_{(11)}$	33.66***			
N (not observed)	107 (39)			

* $\alpha = .10$, ** $\alpha = .05$, *** $\alpha = .01$

Table 4.20: Heckman Estimates of the Determinants of Technical Irrigation Water Use Efficiency (Stochastic Frontier Analysis θ^w as Dependent Variable)

	SFA θ^w Outcome		**SFA θ^w Selection**	
Independent Variable	$\hat{\beta}$	$\hat{\sigma}_\beta$	$\hat{\beta}$	$\hat{\sigma}_\beta$
Constant	1.0634***	0.4043	-0.5949	1.7069
Organic (1 = yes)	0.1850*	0.1023	0.3588	0.4772
Conservation tillage (1 = yes)	0.1599*	0.0820	-0.3250	0.3965
Business structure (1 = solely/family owned)	-0.3219***	0.0915	0.7190**	0.3464
Full-time farmer (1 = yes)	0.2310*	0.1323	-0.7290	0.5202
Production acreage (ac) 1,0,3,2	2.08×10^{-4}***	0.58×10^{-4}	-4.56×10^{-4}**	2.15×10^{-4}
Age of farmer (years)	-0.0215***	0.0055	-0.0758***	0.0221
Education of farmer (years)	0.0538***	0.0209	0.0127	0.0785
Farming experience (years)	0.0156***	0.0045	0.0106	0.0162
Household income from farming (%)	-0.5594***	0.2089	1.2491	0.8157
Acreage allocation Herfindahl index [0,1]	-0.5293***	0.1650	2.2651**	0.9034
Irrigation allocation Herfindahl index [0,1]	-0.2746**	0.1071	-0.2762	0.4547
Motivation hobby [0,1]			-2.0106***	0.6107
Motivation conservation [0,1]			2.3109**	1.0332
Crop rotation [0,1]			1.3551***	0.5171
Green manure [0,1]			-1.5670***	0.6011
Compost [0,1]			2.2007***	0.6220
ρ	-0.7550**	0.1998		
σ	0.2293***	0.0388		
λ	-0.1731**	0.0706		
Log-Likelihood	-36.40			
LR $\chi^2_{(11)}$	52.13***			
N (not observed)	107 (68)			

* $\alpha = .10$, ** $\alpha = .05$, *** $\alpha = .01$

Given that marginal effects calculations are not as intuitive with Heckman estimates as in other models, such as Tobit, Table 4.21 displays the marginal effects of the unrestricted Tobit, Robust Tobit, and Heckman models for DEA and SFA θ^w subvector efficiencies. The two primary models of interest for drawing conclusions are the DEA-Tobit and the SFA-Heckman. The initial discrepancy between the DEA and SFA based models remains unresolved: the effect of household income from farming on technical irrigation water use efficiency. With respect to the DEA-Tobit model, the marginal effect is positive ans significant, though negative and significant in the case of SFA-Heckman. Within the three SFA models presented in this table, the marginal effects estimates are quite consistent across modeling approaches. All of the marginal effects, with the exception of the dummy variables for organic farm and full-time farmer, are statistically significant at $\alpha \leq .05$.

The computed elasticities presented in Table 4.23 are evaluated at the mean (see Table 4.22) and point to age, education, and farming experience as being the three greatest determinants of irrigation water use efficiency, respectively.

Table 4.21: Comparison of Marginal Effects Computed from Tobit and Heckman Estimates

	DEA θ^w			**SFA θ^w**		
Independent Variable	*Tobit*	*Robust Tobit*	*Heckman*	*Tobit*	*Robust Tobit*	*Heckman*
Organic (1 = yes)	0.1392	0.1275	0.1623	0.2646*	0.2093*	0.2272
Conservation tillage (1 = yes)	0.0816	-0.0683	0.0891	0.1530*	0.2342	0.1216*
Business structure (1 = sole/family)	-0.1143	-0.2451*	-0.0982	-0.2773*	-0.2690*	-0.2373*
Full-time farmer (1 = yes)	0.0297	0.2937*	-0.0030	0.2466*	0.2651	0.1452
Production acreage (ac)	0.46×10^{-4}	0.34×10^{-4}	0.45×10^{-4}	1.79×10^{-4}*	1.52×10^{-4}*	1.55×10^{-4}*
Age of farmer (years)	-0.0059	-0.0027	-0.0082	-0.0218*	-0.0329*	-0.0304*
Education of farmer (years)	0.0082	-0.0044	0.0132	0.0534*	0.0531*	0.0553*
Farming experience (years)	0.0032	0.0010	0.0034	0.0149*	0.0177*	0.0168*
Household income from farming (%)	0.3233*	-0.0006	0.3430*	-0.4507*	-0.6466*	-0.4124*
Acreage allocation Herfindahl [0,1]	0.0245	0.0024	0.1513	-0.4659*	-0.7267*	-0.2628*
Irrigation allocation Herfindahl [0,1]	-0.2241	-0.1949	-0.1871	-0.3011*	-0.1311	-0.3071*
$\hat{\theta^w}$	0.5651	0.6036	0.5942	0.3024	0.2747	0.5047

* statistically significant at $\alpha \leq .05$

Table 4.22: Summary Statistics of Continuous Variables in Usable Sample for Tobit and Heckman Models

Variable $(N = 107)$	**Mean**	**Std. Dev.**
Production acreage (ac)	720.65	1197.83
Age (years)	56.533	11.615
Education (years)	15.383	2.077
Farming experience (years)	26.617	15.726
Income from farming (%)	0.497	0.332
Acreage Herfindahl [0,1]	0.766	0.252
Irrigation acreage Herfindahl [0,1]	0.592	0.449

Table 4.23: Comparison of Elasticities Computed from Tobit and Heckman Estimates

	DEA θ^w			SFA θ^w		
Independent Variable	*Tobit*	*Robust Tobit*	*Heckman*	*Tobit*	*Robust Tobit*	*Heckman*
Production acreage (ac)	0.0587	0.0407	0.0548	0.4254*	0.3995*	0.2208*
Age of farmer (years)	-0.5890	-0.2503	-0.7770	-4.0845*	-6.7680*	-3.4044*
Education of farmer (years)	0.2243	-0.1113	0.3421	2.7152*	2.9753*	1.6864*
Farming experience (years)	0.1530	0.0429	0.1545	1.3099*	1.7139*	0.8880*
Household income from farming (%)	0.2843*	-0.0005	0.2868	-0.7406*	-1.1695*	-0.4060*
Acreage allocation Herfindahl index [0,1]	0.0332	0.0030	0.1950	-1.1803*	-2.0261*	-0.3989*
Irrigation allocation Herfindahl index [0,1]	-0.2350	-0.1913	-0.1866	-0.5899*	-0.2828	-0.3605*

* statistically significant at $\alpha \leq .05$

CHAPTER 5

DISCUSSION

5.1 SUMMARY AND POLICY IMPLICATIONS

Agriculture and water are important aspects of Georgia's economy. The technically efficient use of irrigation water in the production of farm revenue is the optimal way to increase the impact of these two aspects on the overall economy simultaneously. While the number of observations on which the analysis was conducted and the conclusions are drawn is small, this sample is still quite representative of the larger population of farmers. Using estimation techniques to produce robust standard errors helps to give credence to any generalizations about farmers in Georgia.

