ASSESSING THE UTILIZATION AND EFFECTS OF SOIL MOISTURE SENSORS FOR AGRICULTURAL IRRIGATION

by

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(Under the Direction of Adam N. Rabinowitz)

ABSTRACT

Irrigation has the potential to significantly mitigate downside production risk in agriculture by optimizing the distribution of irrigation to satisfy crop needs. Additionally, soil-moisture sensors (SMS) may improve water-use efficiency (WUE) by improving irrigation scheduling and preventing overwatering compared to more rudimentary irrigation scheduling techniques. These benefits of SMS are important in the U.S. state of Georgia, where recent drought events and ongoing litigation concerning water use in the Apalachicola-Chattahoochee-Flint (ACF) River Basin have increased producer and public concern about future water availability. This research evaluates producer and farm characteristics related to the utilization of SMS and assesses the impact of SMS-utilization on producer perceptions of on-farm use as a way to inform government and extension programming aimed at improving WUE.

INDEX WORDS: Irrigation technology, soil moisture sensors, propensity score matching, Theory of Planned Behavior

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DEDICATION

This thesis is dedicated to my parents, Dr. and Mrs. John Cartwright, in recognition of how their own pursuit of graduate education has afforded me the opportunity and inspiration to achieve dreams of my own.

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I. INTRODUCTION

Agriculture has always been critical for sustaining human populations. Global food production is set to double from 1990 levels by 2020 due to improvements in farm technology and agricultural practices (FAO, 2017), part of a longer trend of increased agricultural production beginning in the 20th century known as the Green Revolution (Evenson and Gollin, 2003). This improvement is despite an only two percent increase in total land used for agriculture over the same 30-year period (Klein Goldewijk et al., 2017). One catalyst for this global improvement in agricultural productivity was the large expansion of irrigation (Tillman et al., 2001). Irrigation can be defined as the artificial application of water to land in order to entirely or partially satisfy crop needs during the growing period. Assessing the extent and usage of irrigation is imperative in answering questions about future water availability, as it is estimated that irrigation accounts for roughly 70 percent of the world's consumption of freshwater (FAO, 2012).

According to a recent study by Dieter et al. (2016), some 256,000 km2 of cropland in the United States is irrigated. Crop irrigation accounts for approximately 42 percent of total freshwater use in the United States (Dieter, et al., 2016). While agriculture in arid and semiarid regions of the American West has historically been much more reliant on irrigation to satisfy crop water needs, the practice has become increasingly prevalent in wetter regions such as the southeastern United States. Between 1976 and 2013 irrigated acreage in the state of Georgia increased by over 2,200 percent, with most of this increase occurring in the southwestern region of the state (Williams et al., 2013). According to Martin et al. (2013), this regional explosion in the use of irrigation during the second-half of the 20th century was motivated by technological advances (i.e., invention of center-pivot irrigation), financial pressures (i.e., banks requiring irrigation to secure farm loans), and federal subsidy programs motivating more intensive cultivation practices and cropland improvement (i.e., the Conservation Reserve Program). In the 21st century, the primary irrigated crops in Georgia are cotton, peanuts, soybeans, pecans, corn, and turfgrass (Levin & Zarriello, 2013).

The reliability of irrigation in satisfying crop water needs even in the absence of sufficient precipitation allows irrigators to significantly mitigate downside production risks (i.e., yield loss) associated with drought (Groom et al, 2008; Wang et al, 2018). However, there is increasing consensus that the frequency and intensity of heat waves and droughts are likely to increase in the southeastern United States as a result of climate change (Dai, 2011; Mishra et al., 2017; Apruv et al., 2019). These extreme weather events will increase crop evapotranspiration and stress in the region. Recent research (Wada et al., 2011; Wada et al., 2013; Braneon, 2014) has predicted 40–70 percent increases in total irrigation requirements for sustaining agriculture in the southeastern United States under multiple climate change scenarios. This potential for increased agricultural water-use is in direct conflict with ecological water needs as well as municipal water needs for direct human use. Recent legal conflict surrounding water extraction in the Apalachicola Chattahoochee-Flint (ACF) River Basin demonstrates this reality. Upstream water withdrawals from the ACF River Basin in Georgia affect downstream users and environments; for example, Florida has initiated litigation against Georgia claiming that upstream agricultural withdraws from the ACF River Basin damages the sustainability of Florida's multi-million dollar shellfish and oyster industry by limiting freshwater intake at the Apalachicola Bay estuary. Resultantly, agricultural irrigators in Georgia have faced increased legal and regulatory pressure to limit total irrigation requirements through a combination of improved technology, increased monitoring, or decreasing crop water requirements. While new technology has the potential to improve agricultural water-use efficiency (WUE), some research suggests it would not lead to water-saving in practice due to producer reoptimization behavior (Ward & Pulido-Velazquez, 2008; Pfeiffer & Lin, 2014).

One potential mechanism of improving WUE is through improved irrigation scheduling. Irrigation scheduling is the temporal distribution of applied water to cropland over the growing season. Konstantinos et al. (2015) differentiate between static and dynamic irrigation scheduling methods. Static scheduling allocates water without regard to current crop needs, such as applying irrigation a set number of days after planting; whereas, dynamic scheduling applies irrigation to achieve optimal soil water content conditions for the crop at every growth stage (Konstantinos, 2015). It has been suggested that dynamic irrigation scheduling improves WUE by limiting the potential for over- or under-watering (Tam, 2006). Despite these apparent advantages to producers and the environment, adoption of dynamic irrigation scheduling techniques is complicated by their relative complexity. Dynamic irrigation is a more intensive management practice as it requires growers to make real-time adjustments based on climatic, soil, and plant conditions (Dabach et al., 2013). Soil-moisture sensors (SMS) potentially assist in dynamic irrigation scheduling by allowing producers to receive information on soil-moisture in real-time. SMS technology measures the volumetric water content in soil using inserted or handheld probes. Several different versions of the technology are commercially available, ranging from relatively simple, small and inexpensive tensiometers to more complex granular matrix sensors (GMS) and electromagnetic (EM) frequency sensors. Recent advances in wireless technology for EM frequency sensors has significantly decreased their costs and associated management complexities (Blondquist et al., 2006; Ruiz-Garcia et al., 2009) while improving the quality of soil-moisture data communicated to growers. Additionally, commercial SMS vendors have invested in developing more immersive, visual data platforms to communicate soil moisture information to their users. These platforms are often available through online or mobile-based applications (Vedillis et al., 2016). These advances may support producer decision-making for dynamic irrigation scheduling and thus have potential to improve WUE, mitigate production risk, and increase the environmental sustainability of agriculture.