The DEA method of efficiency estimation allows additional, ordinal inputs to be included in the frontier, but SFA allows for the specification of the random statistical noise, including factors exogenous to the farm, such as precipitation. DEA is nonparametric and therefore a specific production function does not have to be specified in order to derive input-specific, subvector technical water use efficiency scores. But SFA computed input-specific efficiency scores are computationally dependent on good data and a good fit of the stochastic production frontier. We find both the linear and log-linear DEA models are good for producing a ranking of firms, but that the failure of this technique to account for any random noise, raises trepidation over the validity of any subsequent point estimates. In sum, SFA is the best procedure for producing reliable input-specific technical efficiency scores in situations where statistical noise, unobservable exogenous factors, or other factors outside the firms control are significant factors in the production process, such as weather.

Many surveys related to farm-level irrigation characteristics have been conducted by both USDA (e.g., Farm Ranch and Irrigation Survey) and the Georgia Cooperative Extension in order to gain an understanding of total water use. As stated in Chapter Two, these numbers differ greatly. Second, and key to the motivation for our survey, was that these surveys are only intended to characterize the amount of irrigation water used and what crops are typically irrigated. However, no information about farm-level cultural practices or additional inputs used was gathered in conjunction with the irrigation data. As shown in Appendix A on page 114, our survey included questions both on farm type and traditional irrigation characteristics.

The importance of the research presented here is clear, given the recent pattern of drought in Georgia, and the results are particularly relevant for policy makers interested in regulating agricultural water use. For more academic audiences, research pertaining to alternative farms, particularly organic farms, is extremely limited due to data availability, and this study serves as an important step in moving the body of literature forward by economically analyzing water use decisions of this group. More generally, a careful analysis of differences among farms will also serve to develop a better understanding of the external and internal factors affecting water use efficiency.

The results of this analysis conclude that a younger, more educated agricultural sector is more likely to efficiently using Georgia's finite water resources. Further, the negative effect of an additional year in age of the farmer can be overcome by an additional year of farming experience and one-quarter of a year of education. That is, if a farmer gains experience farming at the same rate at which he ages, the true marginal effect of an additional year in age on the technical efficiency of water use is negative 1.36 percentage points. While the variable capturing education of farmer represents years of formal education, it is likely that continuing education or other farmer education programs would have comparable positive effects on efficiency with irrigation water.

In line with theoretical expectations, when using DEA technical water use efficiency estimates as the dependent variable in a Tobit model, our results indicated that as off-farm income increases, technical water use efficiency decreases. However, contrary to a body of literature that suggests off-farm labor allocation is negatively related to on-farm production efficiency, with respect to irrigation efficiency, our SFA results imply that the devotion of ones labor to farming has a negative effect on technical water use efficiency. That is, when accounting for precipitation and other random statistical noise with SFA, the results are entirely opposite. Yet, this should not be entirely surprising, given the "price" of water in Georgia–if source of income is solely or largely a function of your agricultural output, you will tend to make more suboptimal resource use choices for those inputs that are the easiest and cheapest to employ.

Consistent with previous research and theoretical expectations, *ceteris paribus*, family or solely owned farms are more technically inefficient than other farm ownership structures such as partnerships and corporations. The magnitude of this effect is sizable, implying that solely or family owned farms are 23.7 percentage points less efficient in water use than other ownership structures. Additionally, as the amount of acreage under production at a single farm increases, so too does technical irrigation water use efficiency; however, this effect reverses to net negative as crop diversification decreases. Specialization in diversification may reflect farmer management prowess, and, therefore, the concentration of crop acreage allocation is indicative of less skilled farm managers thereby translating into the technically inefficient use of water resources.

Conservation tillage and organic agriculture have been shown through numerous field studies to be effective strategies for soil and water conservation. The question then becomes, can these strategies be technically efficient in the production of farm revenue while conserving natural resources and often reducing environmental impacts of agriculture? These results conclude that conservation tillage can in fact meet this criterion. On average, farms that employed conservation tillage on their fields were 12 percentage points more technically efficient in water use. At the policy level, encouraging the adoption of conservation tillage in any cropping situation for which it is feasible is a definitive means of increasing farm-level irrigation efficiency. With respect to organic agriculture, the conclusions from this analysis are less definitive, though suggestive that organic farms are, on average, more technically efficient users of water but for reasons related more to the characteristics of the farmer and farm than the actual cultural farm practice. Further, given the heterogeneity in the on-farm application of organic agricultural techniques, it is improbable that a singular effect could be denoted from just prescribing to the general use of organic production. As such, a closer inspection of the various strategies employed by an organic farm can help to further the equivocacy of this relationship.

The computed efficiency scores point to noteworthy, but limited, conclusions in their own regard. While previous research has suggested that farmers that irrigate are more technically efficient overall (Vicente, 2004), our results imply that the difference between irrigators and non-irrigators is not this clearcut. In fact, DEA estimates indicate that overall, irrigators (73.4 percent) are 13 percentage points less technically efficient than non-irrigators (86.7 percent). An evaluation of the SFA efficiency estimates indicates that, on average, irrigators are 33.5 percent efficient while non-irrigators are 28.2 percent efficient. When the quantity of irrigation water is considered in the initial production function, irrigators appear to be penalized for the use of an additional input in the DEA approach. With respect to the SFA approach to efficiency estimation, irrigators are in fact more technically efficient overall than non-irrigators.

Findings in a previous study (Sherlund, Barrett, and Adesina, 2001) were that failure to incorporate environmental production conditions led to a downward bias on the efficiency estimates. Conversely, are results suggest the opposite conclusion: when accounting for precipitation and other random noise with SFA, the technical efficiency of farms in Georgia is 46 percentage points less than DEA estimates that ignore variations in environmental production conditions. This upward bias implies that farmers are more efficient in the production of farm revenue, relative to one another, when the conditions of their local environment are ignored.

For this sample of farmers, mean technical water use efficiency was 29.82 and 54.70 percent from the SFA and DEA modeling approaches, respectively. Based on this data, farmers can, on average, reduce the use of irrigation water by either 70 or 45 percent without contracting farm revenue. This statement is conditioned by the realization that the use of a small sample and data from one year, 2008, is insufficient to state conclusively that all can farmers can, in all years, use less water to get the same yield. Spatial variability of rainfall exists at much finer scales than the county level, even at the farm level in many cases. Our dataset was limited in that farm-level data was only county specific and did not have identifiers for zip code or latitude/longitude, and the precipitation was aggregated at the county level in lieu of the absence of more specific spatial identifiers. Finally, 2008 is the first year in many that is not really a drought year.

While statewide averages show different average acre inches per crop (see Table 2.1), this observation does not translate to technical efficiency. The estimates of overall technical efficiency and technical water use efficiency were not statistically significantly correlated with cropping system or crop type. However, there did exist a strong, positive, and statistically significant correlation between total acre inches of irrigation water applied and cropping system. These two observations suggest that even though quantity of water may differ based on farm type, the independent effect of cropping system or crop type on technical efficiency is negligible. The dependent variable, farm revenue, may provide insight into why this was observed in this sample and the nature of agricultural production. Quite apparently, yield differs depending on what crop is grown. If the value of that yield is equivalent for two different crops, per unit of water applied during crop growth, then technical water use efficiency is equal between the cropping systems. Therefore, the implication that the type of crop grown does not affect water use efficiency is not without reason.

As was found by Speelman et al. (2008) in the case of South African farmers, Georgia farmers are generally more technically efficient in the use of all inputs than in the use of water. Additionally, similar to a sample of farmers in Kansas (Lilienfeld and Asmild, 2007), Georgia farmers are, on average, water wasters. The explanations for this could again be related to the cost of irrigating in Georgia as well as the supplemental nature of irrigation in agriculture. It is easier and safer for farmers to continue to irrigate when in fact it may be unnecessary, then it is to risk crop failure or yield reduction. If the effective price of water was great enough such that it was a significant factor in a farmer's decision to apply additional irrigation water, policy makers would likely see the adoption of more water conserving technologies, agricultural techniques, and/or micro-management of irrigation systems and scheduling. While the exact reason for the depressed irrigation efficiency scores cannot be concluded upon as a result of this research, it is evident that there are farmers in Georgia from all different backgrounds and farm types who are water wasters. A secondary, but interesting, finding of this study is that not only are on-farm cultural practices related to technical water use efficiency, they are also related to the decision to participate in irrigation. For example, the probit estimates in Table 4.18 imply that farmers employing green manure are less likely to irrigate than farmers using compost or crop rotation.

This research has shown that irrigators within Georgia are unsuccessful in achieving their overall technical efficiency levels when it concerns water use. In the absence of an explicit price of water, it looks as if farmers have little incentive to use water efficiently. The relationships between the subvector irrigation water efficiency measures and farm size, farm type, and farmer attributes, supply policy makers and extension personnel with insight on how to direct efforts to improve technical water use efficiency.

5.2 Limitations and Future Research

In conducting any research, it is important to identify and prepare for potential limitations. One key problem with this study is the statistical power of results concerning alternative farms because of population size in Georgia. This is of particular concern in assessing differences within alternative farms. Even in running a single regression with controls for type of farm, a sample size of 156 lends itself to difficulties in more detailed investigation, such as stochastic production frontier analysis. More generally, there are limitations to the interpretation of results derived from survey-based research (i.e., survey data is subject to bias arising from the unwillingness of people to share potentially embarrassing information). Although a pilot test was conducted prior to implementation, it is probable that there remains room for differences in interpretation of questions, which may influence the response to some items. Moreover, precision and accuracy of responses to both personal and farm-level characteristics, such as income or education, and technical measures of irrigation water use, such as average inches of water applied per acre, from surveys are difficult to evaluate unequivocally.

Further data level limitations are present in the modeling of the production of farm revenue. Many inputs are used in agricultural production, including fertilizers and insecticides. When incorporated in a production function, these variables help to more accurately reflect the transformation of inputs into output. However, when they are omitted, the true elasticity or marginal effect of each input, such as irrigation water, could be misrepresented by the estimation of production function parameters.

Some recent research has considered environmental production conditions as inputs in the production process (Sherlund, Barrett, and Adesina, 2001). The inclusion of precipitation into the DEA and SFA models would be an interesting starting point for additional research in the future. Additional environmental conditions could also be compiled and appended to the dataset such as temperature, elevation, evapotranspiration, and soil characteristics. Finally, the progression from average yearly precipitation to growing season specific precipitation would serve to improve the estimates of the true effect of precipitation on the variance of the idiosyncratic error term. There exists multiple methodological approaches to the interpolation of spatial data, and in the case of the precipitation data used in this study, the most reliable approach may not have been the one employed. As the Southeast Regional Climate Center and other national weather organizations release GIS datasets for precipitation in 2008, this information can be compared for validity.

The analysis presented in this thesis leads one to ask many additional questions related to irrigation, overall technical efficiency, and technical water use efficiency of farms in Georgia. The probit results from the Heckman model only scratch the surface on a larger question: what factors affect a farmer's decision to irrigate? The results presented in this research are suggestive but not conclusive with respect to this line of questioning. Furthermore, what factors affect the adoption of water conserving management practices? Future research should seek to understand why farmers choose to adopt water conserving techniques, such as deficit irrigation, irrigation system maintenance, or irrigation scheduling, and the subsequent effect of these practices on water use efficiency. While cultural farm practices, such as conservation tillage, may increase water use efficiency, is this outcome related to the agronomic principles of reduced tillage or to the farmer who chooses to engage in such practices? To do so highlights a limitation of this research: the cross-sectional nature of the survey data collected. A dataset with observations from multiple growing seasons, in which farmers adopted cultural farm practices during the timeframe of the data collection, would provide reliable insight into the exact effect of the adoption of any particular cultural farm practice. It would also allow for the methodological approach carried out in this research to be repeated over multiple years with different precipitation levels, in order to evaluate the changes in technical water use efficiency in wet, normal, or dry years.

The data collected in the completion of this research was limited in size and scope. Farmers outside of Georgia were excluded from the sample frame as an intentional constraint. As a practically imposed limitation in light of research feasibility, this exclusion prevented a thorough comparison of farmers regionally, nationally, or internationally. In an ideal world, governmental farm agencies around the world would work together to create a single census type survey that could be distributed at regular intervals globally. This is not a likely reality, although the USDA has begun a more detailed survey of organic farms in the United States and the Canadian Census of Agriculture includes some questions on cultural farm practices.

Methodologically, stochastic production frontier analysis can be applied to a different question quite easily. For instance, the inefficiency component of the composed error term was assumed to be homoscedastic. If one is less interested in the factors that affect input-specific technical efficiency, these factors can be included as variables that explain the variance of farm specific technical efficiency.

In sum, a larger sample, spanning multiple years, would shed considerable light onto the effect of cultural farm type on technical water use efficiency in Georgia and elsewhere. The methodological approach and analysis of this research help provide insight into the use of water in agriculture within Georgia and how farm type and farm size, specifically, affect the efficient use of irrigation water.

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Appendix A

Survey Questionnaire

This appendix includes the survey questionnaire that was constructed by the researchers and delivered to all survey participants. While many of the questions in the survey did not yield sufficient data to be used in the formal analysis, the variables available to the researchers in this study were derived from the questions provided herein.

All survey responses are strictly confidential.

Part I. Farm Profile and Production Details

This part of the survey asks for information that will provide an overview of your total farm operation and production details.

Section A. ACREAGE IN 2008

1. In 2008, how many farmed acres in production, pasture, or fallow, were owned by your farm? *(Fill in.)*
   ↳ ______________ acres
2. In 2008, how many farmed acres in production, pasture, or fallow, were rented, leased, or used free-of charge? *(Fill in.)*
   ↳ ______________ acres

Section B. LAND USE IN 2008

In the table below, please fill in how many acres were used in the production of each agricultural category, the number of acres irrigated, and what percent of total farm sales each category accounted for in 2008. *(Fill in acres and percentages for each category and commodity type. Write "0" next to categories that don't apply to your farm. Estimates are OK.)*

Cropland Harvested		Number of Acres	Irrigated Acres	Estimated Percent of Gross Farm Revenue in 2008
1. Field Crops	a. Corn	_______ac	_______ac	_______%
	b. Cotton	_______ac	_______ac	_______%
	c. Peanuts	_______ac	_______ac	_______%
	d. Sorghum	_______ac	_______ac	_______%
	e. Soybeans	_______ac	_______ac	_______%
	f. Wheat	_______ac	_______ac	_______%
	g. All Others	_______ac	_______ac	_______%
2. Vegetables & Melons	a. Bell Peppers	_______ac	_______ac	_______%
	b. Cabbage	_______ac	_______ac	_______%
	c. Green Beans	_______ac	_______ac	_______%
	d. Sweet Corn	_______ac	_______ac	_______%
	e. Tomatoes	_______ac	_______ac	_______%
	f. Watermelons	_______ac	_______ac	_______%
	g. All Others	_______ac	_______ac	_______%
3. Fruit & Orchard Crops	a. Peaches	_______ac	_______ac	_______%
	b. Pecans	_______ac	_______ac	_______%
	c. All Others	_______ac	_______ac	_______%

Cropland Harvested		Number of Acres	Irrigated Acres	Estimated Percent of Gross Farm Revenue in 2008
4. Hay & Forage Crops	a. Hay *(harvested)*	_______ac	_______ac	_______%
	b. Turf Grass	_______ac	_______ac	_______%
	c. All Others	_______ac	_______ac	_______%