Despite these advantages, producer utilization of SMS has remained low and inconsistent in regions where it would be advantageous, such as southwestern Georgia. The USDA reported in the 2013 Irrigation and Water Management Survey[1] that only nine percent of irrigators in Georgia used SMS for dynamic irrigation scheduling. In contrast, observing crop quality (78 percent) or soil condition (40 percent) are the methods most commonly used to schedule irrigation in Georgia. These more rudimentary methods may encourage over-watering due to their ability to be influenced by subjective producer assessments (McGuckin et al., 1992). Therefore, underutilization of SMS limits producers' abilities to improve WUE, mitigate production risk, and enhance the sustainability of their operations. Resultantly, Cooperative Extension Services in the southeast have recently undertaken new programming and education efforts aimed at increasing producer adoption of SMS-technology. In response to this mission, this research considers two major goals:

1. To identify operator- and farm-level characteristics that influence SMS-utilization for agricultural irrigators in Georgia; and,

[1] Table 22: Methods used when deciding when to irrigate: 2013. Farm and Ranch Irrigation Survey. U.S. Department of Agriculture, National Agricultural Statistical Service: Washington.

2. To quantify the possible effects of SMS-utilization on producers' attitudes and perceptions of agricultural water-use and water risk

In response to these objectives, this research uses survey responses from 94 agricultural irrigators collected between December 2017 and January 2018 to identify producers' likelihoods of utilizing SMS. Additionally, we combine the survey data with publically-available data from the Federal Communications Commission (FCC) on rural broadband service to assess the impact of internet connectivity on SMS utilization. Our logistic regression results suggest that producer age, farm size, farm location, crop mix, and some producer perceptions of agricultural water-use are explanatory in predicting SMS utilization. Using propensity score matching (PSM), we use these logistic regressions to quantify the causal effect of SMS-utilization on producers' concern about his their individual farm water-use and perceived agricultural risk from future droughts or limited water availability. The selection of a PSM estimator is suggestible due to the non-random selection of agricultural producers into SMS-utilizing and non-utilizing regimes. These results suggest augmented concern about on-farm water use for SMS-users, suggesting a causal effect from the technology; however, measurable differences in drought risk-assessment between users and non-users becomes insignificant once conditioning on the propensity of using SMS, suggesting that this difference is driven by other observable characteristics beside SMS-utilization. These results are to be informative for future Extension education and programming efforts as well as making a contribution to the existing academic literature on farm technology adoption and utilization.

The remainder of this thesis is as follows: Section II contains a literature review, Section III discusses the data, Section IV details methods of analysis, Section V presents results, and Section VI concludes.

II. LITERATURE REVIEW

The following literature review presents information on soil-moisture sensors (SMS) and their associated attributes, addresses the multiple definitions of water-use efficiency (WUE) in the context of irrigated agriculture, gives relevant information on the study region, and concludes with an overview of theories of farm technology adoption processes.

2.1. Soil moisture sensors in agriculture

In recent years, various technologies have been developed and are commercially available for measuring soil moisture for applications in agriculture and landscape management. For the purpose of this research, soil moisture sensors (SMS) are handheld or in-ground probe-like instruments used to measure the volumetric water content of soil within a plant's root zone to schedule or automate irrigation events. Commercially available SMS include tensiometers, granular matrix sensors (GMS), and high-quality electromagnetic (EM) sensors. SMS technology employed for row crop irrigation management in southwestern Georgia most commonly employs EM sensors, such as electrical capacitance or resistance type sensors, time-domain reflectometer (TDR), or frequency domain refractometry (FDR) sensors to calculate soil moisture (Dukes & Scholberg, 2004; Miranda et al., 2005; Vellidis et al., 2008; and Sui, 2017). Neutron probe sensors have limited commercial viability due to their use of radioactive material, substantial maintenance requirements, and significant costs but may be preferred in research settings or in high-value specialty agriculture where speed and accuracy justify higher equipment costs (Robock, 2015). Hydrologically, true soil moisture can only be measured through manual gravimetric soil sampling involving the weighing and drying of a soil sample. Since such sampling is not always feasible in a crop production setting, SMS relies on proper installation, calibration, and maintenance to produce accurate soil moisture readings (Leib et al., 2003; Evett et al., 2006; and Sui et al., 2013). These procedures can vary substantially depending on soil classification, crop type, or ambient soil moisture. While potential diseconomies may result from inefficiencies in SMS installation or maintenance, they are beyond the scope of this research project. Depending on the type of irrigation system, SMS may automatically initiate an irrigation event if soil moisture is below a certain threshold, cancel a previously-scheduled irrigation event if sufficient soil moisture is detected, or may simply relay information on soil moisture levels to an irrigation operator or manager (Khachatryan et al., 2019). However, the use of SMS systems that utilize automatic irrigation scheduling is rare for large-scale row crop production and more commonly used for residential, commercial, greenhouse, specialty crop, and landscape/turf management applications. Recently, advances in wireless technology have removed the need for wired connections between installed SMS equipment, which has resultantly reduced their associated costs (Ruiz-Garcia et al., 2009) and encouraged utilization.

These variations can generate substantially different user-experiences across potential SMS systems. For these reasons, when using self-selected SMS-utilization as a treatment, it is necessary to establish comparability between different SMS systems available to agricultural irrigators in Georgia. Therefore, this research project included interviews with three large SMS vendors in southwestern Georgia that were conducted by telephone in spring 2019 to capture possible variations in user-experience. The summary results from this survey are presented in Table 1. SMS vendors were asked to describe the equipment specifications, equipment costs, installation costs, data management, time-management, and instrument longevity. Total

Table 1. Interviews of SMS vendors in Georgia

	Equipment:	Data:	Time management:	Misc. notes:
Vendor A:	Suggested equipment: Base station (1) Soil moisture probes (2) $600/base station $525/sensor Equipment lifespan: Sensors (3-5 yrs) Base station (>12 yrs)	Subscription to web/mobile platform required to view sensor data ($300/year) Field-level data presented through interactive line and bar graphs	Described as "minimal". Typical user interaction with the web/ mobile platform is 5-10 minutes/week. No additional data input or measures required from user	–
Vendor B:	Suggested equipment: Base station (1) Soil moisture probes (3) Rain gauge (1) All equipment sold together for $2,000, leasing option available for $1,000/season Equipment lifespan: Sensors (4-5 yrs) Base station (unsure)	Subscription required to access soil sensor data ($225/year) Field-level data presented in weekly email reports including static line and bar graphs Mobile app for sensor data in development	Each user receives email alerts twice a week No additional data input or measures required from user	Over 90% of users opt for the leasing option Most employed crop production pattern for users is vegetable/row crop double-cropping
Vendor C:	Suggested equipment: Base station (1) Soil moisture probes (3) $600/base station $480/sensor Equipment lifespan: Sensors (3-5 yrs) Base station (10-15 yrs)	Subscription to web/mobile platform required to view sensor data ($220/year) Field-level data presented through interactive line and bar graphs	Estimated as 5-20 minutes/ week interacting with the web/mobile platform. No additional data input or measures required from user	Stressed that site-specific costing depends on: (1) Site topography (2) Soil type

equipment and installation costs for a 100-acre, single soil-type row crop operation ranged from \$1,650–\$2,040 and consisted of 2–3 soil moisture probes (12”–16” long), a base station, and an optional rain gauge. One vendor offered an option to lease the equipment for \$1,000 per growing season and anecdotally communicated that more than 90 percent of users selected the leasing option. The soil moisture probes had an expected lifespan of 3–5 years while the base stations had an expected lifespan of 10–15 years. Data management costs ranged from \$220–\$300 per year. These costs include the use of physical data storage (i.e., Cloud storage) and access to either an online dashboard displaying soil moisture information or twice-weekly email messages containing similar information presented in visual form using charts, graphs, and/or tables. The time-management requirement for users was described as minimal, as user interaction with online dashboards/emails was estimated to range from only 5–20 minutes per week during the growing season. However, there is no attempt to quantify how these SMS systems affect users’ time spent interpreting, discussing, or supplementing the information communicated away from measurable interaction with the online- or email-based platforms, and the complexity or time involved with these tasks may be significant, especially for new users. The survey responses describe a sufficiently comparable set of SMS technology options in terms of cost and management.