Cropland Used Only for Pasture or Grazing	Number of Acres	Irrigated Acres	Estimated Percent of Gross Farm Revenue in 2008
5. Pasture or Grazing Land	_______ac	_______ac	_______%

Section C. FERTILIZERS AND CHEMICALS APPLIED

1. Were any commercial or organic fertilizers, manure, herbicides, insecticides, fungicides, nematicides, other pesticides, growth regulators, or other chemicals used on this operation during 2008? *(Select one response.)*
   - ☐ Yes
   - ☐ No → *Skip to Section D*

2. Which of the following materials do you use, and how frequently? *(Select one response for each material.)*

Material	Never	Rarely or as a last resort	On occasion	Frequently or regularly
Herbicides	☐	☐	☐	☐
Insecticides	☐	☐	☐	☐
Fungicides	☐	☐	☐	☐
Commercial fertilizer	☐	☐	☐	☐
Lime or Gypsum	☐	☐	☐	☐
Compost	☐	☐	☐	☐
Manure	☐	☐	☐	☐
Other ___________	☐	☐	☐	☐

Section D. OPERATING ARRANGEMENT

1. Which of the following business structures best describes your farm operations? *(Select one response.)*
   - ☐ Sole proprietorship
   - ☐ Non-family corporation
   - ☐ Family corporation
   - ☐ Partnership with a written agreement
   - ☐ Partnership without a written agreement

All survey responses are strictly confidential.

2. How many years has your farm been in production? *(Fill in.)* ______________ years

Section E. MANAGEMENT STRATEGIES

1. Which of the following management practices/strategies are used on this farm, and how frequently? *(Select one response for each practice.)*

Practice	Never	Rarely or as a last resort	On occasion	Frequently or regularly
Crop rotation	☐	☐	☐	☐
Rotational grazing	☐	☐	☐	☐
Cover crops	☐	☐	☐	☐
Green manure	☐	☐	☐	☐
Integrated pest management	☐	☐	☐	☐
Intercrops	☐	☐	☐	☐
Reduced/conservation tillage	☐	☐	☐	☐
Organic agriculture	☐	☐	☐	☐
Soil quality management	☐	☐	☐	☐

Section F. FARM LABOR

1. Including yourself and any farm family/household members, how many people were employed in your farm's operation, full-time or part-time in 2008? *(Fill in.)*
   a. Full-time ______________
   b. Part-time ______________

2. How many people, including you, are involved in major decisions regarding farm planning, production, irrigation, marketing, and other management decisions? *(Fill in.)*
   a. Full-time ______________
   b. Part-time ______________

Section G. GOVERNMENT PROGRAMS

1. During 2008, did you receive direct payments, counter-cyclical payments, loan deficiency payments, marketing loans, or participate in any quota programs or any buy-out programs? *(Select one response.)*
   - ☐ Yes
   - ☐ No

2. In the past 5 years have you received cost-share payments for irrigation/drainage improvements or conservation techniques from any organizations? *(Select one response.)*
   - ☐ Yes
   - ☐ No → *Skip to Part II*

3. Under which program(s), and for what objective(s), was the assistance provided? *(Mark all that apply.)*

Program	**Reduce Soil Erosion**	**Nutrient Management**	**Pest Management**	**Irrigation Water Management**	**Manure Management**
Conservation Reserve Program (CRP)	☐	☐	☐	☐	☐
Environmental Quality Incentive Program (EQIP)	☐	☐	☐	☐	☐
Wetland Reserve Program (WRP)	☐	☐	☐	☐	☐
Wildlife Habitat Incentive Program (WHIP)	☐	☐	☐	☐	☐
Grazing Land Reserve Program (GRP)	☐	☐	☐	☐	☐
Other ______________	☐	☐	☐	☐	☐

All survey responses are strictly confidential.

Part II. Water Usage

This part of the survey asks for information that will provide an overview of your farm's water use decisions.

Section A. TYPE OF IRRIGATION SYSTEM IN 2008

1. Was an irrigation or water delivery system used on this operation to apply water on land in 2008? *(Select one response.)*
   - ☐ Yes
   - ☐ No → Why not? (*Select up to two responses and then skip to Part III.)*
     - ☐ Equipment costs
     - ☐ Sufficient soil moisture
     - ☐ High energy costs
     - ☐ Water withdrawal permitting
     - ☐ Water availability
     - ☐ Low commodity prices

2. How many acres were irrigated with each of the following systems? *(Fill in.)*

	Type of System	Number of Acres
Sprinklers	a. Total Center pivot & Linear-move sprinklers *(if "0" skip (1) – (3).)*	_______ ac
Sprinklers	(1) High pressure (60 PSI or greater)	_______ ac
Sprinklers	(2) Medium pressure (30 to 59 PSI)	_______ ac
Sprinklers	(3) Low pressure (Under 30 PSI)	_______ ac
Sprinklers	b. Solid set and permanent sprinkler systems	_______ ac
Sprinklers	c. Hand move sprinklers, travelers, and/or cable tow	_______ ac
	d. Drip or trickle irrigation	_______ ac
	e. Gravity	_______ ac

Section B. SOURCE AND QUANTITY OF WATER USED IN 2008

How many irrigated acres used ground water or surface water as their primary source? *(Please fill in.)* What was the average amount of water applied from each primary source? *(Please fill in.)*

Estimated Quantity	Ground Water	Surface Water
1. Acres irrigated	___________ ac	___________ ac
2. Average inches applied per acre in 2008	______________	______________

3. Does your farm use any practices to harvest or store water? (*Select one response.)*
   - ☐ Yes → If so what do you use? *(Fill in.)* ______________
   - ☐ No

4. Have you ever used groundwater to maintain a retention pond? *(Select one response.)*
☐ Yes
☐ No

Section C. CROP IRRIGATION FREQUENCY AND METHOD OF WATER DISTRIBUTION IN 2008

What type of irrigation system do you use on the crops that you grow? *(Select one response. If you use multiple types of systems, please mark the type that is most used for that particular crop.)* How often were your different crops irrigated? (*Select one response.)*

Cropland Use		**Primary Type of Irrigation System**			**How many times were crops irrigated in 2008?**		
		Sprinklers	**Drip or Trickle**	**Gravity**	**Less than 3**	**3 to 7**	**8 or more**
1. Field Crops	a. Corn	☐	☐	☐	☐	☐	☐
	b. Cotton	☐	☐	☐	☐	☐	☐
	c. Peanuts	☐	☐	☐	☐	☐	☐
	d. Sorghum	☐	☐	☐	☐	☐	☐
	e. Soybeans	☐	☐	☐	☐	☐	☐
	f. Wheat	☐	☐	☐	☐	☐	☐
	g. All Others	☐	☐	☐	☐	☐	☐
2. Vegetables & Melons	a. Bell Peppers	☐	☐	☐	☐	☐	☐
	b. Cabbage	☐	☐	☐	☐	☐	☐
	c. Green Beans	☐	☐	☐	☐	☐	☐
	d. Sweet Corn	☐	☐	☐	☐	☐	☐
	e. Tomatoes	☐	☐	☐	☐	☐	☐
	f. Watermelons	☐	☐	☐	☐	☐	☐
	g. All Others	☐	☐	☐	☐	☐	☐
3. Fruit & Orchard Crops	a. Peaches	☐	☐	☐	☐	☐	☐
	b. Pecans	☐	☐	☐	☐	☐	☐
	c. All Others	☐	☐	☐	☐	☐	☐
4. Hay & Forage Crops	a. Hay *(harvested)*	☐	☐	☐	☐	☐	☐
	b. Turf Grass	☐	☐	☐	☐	☐	☐
	c. All Others	☐	☐	☐	☐	☐	☐
5. Pasture or Grazing Land		☐	☐	☐	☐	☐	☐

All survey responses are strictly confidential.

Section D. PUMPING CAPACITY AND ENERGY SOURCE

1. How many water pumps are used on your farm? (*Fill in.*) ______________

2. How many of your farm's water pumps have meters or other flow measurement devices? (*Fill in.*) ______________

3. How many of your farm's water pumps have running time gauges? (*Fill in.*) ____________

4. What power sources are used for your pumps? (*Fill in all that apply.*)

Power Source	Number of Pumps	Acres Irrigated
a. Electricity	____________	____________ ac
b. Natural Gas	____________	____________ ac
c. Diesel fuel	____________	____________ ac
d. Gasoline	____________	____________ ac
e. Biofuels (*such as soy or peanut diesel, other biodiesels, or ethanol)*	____________	____________ ac
f. Other renewable sources	____________	____________ ac

Section E. IRRIGATION MANAGEMENT PRACTICES

1. How do you decide when to irrigate? *(Mark all that apply.)*
   - ☐ Observing condition of crop
   - ☐ Feeling the soil moisture
   - ☐ Soil moisture sensing devices
   - ☐ Plant moisture sensing devices
   - ☐ Irrigation scheduling software
   - ☐ Calendar
   - ☐ Neighbors
   - ☐ Remote sensing
   - ☐ Time of day

2. As of your most recent irrigation audit, or estimate, what is the current irrigation efficiency of your primary irrigation system? (*Select one response and fill in date of last audit.)*
   - ☐ 90% to 100%
   - ☐ 80% to 89%
   - ☐ 70% to 79%
   - ☐ 50% to 69%
   - ☐ Less than 50%

   → Date of most recent audit *(Fill in.*) ____________
   - ☐ Do not know

3. How do you decide which crops to irrigate or to grow in irrigated fields? *(Mark all that apply.)*
   - ☐ Cost of irrigating
   - ☐ Availability of water
   - ☐ Crop prices
   - ☐ Crop water requirements
   - ☐ Other ____________

4. How often do you make adjustments, calibrate, and/or perform a uniformity test on your irrigation systems? (*Select one response.)*
   - ☐ Never
   - ☐ Once, when first installed
   - ☐ Less than once a year
   - ☐ Yearly
   - ☐ Monthly
   - ☐ Weekly
   - ☐ Daily

5. In the past 5 years *(Answer parts a. and b.)*:
   a. Has your farm expanded total irrigated acreage?
      - ☐ Yes *(Fill in.)* → expanded irrigated acres by ______________ acres
      - ☐ No

   b. Has your farm implemented any improvements to your irrigation system?
      - ☐ Yes
      - ☐ No

6. What are barriers to implementing improvements that might reduce energy and/or conserve water in your irrigation system? *(Mark all that apply.)*
   - ☐ Investigating improvements not a priority at this time
   - ☐ Risk of reduced yield or poorer quality crop yields from not meeting water demands
   - ☐ Physical field/crop conditions limit system improvements
   - ☐ Improvement(s) will reduce costs, but not enough to cover installation costs
   - ☐ Cannot finance improvements
   - ☐ Landlord(s) will not share cost of improvements
   - ☐ Uncertainty about future availability of water
   - ☐ Will not be farming this operation long enough to justify new improvements
   - ☐ Other ______________
   - ☐ I irrigate as efficiently as I think I can

7. How effective is soil fertility or soil quality management for water conservation on your farm? *(Select one response.)*
   - ☐ Very effective
   - ☐ Somewhat effective
   - ☐ Not at all effective

All survey responses are strictly confidential.

Part III. Policy Options

In this part of the survey, we will present eight policies that, as a combination of short and long-term water usage policies, represent a set of available options for Georgia and other states. Some of these policies are similar to local and/or national programs both within Georgia and across the country. For each of the hypothetical policies below, please answer how you feel about these policies if they were implemented in Georgia or other states. As a farm operator, indicate how, or if, you would change your water use behavior and then how this would affect your production were a policy of this nature to be put in place.

Section A. RANKING AVAILABLE WATER POLICIES

Please rank the following eight water policies from 1 (most preferred) to 8 (least preferred) using each number only once. *(Fill in.)*Also, indicate how familiar you are with a particular policy *(Select one response per policy).*

Policy	Description	Familiarity	Rank from 1 (best) to 8 (worst)
1. Quota	Yearly allotted number of pump running hours or acre-inches: guidelines provided based on current cropping, irrigation system, pump type, soil conditions, and expected rainfall.	☐ Very ☐ Somewhat ☐ Not at All	__________
2. One Day a Week Watering Ban	Irrigation only permitted six days a week. Your banned day is assigned for entire farm. Easements provided for system failures.	☐ Very ☐ Somewhat ☐ Not at All	__________
3. Water Pump Monitoring	Flow meter installed on water pumps: compensation for below average water use, penalty for above average water use.	☐ Very ☐ Somewhat ☐ Not at All	__________
4. Subsidy for Improving Irrigation Efficiency	Onetime payment to assist in replacing and/or repairing inefficient irrigation equipment.	☐ Very ☐ Somewhat ☐ Not at All	__________
5. Regional 80% Irrigation Efficiency Requirement	Community monitored and enforced with annual irrigation audits conducted.	☐ Very ☐ Somewhat ☐ Not at All	__________
6. Water Pricing	Prices based on expected future groundwater and surface water levels.	☐ Very ☐ Somewhat ☐ Not at All	__________
7. Tiered Water Pricing	Prices based on consumption of water. Standard tiered rate system: as amount of water increases, price per unit decreases.	☐ Very ☐ Somewhat ☐ Not at All	__________
8. Water Market	Water withdrawal permits can be sold, leased, or traded.	☐ Very ☐ Somewhat ☐ Not at All	__________

Section B. EFFECTS OF WATER POLICIES

Please indicate how the same eight water policies might affect the amount of water applied, your farm's production output, and if your farm might switch to new management practices/strategies. (*Select one response under 'Water Usage' and one response under 'Production Output' for each policy.) (Select all that apply under 'Management Practices' for each policy.)*

Policy	**Water Usage**			**Production Output**		
	Increase	**Decrease**	**No Change**	**Increase**	**Decrease**	**No Change**
1. Quota	☐	☐	☐	☐	☐	☐
2. One Day a Week Watering Ban	☐	☐	☐	☐	☐	☐
3. Water Pump Monitoring	☐	☐	☐	☐	☐	☐
4. Subsidy for Improving Irrigation Efficiency	☐	☐	☐	☐	☐	☐
5. Regional 80% Irrigation Efficiency Requirement	☐	☐	☐	☐	☐	☐
6. Water Pricing	☐	☐	☐	☐	☐	☐
7. Tiered Water Pricing	☐	☐	☐	☐	☐	☐
8. Water Market	☐	☐	☐	☐	☐	☐

Policy	**Management Practice**				
	Conservation Tillage	**Higher Value Crops**	**More Drought Tolerant Varieties**	**Improve Irrigation System**	**Time of Watering**
1. Quota	☐	☐	☐	☐	☐
2. One Day a Week Watering Ban	☐	☐	☐	☐	☐
3. Water Pump Monitoring	☐	☐	☐	☐	☐
4. Subsidy for Improving Irrigation Efficiency	☐	☐	☐	☐	☐
5. Regional 80% Irrigation Efficiency Requirement	☐	☐	☐	☐	☐
6. Water Pricing	☐	☐	☐	☐	☐
7. Tiered Water Pricing	☐	☐	☐	☐	☐
8. Water Market	☐	☐	☐	☐	☐

All survey responses are strictly confidential.