SMS presents several advantages and disadvantages in a crop production setting. Advantageously, SMS allow site specific crop management, which is considered the most crucial part of precision agriculture techniques (Badewa et al., 2018). Other documented benefits included lower potential for crop loss, less need for pesticide application, and higher yields and qualities (Lichtenberg, 2013) as well as substantial cost-savings to farmers through reducing total water requirements (Belayneh et al., 2013). However, most research on SMS-utilization has focused on its application in greenhouse or specialty crop environments. More research in needed to confirm the benefits of SMS over more rudimentary irrigation scheduling practices in the context of large-scale row crop production.

2.2. Soil moisture sensors and water-use efficiency

Various definitions of WUE exist within the literature. In the context of plant metabolism, WUE is defined as the ratio of the total volume of water that is productively used by the crop (Stanhill, 1986). Only 0.5 to three percent of water taken up by the roots is used for crop growth and metabolism; however, additional water is necessary to support critical crop processes such as plant cooling, osmotic structuring, and nutrient flow (Sinha, 2004). Increased WUE in this context implies reducing irrigation to the minimal levels necessary to support physiological plant processes. Excess water not used for these processes reenters the water cycle through evapotranspiration, runoff, or percolation. Understandably, this definition is then of particular interest to water districts or management agencies due to its relevancy for environmental outcomes. Alternatively, the engineering literature suggests WUE as a measure of technical efficiency in irrigation systems. Burt et al. (1997) describe several measures of irrigation system performance, including "irrigation efficiency" (IE) which they define as the ratio of applied irrigation water that infiltrates a plant's root zone. Since under this definition any water that reaches the root zone is efficiently used, IE stands to be increased by improving technical systems to reduce system distribution and conveyance inefficiencies, such as those caused by leaks. While this definition may be of importance to engineers and irrigation operators, it is not primarily concerned with assessing crop needs, irrigation scheduling, or environmental impacts. For example, Pfeiffer and Lin (2014) find that irrigators who transitioned to more technically-efficient irrigation application systems in the Oglala aquifer region of western Kansas actually increased total groundwater withdrawals by an average of 2.5 percent. Finally, crop scientists in multiple studies (Leib et al, 2003; Laikos et al., 2015; and Vellidis et al., 2016) have defined WUE as a measure of production efficiency: the crop yield produced per acre-inch of irrigation applied. This definition is attractive to yield-maximizing producers for obvious reasons. While this definition does employ some aspects of production efficiency theory as first explained by Farrell (1957), it may be over-simplistic in assuming production efficiency across inputs other than water nor does it consider the relative costs (prices) of inputs (outputs). Moreover, it is not immediately clear what relevancy such a definition has for environmental or water district managers.

These competing definitions of WUE demonstrate the multidimensionality of agricultural water use across scientific, public, technical, and farm audiences. However, even given these multiple definitions, WUE is still often distant from most producers' concerns. Multiple surveys have demonstrated that water-saving is not a priority for most farmers, even in the developed world (Luquet et al, 2005; Molden et al, 2010; Knox et al., 2012). This is because producers generally act to maximize net revenue rather than water-saving (Knox et al., 2012). Therefore, any definition of WUE that does not incorporate economic costs/benefits of irrigation decisions cannot sufficiently demonstrate the producer's optimization problem. Unfortunately, all three of the definitions presented in the literature are lacking in this regard.

Despite inconsistent understandings and definitions of WUE across disciplines, irrigation scheduling has very practical impacts on producers' crop yields and cost structures. Vories et al. (2006) estimate that improper irrigation scheduling can contribute to average losses of \$150–\$750 per acre for mid-South cotton due to yield loss. Vellidis et al. (2016) observe that WUE (as measured as crop produced per acre-inch of water applied) is higher even in wet years for cotton fields employing SMS to schedule irrigation than those irrigated under alternate calendar (i.e., “days-after-planting”) methods or evapotranspiration calculations. Most recently, Haghverdi et al. (2019) estimated local yield improvements of 13 percent to 44 percent for Bt Cotton grown in researcher-controlled plots in West Tennessee under dynamic irrigation scheduling with SMS. These studies collectively highlight the potential environmental and financial benefits of SMS; however, more research in needed to confirm the benefits of SMS over more rudimentary irrigation scheduling practices, especially in the context of large-scale row crop production.

2.3. Water usage and conflict in the ACF River Basin

The Apalachicola–Chattahoochee–Flint (ACF) River Basin drains approximately 20,000 square miles in north-central, west-central, and southwestern parts of Georgia, southeastern Alabama, and northwestern Florida and consists of multiple freshwater streams, natural lakes, reservoirs, and aquifer systems (see Figure 1). Within Georgia, the northern portions of the basin are rural and heavily forested, the middle part is highly urbanized, and the southern part is defined primarily by farmland and wetlands on the South Georgia Coastal Plain (Couch et al., 1996). The agriculturally-intensive region of southwestern Georgia relies on the ACF River Basin for both public and self-supplied groundwater and surface water withdrawals. In 2010, total withdrawals from the ACF River Basin for use in agriculture (i.e., crop irrigation, livestock, and aquaculture) averaged 539.5 million gallons per day (Mgal/d) in Georgia compared to 16.4 Mgal/d in Alabama and 20.2 Mgal/d in Florida (Lawrence, 2016). Agriculture is the largest single-user of water in the ACF River Basin and accounted for 35 percent of total water withdrawals in 2010. Groundwater- and surface water-use solely for crop irrigation represents the vast majority of agricultural

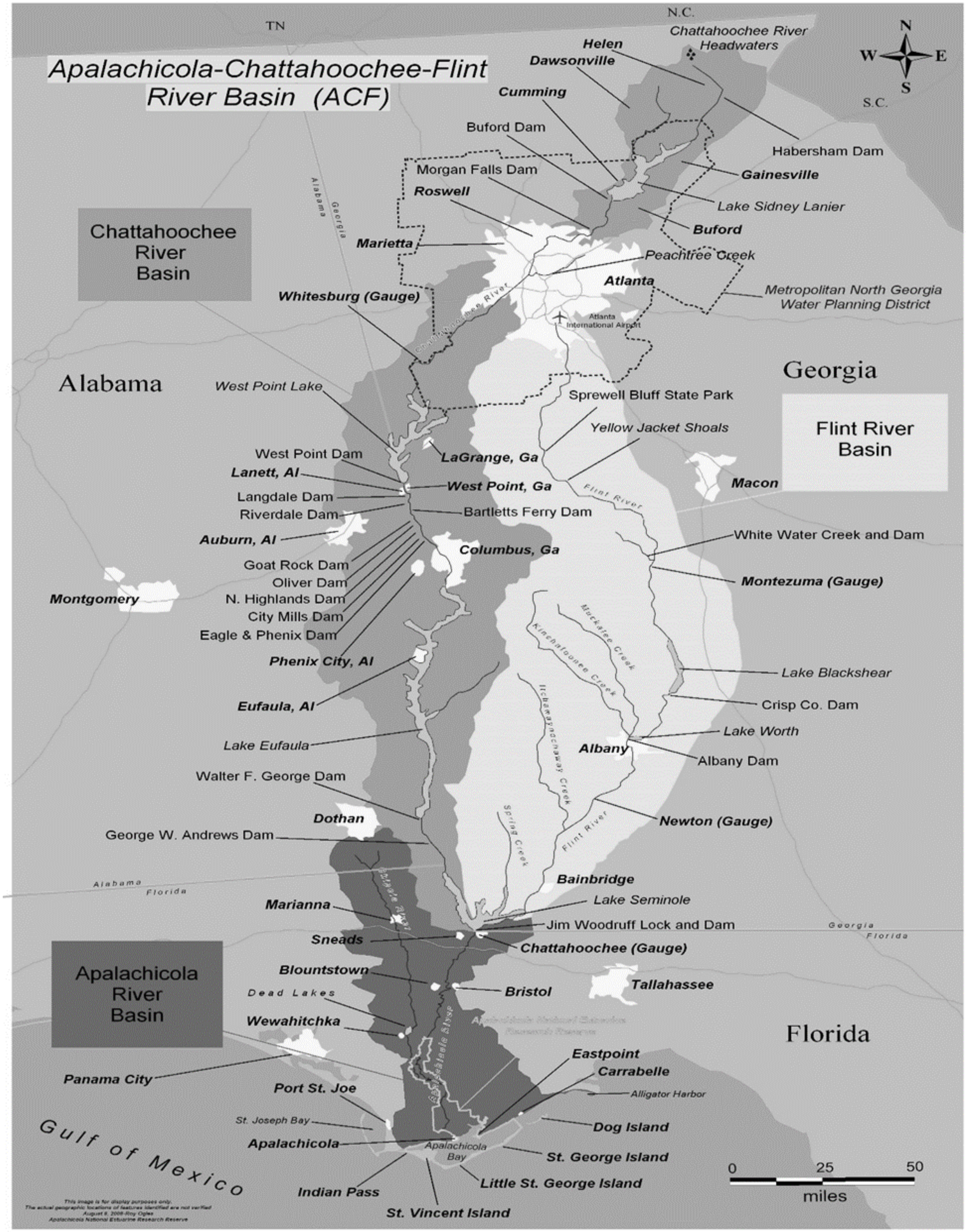

Figure 1. Apalachicola-Chattahoochee-Flint River Basin
Created by Roy Oglee (2008), Appalachicola National Estuarine Research Reserve

withdrawals from the ACF River Basin at 549.9 Mgal/d with over 90 percent (515.8 Mgal/d) coming from Georgia. While Georgia's usage patterns may appear extreme, the state accounts for 71 percent (14,362 mi^2) of the ACF River Basin's total area.

The population of the ACF River Basin was approximately 3.8 million in 2010, a 45 percent increase from the 1990 population of 2.6 million (U.S. Census Bureau, 1991/2011a/2011b). About 75 percent of the 2010 ACF River Basin's total population lives within the Atlanta—Sandy Springs—Roswell, GA Metropolitan Statistical Area, which had a 1.6 percent annual population growth rate between 2010 and 2018 (U.S. Census Bureau, 2018). Urban population growth within the ACF River Basin has increased demand for groundwater and surface water withdrawals to supply public municipal water utilities for residential, commercial, and industrial use. Between 1990 and 2010, groundwater and surface water withdrawals from the ACF River Basin for these uses increased by 16.8 percent (81.5 Mgal/d), while withdrawals for agricultural irrigation increased by 115.6 percent (294.9 Mgal/d); however, groundwater and surface water withdrawals for urban uses constituted 44.6 percent of all ACF River Basin withdrawals in 2010 compared with 35 percent in 1990 (Marella, 1991 and Lawrence, 2016). This change in statewide water-use patterns has increased competition between growing urban populations in Metro Atlanta and traditional downstream agricultural users in southwestern Georgia for groundwater and surface water withdrawals from the ACF River Basin. In response to growing statewide water demand, Georgia has developed the 2010 Water Conservation Implementation Plan[2] which lists goals and best practices for improving water conservation for agricultural irrigation. These best practices included the deployment of soil moisture sensors and

[2] https://epd.georgia.gov/sites/epd.georgia.gov/files/related_files/site_page/WCIP%20March%202010%20FINAL.pdf

timer controls for irrigation systems as well as the adoption of real-time soil moisture and weather-data to aid irrigation scheduling decisions.

In addition to intrastate policy initiatives, concern about water scarcity in the ACF River Basin has generated substantial interstate legal conflict over the past three decades. The states of Alabama, Florida, Georgia, and the United States Army Corps of Engineers (“the Corps”) have all been parties in lawsuits concerning utilization of the ACF River Basin’s groundwater and surface water resources. In 1989, the Corps issued a directive recommending that 20 percent of the water currently stored in Lake Lanier and Allatoona Lake, two reservoirs along the Chattahoochee River, be reallocated for water supply to support growing demand in the Metro Atlanta region. Alabama resultantly initiated litigation against the Corps, claiming that the proposed reallocation came at the expense of downstream interests and that the Corps had violated the National Environmental Policy Act (NEPA) by failing to consider potentially adverse environmental effects (Carriker, 2000). Florida and Georgia joined the lawsuit on behalf of their respective interests. In 1992, litigation was stayed when Alabama, Florida, Georgia, and the Corps initiated a Memorandum of Agreement to delay any subsequent legal action until the Corps conducted a comprehensive water usage study for the region. While a comprehensive water study for the ACF River Basin was never implemented, all three states initiated a Congressionally-approved interstate compact in 1997. The compact did not allocate water – rather, it established a commission of representatives from the three affected states and the Corps and charged it with negotiating a withdrawal formula. While negotiators did sporadically meet during the effective period of the compact, it was allowed to expire without having reached an agreement in 2003 (Lathrop, 2009).

Since the expiration of the ACF River Basin compact in 2003, interstate litigation rather than cooperation has once again persisted as the norm. Dozens of lawsuits have been initiated by the three states, consumer groups, and environmental advocates since the early 2000s. The urgency and frequency of these lawsuits was aggravated by severe drought conditions across the southeastern United States in 2005–2007 (Manuel, 2008) and 2010–2013 (Kunkel et al., 2013). A major decision came in 2009 when a U.S. District Court ruled that the Corps did not have the proper authority to reallocate water stored in Lake Lanier for withdrawals beyond those Congress had authorized in the 1970s, which did not include any allocations for Atlanta. The ruling was ultimately reversed on appeal to the 11th Circuit Court of Appeals. Florida initiated new litigation in 2013, alleging that withdrawals from the ACF River Basin had contributed to poor Apalachicola Bay shellfish/oyster harvests in 2011 and 2012. A court-appointed special master reviewed the matter and ultimately chose to reject Florida's petition in 2016 citing no "clear and convincing evidence" that decreasing upstream withdrawals would have prevented the damages. On appeal to the U.S. Supreme Court, it was ruled that the special master's standard was too strict and ordered the case to be remanded to a new special master (*Florida v. Georgia*, 2018).