Part IV. Additional Farm Information

This part of the survey asks for additional information about you and your farm.

Section A. ABOUT YOU

1. How many years have you been farming? *(Fill in.)* _____________ years

2. Do you farm full time or part time? *(Select one response.)*
   ☐ Full time
   ☐ Part time

3. How important are the following concepts to you and your farm? Using a scale of 1 (not important) to 5 (very important) please indicate how important the following possible motivations are for you. *(Select one response per category.)*

Motivations	**Not important** **1**	**2**	**Moderately important** **3**	**4**	**Very important** **5**
Profit	☐	☐	☐	☐	☐
Conservation	☐	☐	☐	☐	☐
Hobby / Recreation	☐	☐	☐	☐	☐
Tax credits/deductions	☐	☐	☐	☐	☐
Sustainability	☐	☐	☐	☐	☐
Other _____________	☐	☐	☐	☐	☐

4. What is your highest level of formal education? *(Select one response.)*
   ☐ No formal education
   ☐ Some high school
   ☐ Completed high school
   ☐ Some college
   ☐ Completed junior college/trade school degree
   ☐ Completed bachelor's degree
   ☐ Some graduate work
   ☐ Graduate degree

5. What is your age? *(Fill in.)* _____________ years

6. What is your gender? *(Select one response.)*
   ☐ Female
   ☐ Male

7. Do you have internet access at your farm office? *(Select one response.)*
   ☐ Yes → What speed? *(Fill in.)* _____________
   ☐ No

Section B. FARM INCOME

1. What percentage of your net household income came from farm production in 2008? *(Select one response.)*
   - ☐ 1% - 25%
   - ☐ 26% - 50%
   - ☐ 51% - 75%
   - ☐ 76% - 100%

2. What was your farm's gross farming income in 2008? NOTE: ALL SURVEY RESPONSES, INCLUDING FINANCIAL FIGURES, ARE STRICTLY CONFIDENTIAL! *(Select one response.)*

☐ No income or loss	☐ $100,000 to $249,999
☐ Less than $5,000	☐ $250,000 to $499,999
☐ $5,000 to $14,999	☐ $500,000 to $999,999
☐ $15,000 to $29,999	☐ $1 million to $4.9 million
☐ $30,000 to $49,999	☐ $5 million to $19.9 million
☐ $50,000 to $99,999	☐ $20 million or more

Section C. FIELD COUNTIES

1. How many fields does your farm have in production, and in what counties? *(Fill in.)*

a. Primary county ______________ → Number of fields ______________
b. Other counties ______________ → Number of fields ______________
______________ → Number of fields ______________

APPENDIX B

COVER LETTERS

This appendix includes the cover letters used in the two mailings of the surveys. The first cover was included in the survey that was mailed during the first week of April 2009. All non-respondents were then mailed with an additional copy of the survey and the second cover letter during the third week of May 2009.

The University of Georgia

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April 2009

Dear Georgia farm owner:

The State of Georgia is considering a possible program to increase agricultural practices that make the best use of water for irrigation. In order to develop sound agricultural policy to support Georgia's farmers, research is being conducted about the effects of water policies on the agricultural practices of Georgia farms, the state's water resources, and its economy. The state must weigh the costs and benefits of adopting water policies for agriculture. The University of Georgia is directing the analysis of this possible program.

Your farm is one of a small number in Georgia that is being asked to provide information about the impact of the policy alternatives on your operation. Your farm was drawn at random from all farms in the state. To ensure that the results are representative of Georgia farmers, it is essential that each booklet be completed and returned. Any adult (18 years or older) in charge of farm operations may answer the questions. Doing so will help the State of Georgia to base its policy on the best information possible.

You are assured complete confidentiality. The identification number on the booklet is for mailing purposes only. This enables us to check your name off the mailing list when your completed booklet is returned. Your name or farm will never be associated with the answers you give.

Interested legislators and policymakers in future deliberations on the policy will use the results of this research. The information you provide will have a direct effect on the discussion of the policy. Thank you for your assistance.

Sincerely,

Rebecca Moore

Rebecca Moore, Ph.D.
Project Director

Questions or concerns about your rights as a research participant should be directed to The Chairperson, University of Georgia Institutional Review Board, 612 Boyd GSRC, Athens, Georgia 30602-7411; telephone (706) 542-3199; email address irb@uga.edu.

The University of Georgia

WARNELL
SCHOOL OF FORESTRY AND NATURAL RESOURCES
THE UNIVERSITY OF GEORGIA

May 2009

Dear Georgia farm owner:

In the last few weeks a booklet was mailed to you seeking information on your farm's use of water for irrigation and how various agricultural water policy options might affect your operation. This study is being carried out in response to the State of Georgia's consideration of a possible program, or programs, to increase agricultural practices that make the best use of water for irrigation. In order to develop sound agricultural policy to support Georgia's farmers, research is being conducted about the effects of water policies on the agricultural practices of Georgia farms, the state's water resources, and its economy. The state must weigh the costs and benefits of adopting water policies for agriculture. The University of Georgia is directing the analysis of this possible program.

Your farm is one of a small number in Georgia that is being asked to provide information about the impact of the policy alternatives on your operation. Your farm was drawn at random from all farms in the state. To ensure that the results are representative of Georgia farmers, it is essential that each booklet be completed and returned. Any adult (18 years or older) in charge of farm operations may answer the questions. Doing so will help the State of Georgia to base its policy on the best information possible.

If you have already completed and returned the booklet, please accept our sincere thanks. If not, please do so at your earliest convenience. It is extremely important that your views be included in the study.

You are assured complete confidentiality and anonymity. The identification number on the booklet is for mailing purposes only. This enables us to check your name off the mailing list when your completed booklet is returned. Your name or farm will never be associated with the answers you give. Additional questions or problems can be addressed by myself and my research assistant, Joe Price. He can be reached directly on his cell phone at 803.446.1802. Thank you for your assistance.

Sincerely,

Rebecca Moore

Rebecca Moore, Ph.D.
Project Director
Phone: 706.542.2686

Questions or concerns about your rights as a research participant should be directed to The Chairperson, University of Georgia Institutional Review Board, 612 Boyd GSRC, Athens, Georgia 30602-7411; telephone (706) 542-3199; email address irb@uga.edu.

Appendix C

Survey Approval

This appendix includes the approval form for the use of survey gathered data from the University of Georgia, Office of the Vice President for Research, Human Subjects Office, Institutional Review Board.

The University of Georgia

Office of The Vice President for Research
DHHS Assurance ID No. : FWA00003901

Institutional Review Board
Human Subjects Office
612 Boyd GSRC
Athens, Georgia 30602-7411
(706) 542-3199
Fax: (706) 542-3360
www.ovpr.uga.edu/hso

APPROVAL FORM

Date Proposal Received: 2008-09-05 **Project Number:** 2009-10151-0

Name	Title	Dept/Phone	Address	Email
Dr. Rebecca L. Moore	PI	Forestry and Natural Resources Warnell School of Forestry 706-583-8932		rmoore@warnell.uga.edu
Mr. Joseph Price	CO	Agricultural and Applied Economics 309 Conner Hall 0854 803-446-1802		pricejn2@uga.edu

Title of Study: Water use Differences Among Farm Types and Sizes in Georgia

45 CFR 46 Category: Administrative 2
Parameters:
None;

Change(s) Required for Approval:
Revised Application;
Revised Consent Document(s);

Approved : 2008-09-30 **Begin date : 2008-09-30** **Expiration date : 2013-09-29**

NOTE: Any research conducted before the approval date or after the end data collection date shown above is not covered by IRB approval, and cannot be retroactively approved.