Motivating continued conflict and litigation in the matter are the competing needs of Florida, where the vitality of economically-productive Apalachicola Bay shellfish and oyster beds rely on a delicate estuarine balance of salt and freshwater, and municipalities in Metro Atlanta that require additional withdrawals to support continued population growth. Production and regulatory risk for agricultural irrigators in southwestern Georgia have become extremely potent given this combination of needs. These irrigators are being challenged to limit their withdrawals from the ACF River Basin through technology adoption, increased water-use efficiency, and less intensive crop practices while simultaneously receiving less from upstream flows due to increased withdrawals in the Metro Atlanta region. This environment of risks has supported increased investment and awareness of SMS, but there is still limited empirical data on SMS-utilization's effects on producer beliefs, perceptions, and practices.

2.4. Farm technology adoption and producer perceptions

The two primary research questions for this project are primarily concerned with 1) farm technology utilization and 2) evaluating the impact of technology-utilization on producer beliefs and/or production practices (especially those related to environmental or water-related outcomes). As such, it is appropriate to review contributions to the literature from these two areas to more broadly place this study within a relevant context.

Firstly, there is ample literature on farm technology usage and adoption. Beale and Bohlen's seminal work in 1957 identified five categories of producers based on how long it takes them to adopt a farm technology after it is introduced: innovators, early adopters, the early majority, late majority, and laggards (Beale and Bohlen, 1957). Later empirical work by Rogers (1962) approximated the distribution of producers within these categories as that of a bell curve (i.e., normal distribution). This distribution results in a sigmoidal curve when plotting technology penetration over time – the beginning period is defined by low rates of utilization as adoption is limited to innovators and early adopters, adoption is prolific and utilization rapidly increases as the technology diffuses to the majority, and slow adoption rates return in the late period when there are only a small number of laggards remaining (see Figure 2). Beale and Bohlen (1957) describe the sociological attributes of each class based on in-person survey responses. They characterize innovators and early-adopters as higher-status, younger, more educated, more willing to take risks, and more institutionally-connected (i.e., farm commodity groups, university extension, etc.) than late-stage adopters. Further theoretical work was presented by Davis' technology acceptance model (TAM) which suggests technology choice is affected by the perceived usefulness (PU) and perceived ease-of-use (PEOU) of an innovation. While Davis' initial theories focused on acceptance of productive technologies, expansions of TAM have incorporated user-perceptions of information technology (Venkatesh et al., 2003; and Venkatesh & Bala, 2008). Recent improvements in SMS have increased its value as an information technology, so an analysis of SMS-utilization within a TAM 3 context may be warranted. In addition to potential theoretical considerations, empirical research has also focused on dimensions of irrigation technology adoption. Caswell and Zilberman (1985) apply a multinomial logit to predict irrigation technology choice (i.e., drip, sprinkler, or surface) in the California San Joaquin Valley. They find that variations in technology utilization are mainly driven by locational differences in the quality and availability of groundwater resources. Negri and Brooks (1990) use a national dataset and logistic estimation to conclude optimal irrigation technology decisions differentiate across heterogeneously-sized firms (as measured by total number of irrigated acres). Koundouret al. (2006) demonstrated from a sample of 256 Cretan farms that improvements in a farmer's human capital (i.e., education, access to extension services, and farming information accumulation) increased the adoption of modern irrigation technologies. More recently, Pokhrel et al. (2018) found that the utilization of 14 advanced irrigation technologies in Texas and Oklahoma cotton production were affected by producer age, education, information sources used, and crop yields.

While the calculation of associated costs and benefits is considered critical in a producer's technology utilization decision, this study will attempt to capture the complexity of producer motivations and beliefs on encouraging or inhibiting the utilization of SMS. This is in direct response to the established empirical literature suggesting some of these characteristics as significant. An understanding of how these producer attributes, in combination with farm characteristics, can influence or impede SMS-utilization can lead to more effectively directed extension programming, which in turn can facilitate further improvements in WUE on irrigated operations.

The second goal of this research is to assess the potential of SMS technology as a mechanism for altering producer perceptions or beliefs about agricultural water use. To consider this question, we look towards the Theory of Planned Behavior (TPB). Ajzen (1991) suggests an individual's behavior can be predicted with a high-degree of accuracy from three conceptually-independent determinants of intention: an attitude toward the behavior (ATB), defined as the degree to which an individual has a positive or negative appraisal of the behavior in question; subjective norms (SN), which include the perceived social pressures to perform or not perform the behavior; and perceived behavioral control (PBC), which refers to the perceived ease or difficulty of performing the behavior. As a general rule, the more favorable ATB and SN with respect to the behavior and the greater the perceived PBC, the stronger an individual's intention to perform the behavior should be. Figure 3 presents a simple schematic of the TPB intention-behavior mechanism.

The relevance of the TPB in predicting irrigation behavior is because such behavior is not only influenced by external factors – such as water pricing, weather conditions, technical considerations, etc. – but also by the perceptions of a single irrigation decision-maker. There is a wealth of empirical literature to support this assumption. Lynne et al. (1995) used attitudinal questionnaires to successfully identify ATB, SN, and PBC as significant predictors of Florida strawberry farmers' investments in microirrigation technology. More recent research by Far and Moghaddam (2015) demonstrated that the willingness of farmers in rural Iran to volunteer for a state-sponsored, large-scale irrigation and drainage project depended on their attitudes toward water resource management, and Chang et al. (2016) found that Chinese farmers' favorable attitudes towards restricting water consumption predicts their acceptance of government-imposed water-saving policy. Beyond an agricultural context, several studies have shown that TPB variables effectively predict household's intentions to save water in a residential North American context (Lam, 1999; Trumbo, et al., 2001; Lam, 2006; Clark & Finley, 2007; Salvaggio et al., 2014).

However, the current understanding of the impact for TPB variables on producers' intentions to adopt WUE-improving measures remains limited and previous research has not considered the potential impact of dynamic irrigation scheduling technology. SMS-utilization could potentially influence farmers' TPB variables by altering ATB through information effects, augmenting or creating social pressure (SN) through network effects, or improving PBC through a technology exposure effect, among others hypotheses. However, since SMS-treatment is not randomly-assigned to farmers, it is empirically difficult to estimate causal effects on these variables due to potential selection bias. In Section IV, we present a propensity score matching (PSM) technique as a way to quantify SMS-utilization's effect on producer attitudes and beliefs. To our knowledge, this is the first research to apply a PSM estimation technique to a question involving irrigation scheduling in the United States.

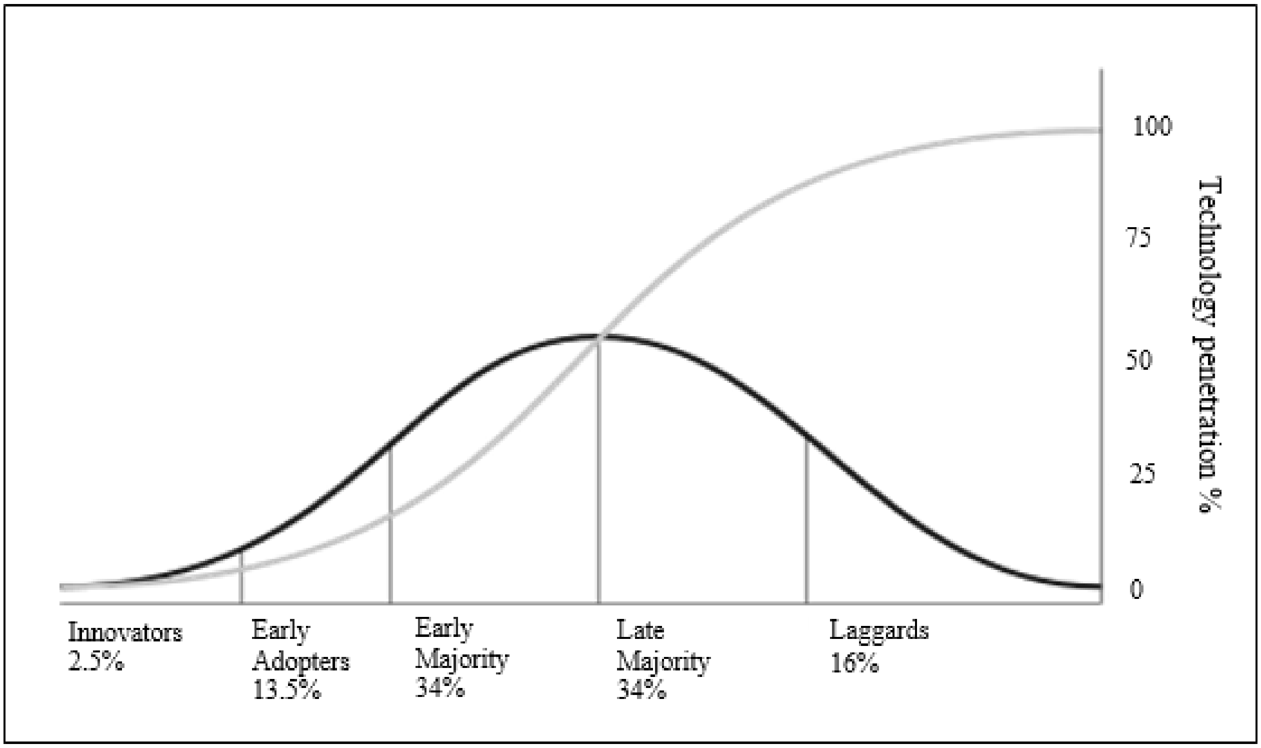

Figure 2. Technology adoption curve. (Rogers, 1962)

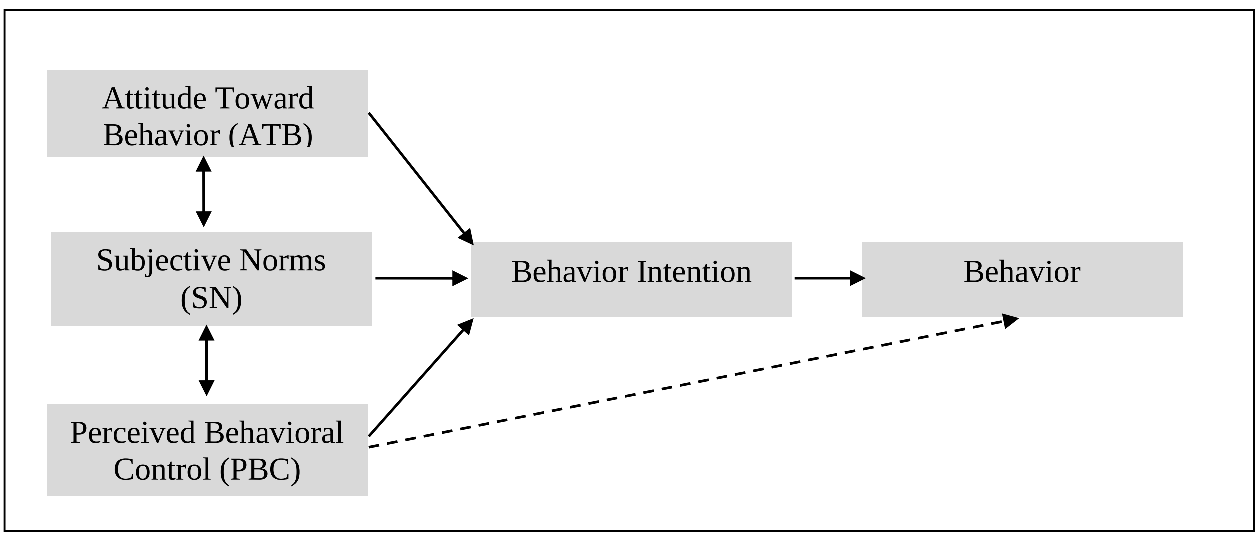

Figure 3. Theory of Planned Behavior. (Ajzen, 1991)

III. DATA

The data for this research was acquired through a survey instrument and from publically-available data from the Federal Communications Commission (FCC). Descriptive statistics for the survey instrument are presented in Table 2. For the text of the complete survey instrument, see Appendix A.

3.1. Survey instrument

A survey instrument broadly assessing farm and operator characteristics, irrigation behavior, and attitudinal assessments of agricultural water use, farm technology, and risks to future agricultural production was developed in fall 2017. The survey consisted of 28 dichotomous/ discrete choice, five-point Likert rating, and numeric-entry questions. A total of five contingency questions were available to subsets of agricultural irrigators and row crop producers. The content and wording of the survey questions was generated through iterative consultations between members of an interdisciplinary agricultural irrigation research group at the University of Georgia (known as the "AgWET" project team). The literature reviewed above was also consulted during the process of instrument development.

The survey instrument relied on five-point Likert scales to assess respondent beliefs and attitudes. Possible responses used in the survey instrument ranged from *strongly disagree* to *strongly agree* and *none at all* to *a great deal*. One feature of Likert's fixed-point method is that it imposes ordinality and continuity onto subjective respondent preferences, thus making it possible to construct quantitative variables. Likert ratings are routinely used when constructing TPB attribute variables, such as in Lynne et al. (1995).

The survey was administered at the 2017 Georgia Farm Bureau annual convention on Jekyll Island, Georgia in December 2017 and at peanut/cotton farm shows in Tifton, Georgia in January 2018. At both locations, responses were collected by AgWET project team enumerators using paper survey instruments, laptop, and tablet computers. Some potential respondents were given paper print-outs with QR codes that could be used to access the online survey instrument on another device. To incentivize participation, survey respondents at each location were allowed to enter a raffle awarding a prize valued at approximately 250 USD. After adjustment for non-consent and incomplete response, there were 134 usable responses from the Farm Bureau convention and 76 from the peanut/cotton farm shows (n=210). Ninety-four respondents (44.8%) had used irrigation in 2017 and, of this total, 26 (29.2%) had used SMS for irrigation scheduling. The 29 percent utilization rate is substantially higher than the 9 percent utilization rate the USDA reported for Georgia in the 2013 Farm and Ranch Irrigation Survey[3]. Ostensibly, this is because diffusion of SMS technology has increased its utilization over the five-year period since the USDA report; however, we cannot statistically demonstrate how much of this observed increase is continued diffusion versus sample bias in the survey data.