Number Assigned by Sponsored Programs:

Funding Agency:

Your human subjects study has been approved.

Please be aware that it is your responsibility to inform the IRB:
. . . of any adverse events or unanticipated risks to the subjects or others within 24 to 72 hours;
. . . of any significant changes or additions to your study and obtain approval of them before they are put into effect;
. . . that you need to extend the approval period beyond the expiration date shown above;
. . . that you have completed your data collection as approved, within the approval period shown above, so that your file may be closed.

For additional information regarding your responsibilities as an investigtor refer to the IRB Guidelines.
Use the attached Researcher Request Form for requesting renewals, changes, or closures.
Keep this original approval form for your records.

Chairperson or Designee,
Institutional Review Board

Appendix D

Data Envelopment Analysis and Stochastic Frontier Analysis Efficiency Scores

	Linearθ^{DEA}_{AWL}		Linearθ^{DEA}_{FIC}		Log-Linearθ^{DEA}_{AWL}		Log-Linearθ^{DEA}_{FIC}		θ^{SFA}	
Obs.	θ	θ^w	θ	θ^w	θ	θ^w	θ	θ^w	θ	θ^w
1	0.92	0.76	1	1	0.98	0.87	0.98	0.87	0.87	0.61
2	0.06	0.01	0.43	1	0.51	0.27	0.94	1	0.10	
3	0.24	0.04	0.33	0.04	0.73	0.59	0.87	0.59	0.19	
4	0.16	0.02	0.19	0.02	0.68	0.53	0.8	0.54	0.14	
5	0.24	0.03	0.39	0.12	0.65	0.55	0.93	0.75	0.22	
6	0.06	0.01	0.41	1	0.51	0.27	0.94	1	0.10	
7	0.01	0.01	0.28	1	0.55	0.02	0.75	1	0.00	
8	1		1		1		1			
9	1	1	1	1	1	1	1	1	1.00	0.98
10	0.75	0.27	0.75	0.27	0.96	0.83	0.96	0.83	0.49	
11	0.12	0.01	0.21	0.01	0.58	0.44	0.81	0.49	0.10	
12	0.38		0.64		1		1		0.82	0.54
13	1		1		1		1		0.88	
14	1	0.38	1	1	1	0.89	1	1		
15	0.36	0.03	0.44	0.08	0.66	0.55	0.89	0.6	0.36	0.04
16	0.38	0.09	0.46	0.09	0.84	0.64	0.84	0.64	0.38	
17	0.02	0	0.34	0.04	0.45	0.11	0.72	0.32	0.03	
18	0.17	0.01	0.28	0.01	0.6	0.44	0.85	0.45	0.12	
19	1		1		1		1		0.28	0.01
20	0.02	0.01	0.17	0.01	0.44	0.19	0.74	0.23	0.04	
21	0.07	0.01	0.29	0.2	0.48	0.23	0.83	0.58	0.10	
22	0.12		0.5		1		1		0.27	
23	0.24	0.01	0.32	0.02	0.62	0.49	0.85	0.54	0.23	
24	1		1		1		1			

	Linearθ^{DEA}_{AWL}		Linearθ^{DEA}_{FIC}		Log-Linearθ^{DEA}_{AWL}		Log-Linearθ^{DEA}_{FIC}		θ^{SFA}	
Obs.	θ	θ^w	θ	θ^w	θ	θ^w	θ	θ^w	θ	θ^w
25	0.55	0.16	0.62	1	0.8	0.67	1	1	0.30	0.01
26	0.22		0.61		0.8		1			
27	0.26	0	0.35	0	0.7	0.46	0.88	0.46	0.28	
28	0.1		0.24		0.74		0.74		0.00	
29	0.4	0.09	0.45	0.17	0.76	0.63	0.9	0.74	0.41	0.01
30	0.28	0.03	0.41	0.08	0.66	0.56	0.91	0.7	0.28	0.00
31	0.03	0	0.29	0.2	0.45	0.17	0.85	0.64	0.05	
32	0.11		0.22		0.8		0.82		0.20	
33	0.02	0	0.35	0.19	0.44	0.11	0.88	0.75	0.02	
34	0.67		0.94		1		1		0.39	0.01
35	0.03	0	0.35	0.05	0.44	0.17	0.91	0.62	0.02	
36	0.18	0.01	0.26	0.01	0.62	0.49	0.63	0.49	0.17	
37	0.98	1	1	1	0.84	1	0.92	1	0.68	
38	0.04	0	0.21	0.01	0.44	0.25	0.84	0.4	0.03	
39	0.36		0.87		0.87		0.91		0.00	
40	0.11		0.28		0.8		0.8		0.00	
41	0.06		0.22		0.71		0.73		0.00	
42	0.15		1		0.76		1		0.31	
43	0.24		1		1		1		0.00	
44	0.12	0.05	0.24	0.08	0.58	0.48	0.77	0.63	0.23	
45	0.41	0.12	0.5	0.15	0.78	0.64	0.94	0.74	0.39	0.02
46	0.11		0.68		0.76		0.94		0.12	
47	0.12		0.31		0.74		0.81		0.04	
48	0.34		0.85		0.87		0.91		0.00	
49	0.21		0.25		0.73		0.79		0.24	0.00
50	0.19		0.38		0.79		0.8		0.33	
51	0.28		0.36		0.86		0.87		0.55	
52	0.41		0.7		0.87		0.87		0.00	
53	0.44		1		0.9		1		0.13	
54	0.36		1		0.87		1		0.39	
55	1		1		1		1			
56	0.13		0.37		0.74		0.91		0.16	
57	0.09		0.2		0.7		0.75		0.08	
58	1		1		1		1		0.74	0.12

	Linearθ^{DEA}_{AWL}		Linearθ^{DEA}_{FIC}		Log-Linearθ^{DEA}_{AWL}		Log-Linearθ^{DEA}_{FIC}		θ^{SFA}	
Obs.	θ	θ^w	θ	θ^w	θ	θ^w	θ	θ^w	θ	θ^w
59	0.08	0.04	0.16	0.04	0.65	0.37	0.65	0.37	0.12	0.00
60	0.77	0	0.85	0	0.9	0.52	0.91	0.52	0.23	0.02
61	0.49	0.14	0.61	0.14	0.9	0.72	0.9	0.72	0.42	
62	0.67	0.24	0.94	0.45	0.89	0.72	0.95	0.86	0.65	0.10
63	1	1	1	1	1	1	1	1	0.94	0.87
64	0.55	0.1	0.6	0.1	0.85	0.71	0.86	0.71	0.46	
65	0.17	0.08	1	1	0.75	0.52	0.93	0.82	0.20	0.02
66	0.35		0.86		0.87		0.91		0.00	
67	0.11	0.6	0.24	1	0.6	0.8	0.82	1	0.28	
68	0	0	0.33	0.01	0.45	0.01	0.79	0.21	0.02	
69	0.01	0.01	0.49	1	0.61	0.02	0.82	1	0.05	0.00
70	0.05	0.01	0.33	0.09	0.49	0.21	0.87	0.58		
71	0.55	1	0.76	1	1	1	1	1	0.68	0.47
72	0.09	0.02	0.43	0.04	0.85	0.24	0.88	0.29	0.07	0.01
73	0.2	0.09	0.81	0.39	0.91	0.44	0.97	0.74	0.20	0.05
74	0.27		0.41		0.81		0.82		0.89	0.71
75	0.27	0.27	0.43	0.27	0.83	0.67	0.83	0.67	0.70	0.51
76	0.18	0.05	0.54	0.11	0.94	0.4	0.94	1	0.23	0.10
77	0.06	0	0.29	0	0.63	0.01	0.74	0.01	0.01	0.00
78	0.33		0.41		0.82		0.82		0.95	0.88
79	0.27	0.24	1	1	0.95	0.64	1	1	0.35	0.04
80	0.28		0.53		0.94		0.96		0.99	0.96
81	0.09	0.13	1	1	0.62	0.57	0.87	0.91	0.14	
82	1	1	1	1	1	1	1	1	0.36	0.11
83	1		1		1		1		0.41	0.19
84	0.32		0.64		0.8		0.87		0.00	
85	0.28		0.79		0.87		0.9		0.00	
86	0.07	0.01	0.26	0.01	0.58	0.23	0.65	0.23	0.13	0.00
87	0	0	0.3	0.04	0.49	0.01	0.74	0.28	0.00	
88	0.43		0.5		0.81		0.86		0.00	
89	0.1		1		0.9		1		0.28	
90	0.88	1	1	1	0.81	0.9	0.96	1	0.99	0.98
91	0.31	0.04	0.87	1	0.71	0.49	0.97	1	0.34	0.10
92	0.11	0.12	0.51	0.12	0.68	0.53	0.76	0.53	0.47	0.14