3.2. Broadband Internet connectivity

Following previous research that has established improved rural broadband connectivity can increase farm profits (Kandilov et. al, 2017), this research identified farmer broadband access as a possible predictor for irrigation technology choice, producer perceptions, and water-use efficiency efforts. Broadband is any reliable, permanent Internet connection that is consistently faster than traditional dial-up service. These connections are most commonly available through

[3] Table 22. Methods Used in Deciding When to Irrigate: 2013. (2014). Farm and Ranch Irrigation Survey. National Agricultural Statistical Service, U.S. Department of Agriculture.

cable, DSL, fiber, fixed wireless or satellite connections. Since 2015, the Federal Communications Commission (FCC) benchmark for broadband-level service speeds are 25 Mbps (download) and 3 Mbps (upload)[4]. The FCC considers this service level to be sufficient for the vast majority of typical residential and commercial use, such as social media, file downloading and video conferencing.

In December 2017, the FCC collected updated data on the number of broadband service providers available to the rural population in all 159 Georgia counties and made it publically accessible through an interactive online application.[5] Since the FCC data reports the total percentage of a county's rural population with access to a discrete number of broadband service provides (i.e., 0 providers, 1 provider, etc.), the researchers identify two possible variables of interest:

1. *Density of Service* – which is the weighted arithmetic mean of the number of internet service providers offering a cable, DSL, fixed wireless, or fiber broadband connection (25/3 Mbps) to the rural population of a specified geographic area (i.e., county), and

2. *Penetration of Service* – which is the percentage of a county's rural population having access to at least one ISP offering a cable, DSL, fixed wireless, or fiber broadband connection at the 25/3 Mbps level.

The distinction between the two variables is important considering the object of analysis. Representing density of service may misrepresent broadband penetration in a particular county if such county has a small number of residents with access to multiple providers. However,

[4] https://www.fcc.gov/reports-research/reports/broadband-progress-reports/2015-broadband-deployment-report
[5] https://broadbandmap.fcc.gov/#/areasummary?version=dec2017&type=nation&geoid=0&tech=acfosw&speed=25_3

penetration of service may not accurately represent improvements in service quality and pricing that are associated with multiple, competitive providers. For the purposes of these measures, we did not consider satellite-based broadband connections due to issues surrounding the reliability of these networks in rural areas, as suggested by a recent regulatory comment filed to the FCC by the Rural Broadband Association (NTCA).[6]

Using Zone Improvement Plan (ZIP) codes self-reported as the location of their primary farming operation in the survey instrument, 206 respondents were assigned the rural broadband characteristics (i.e., density and penetration) of their respective county. Despite the survey instrument only being administered at events targeting Georgia farmers, 8 respondents (3.9%) indicated having their primary farm operation in the U.S. state of Florida. The two measures of broadband connectivity are positively correlated among the complete set of 159 counties in Georgia (p=0.79) and the 98 unique counties selected by respondents in the survey instrument (p=0.87). Rural broadband service connections are less dense in southern Georgia (see Figure 5).

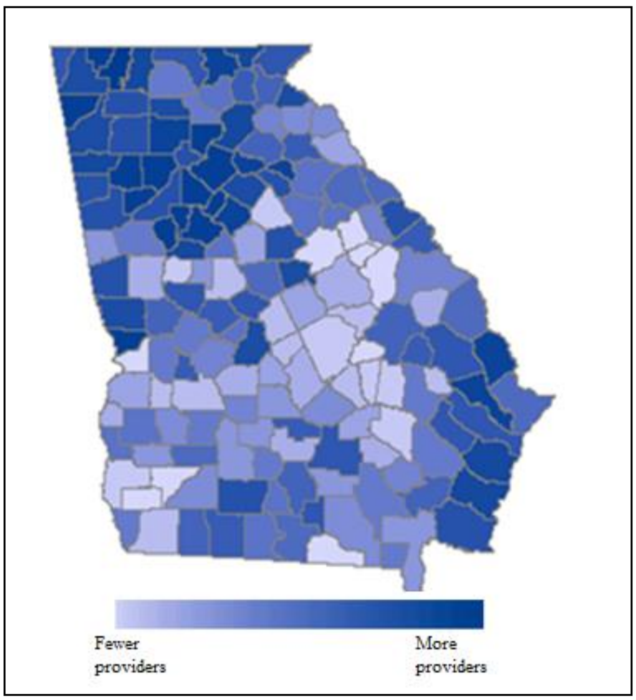

Figure 5. Rural broadband in Georgia

[6]https://ecfsapi.fcc.gov/file/10921173109916/09.21.17%20NTCA%20Comments%20on%20Section%20706%20NOI%2C%20GN%2017-199.pdf

3.3. Missing data imputation

The survey instrument includes a discrete choice question about gross farm sales. Gross farm sales (sometimes referred to as "farm class size") is the total amount of cash receipts from crop, seed, and other agricultural product sold by a farm over the course of one year. Gross farm sales is generally considered a more appropriate measure of farm size than farm household income because it does not include transfer payments, insurance payouts, or income from non-farm activities (MacDonald et al., 2013). Given the large number of categorical ranges available for survey respondents to select from (eight; from *Less than $50,000* to *$10 million or greater*), the `group1d` SSC command was used in Stata/IC 14.1 to approximate the Jenks natural classification method in order to reduce the number of categories for analysis. The method is an iterative process that minimizes each classification's average deviation from the within-classification mean while maximizing each classification's deviation from the without-classification means (Jenks, 1967). The optimal categorization of irrigated operations into three gross farm sales income categories were: low–less than $100,000/year (30.9%), middle–$100,000 to $999,999/year (44.4%), and high–greater than $1 million/year (24.7%).

In addition to the eight discrete categories from which respondents could select, they were also presented with a *prefer not to answer* option given the potentially sensitive nature of the requested information. Thirteen (13.8%) agricultural irrigators either did not respond to the gross farm sales question or selected the *prefer not to respond* response. The three main problems posed by item non-response is that it may introduce a substantial amount of bias if non-response is non-random, limit statistical power by shrinking the available sample size, and reduce efficiency (Gelman & Hill, 2007).

Given the theoretical importance of farm income for many variables of interest to this research and the limited sample size (n=89), the decision was made to impute missing values into the dataset using an ordered logit model. Ordered logistic regression is used when the dependent variable in categorical and ordinal in nature and was first described by McCullagh (1980). We recognize imputed data obtained from fitted values of a regression does not reflect the uncertainty associated with such predictions, thus suggesting greater precision in the imputed values than is warranted. However, the dependency of gross farm sales on several variables elsewhere suggests that we possess enough data to make reasonably well-fit predictions for the imputed values.