	Linearθ_{AWL}^{DEA}		Linearθ_{FIC}^{DEA}		Log-Linearθ_{AWL}^{DEA}		Log-Linearθ_{FIC}^{DEA}		θ^{SFA}	
Obs.	θ	θ^w	θ	θ^w	θ	θ^w	θ	θ^w	θ	θ^w
93	1		1		1		1		0.35	
94	0.08		0.1		0.6		0.63		0.00	
95	0	0	0.51	1	0.46	0.01	0.87	1	0.00	
96	0.28	0.04	0.36	0.04	0.68	0.56	0.81	0.67	0.31	
97	0.78	0.24	0.79	0.24	0.96	0.81	0.96	0.81	0.65	0.18
98	0.85	0.85	0.85	0.85	0.9	0.97	0.97	0.97		
99	0.07	0.22	0.15	0.35	0.57	0.64	0.72	0.75	0.24	
100	1	1	1	1	1	1	1	1	0.95	0.87
101	0.82	0.41	0.88	0.41	0.95	0.73	0.95	0.73	0.69	0.31
102	1	1	1	1	1	1	1	1	0.73	
103	0.78	1	1	1	0.8	0.73	1	1	0.90	0.82
104	1	1	1	1	1	1	1	1	0.75	0.70
105	0.3	0.17	0.3	0.17	0.87	0.85	0.87	0.85	0.34	
106	1	1	1	1	1	1	1	1	1.00	0.98
107	0.13	0.02	0.24	0.03	0.59	0.42	0.75	0.49	0.18	0.00
108	0.43	0.19	0.56	0.19	0.83	0.78	0.83	0.78	0.46	
109	0.19		0.36		0.8		0.8		0.00	
110	0.45	0.06	0.52	0.06	0.84	0.67	0.84	0.67	0.45	
111	0.19	0.02	0.45	0.34	0.59	0.4	0.9	0.71	0.25	0.03
112	0.18		0.51		0.87		0.94		0.29	

Appendix E

2008 Average Precipitation by County

County	Average Precipitation
Appling	38.1977
Atkinson	36.2540
Bacon	37.4657
Baker	38.8786
Baldwin	37.8006
Banks	35.9873
Barrow	33.9005
Bartow	33.1995
Ben Hill	38.5046
Berrien	37.5498
Bibb	37.4304
Bleckley	39.0328
Brantley	36.9037
Brooks	39.8125
Bryan	41.6015
Bulloch	43.9590
Burke	36.9722
Butts	32.6895
Calhoun	38.8117
Camden	34.6280
Candler	42.5222
Carroll	36.0809
Catoosa	34.8152
Charlton	35.9474
Chatham	39.0799
Chattahoochee	36.2831

County	Average Precipitation
Chattooga	35.2367
Cherokee	31.1169
Clarke	37.3653
Clay	39.9958
Clayton	30.0298
Clinch	36.0634
Cobb	30.8827
Coffee	36.7646
Colquitt	43.1508
Columbia	32.1053
Cook	39.8818
Coweta	34.0342
Crawford	35.7874
Crisp	39.7260
Dade	35.3376
Dawson	31.1778
Decatur	33.3501
DeKalb	29.9114
Dodge	38.6697
Dooly	37.7979
Dougherty	40.7942
Douglas	32.9218
Early	37.1976
Echols	35.9557
Effingham	41.7099
Elbert	36.5511
Emanuel	40.0627
Evans	42.6578
Fannin	33.4479
Fayette	31.1889
Floyd	35.2022
Forsyth	31.2863
Franklin	37.9281
Fulton	30.6550
Gilmer	32.0867

County	Average Precipitation
Glascock	34.4724
Glynn	35.8803
Gordon	33.5228
Grady	37.8739
Greene	36.7126
Gwinnett	31.2358
Habersham	35.3904
Hall	32.6736
Hancock	36.5872
Haralson	36.1497
Harris	36.7174
Hart	37.6730
Heard	37.1441
Henry	30.8261
Houston	37.8747
Irwin	38.7775
Jackson	35.5528
Jasper	34.8163
Jeff Davis	37.5997
Jefferson	35.6708
Jenkins	40.4989
Johnson	38.9937
Jones	36.9978
Lamar	32.8899
Lanier	36.2500
Laurens	39.3456
Lee	39.2546
Liberty	40.0826
Lincoln	32.9213
Long	39.7687
Lowndes	37.0685
Lumpkin	32.5012
Macon	35.5738
Madison	38.6388
Marion	34.6736

County	Average Precipitation
McDuffie	32.4683
McIntosh	37.5319
Meriwether	34.4501
Miller	35.6303
Mitchell	40.8499
Monroe	34.8475
Montgomery	39.0531
Morgan	35.7148
Murray	33.7571
Muscogee	36.6525
Newton	32.6969
Oconee	36.2969
Oglethorpe	37.3111
Paulding	33.3468
Peach	37.0971
Pickens	31.2830
Pierce	37.5571
Pike	32.1922
Polk	35.5094
Pulaski	38.4605
Putnam	36.6823
Quitman	40.4707
Rabun	35.8962
Randolph	38.7498
Richmond	33.7596
Rockdale	31.1207
Schley	33.8806
Screven	41.5529
Seminole	32.0128
Spalding	31.0975
Stephens	36.8869
Stewart	37.8387
Sumter	35.4127
Talbot	34.7250
Taliaferro	35.4424

County	Average Precipitation
Tattnall	41.0398
Taylor	34.5360
Telfair	37.8764
Terrell	38.4051
Thomas	40.3412
Tift	42.7021
Toombs	39.8667
Towns	35.3108
Treutlen	39.6047
Troup	36.9396
Turner	42.0425
Twiggs	38.8209
Union	34.2973
Upson	33.7297
Walker	34.8600
Walton	33.6955
Ware	36.6251
Warren	34.0308
Washington	37.5554
Wayne	38.2817
Webster	35.3093
Wheeler	38.5123
White	34.2611
Whitfield	34.4357
Wilcox	38.8754
Wilkes	34.7787
Wilkinson	38.8120
Worth	43.1271