The ordered logit results are reported in Table 3. The estimation is limited to agricultural irrigators given many observable differences between irrigators and non-irrigators in the survey data. The pseudo-R^2 of the model is 0.5052 and the LR-χ^2 statistic is 74.16 (p<0.01). Total row crop acreage, total row crop acreage-squared, and dummy =1 if the respondent was a specialty crop (i.e., fruit, vegetable, or field nursery) producer were all significant at the 5 percent level. A dummy =1 if a respondent was a livestock farmer selected irrigation-related costs as a major barrier to adopting new irrigation technology was statistically significant at the 10 percent level and had negative signs. The model predicted, for the seven non-respondents with full cases on the explanatory variables, one (14.3%) would have gross farm sales of less than \$100,000; five (71.4%) would have gross sales between \$100,000 and \$1 million, and one (14.3%) would have gross sales of over \$1 million.

Table 2. Descriptive Statistics From Survey Sample
(*n*=89; irrigators only)

Independent variable	Mean (SD)	Min	Max
Uses SMS to schedule irrigation (Yes = 1, No = 0)	0.29	0	1
Respondent age (years)	48.7 (16.7)	21	80
Respondent experience in agriculture (years since age 18)	25.5 (16.5)	1	62
Gross farm sales: (thousand USD/year)	1,087.8 (1,843.5)	25	10,000
Gender (Male = 1, Female=0)	0.88	0	1
Respondent produces row crops (Yes = 1, No = 0)	0.79	0	1
Respondent produces fruits or vegetables (Yes = 1, No = 0)	0.31	0	1
Respondent has land in pasture (Yes = 1, No = 0)	0.31	0	1
Extension meetings preferred source of farm technology information (Yes = 1, No = 0)	0.31	0	1
County agents preferred source of farm technology information (Yes = 1, No = 0)	0.35	0	1
Consultants preferred source of farm technology information (Yes = 1, No = 0)	0.16	0	1
"Other" preferred source of farm technology information (Yes = 1, No = 0)	0.18	0	1
Number of rural broadband internet service providers in county	0.95 (0.49)	0.02	2.57
Respondent agreement that farmers should use irrigation scheduling technology (5-point Likert scale)	3.83 (1.10)	0	5
Respondent perception of irrigation scheduling technology ease-of-use (5-point Likert scale)	3.52 (1.16)	0	5
Respondent willingness to learn more about irrigation scheduling technology (5-point Likert scale)	3.95 (1.20)	0	5
Respondent rates "environmental group opposition" as major threat to future agriculture (Yes = 1, No = 0)	0.82	0	1
Respondent rates "increased government regulation" as major threat to future agriculture (Yes = 1, No = 0)	0.85	0	1
Respondent rates "drought" or "future water availability" as major threat to future agriculture (Yes = 1, No = 0)	0.77	0	1
Respondent rates concern about on-farm water usage as "high" (Yes = 1, No = 0)	0.59	0	1
Respondent rates concern about Georgia state water issues as "high" (Yes = 1, No = 0)	0.66	0	1
Respondent rates concern about United States water issues as "high" (Yes = 1, No = 0)	0.73	0	1
Respondent located in northwestern Extension district (Yes = 1, No = 0)	0.09	0	1
Respondent located in northeastern Extension district (Yes = 1, No = 0)	0.11	0	1
Respondent located in southeastern Extension district (Yes = 1, No = 0)	0.18	0	1
Respondent located in southwestern Extension district (Yes = 1, No = 0)	0.61	0	1

Table 3. Ordered Logistic Results for Data Imputation
Dependent: Gross sales category (=low, medium, high)

Variable	Level (mean, S.E.)	Coefficient (S.E.)	*p*-value
Age	*Continuous* (48.0, 16.9)	0.0164 (0.1256)	0.90
Age-squared		0.0008 (0.0012)	0.67
Total row crop acreage	*Continuous* (825.7, 796.9)	0.0082*** (0.0021)	<0.01
Total row crop acreage, squared		0.0001*** (0.95)	<0.01
Crop Mix	Specialty crop (0.34, 0.47)	3.87*** (1.01)	<0.01
	Livestock (0.28, 0.45)	1.56* (0.95)	0.10
	Pasture(0.28, 0.45)	-1.12 (0.96)	0.24
	Orchard (0.21, 0.41)	-0.45 (0.94)	0.64
Irrigation Technology (IT):	Soil-moisture sensors (0.28, 0.45)	-0.19 (0.81)	0.81
	Consultants (0.15, 0.36)	0.66 (1.03)	0.64
Barrier to improved IT:	High costs (0.15, 0.36)	-1.68* (0.95)	0.07
Regional fixed-effect?	*Yes*		
Cuts (S.E.)	7.59 (3.27), 12.78 (3.81)		
Observations	70		
Log-likelihood	-36.31		
LR chi^2 (15)	74.16		
Prob > chi^2	<0.01		
McFadden's Pseudo R^2	0.5052		

Note: Ordered categories report gross farm sales categories. Low, <\$100,000; Med, \$100,000-\$1 million; High >\$1 million

IV. METHODOLOGIES

The following three sub-sections detail the two empirical methods of analysis that will be used for to conduct this research. Additionally, this chapter will include a discussion of model specification and variable selection.

4.1. Simple Logistic Regression

For the first research question, we are interested in identifying farm- and operator-level characteristics that predict SMS-utilization. SMS-utilization, like many variables across the social sciences, follows a binomial distribution. Such distributions are generated by binary outcomes such as compliance/non-compliance, alive/dead, agree/disagree, or other variables communicating the general occurrence or non-occurrence of an event. In this case, the binomial distribution occurs when SMS-utilization is =1 if a survey respondent indicated using soil moisture sensors to schedule irrigation in 2017 and =0 if a survey respondent did not indicate such.

Logit and probit models are commonly used when the dependent variable follows a binomial distribution. Despite often similar results between logit and probit estimations, Gujarati (2009) explains two practical advantages of the logit model over the probit model. Firstly, the inverse linerazing transformation of the logit model is directly interpretable as log-odds, while a similar transformation of the probit model does not have such a direct interpretation (Gujarati, 2009). Secondly, the cumulative distribution function (CDF) of the logistic distribution is simpler than the CDF of the standard normal distribution used in probit models because it does not involve an unevaluated integral. While this second difference is somewhat trivial for dichotomous data, it requires that polychromous (i.e., ordinal categories) data follow a normal distribution. Considering the advantages of the logit model in interpretability and simplicity, it is the preferred model specification for this analysis.

As Brown (1991) succinctly described, the binomial logit model is based on the cumulative logistic distribution, which is:

$$P_i = E(Y_i = 1|X_i) = \frac{1}{1+e^{-z_i}}\,, \qquad \text{(Eq. 1.1)}$$

where $z_i = \beta_0 + \beta_1 X_i$, e is the base of natural logarithms (approximately equal to 2.718), Y_i=1 for SMS-utilization ("success") and Y_i=0 for SMS non-utilization ("failure"). P_i is the probability that an observation exhibits success given a vector or independent variables (X_i). Equation (1) implies that:

$$1 - P_i = \frac{1}{1+e^{z_i}}\,. \qquad \text{(Eq. 1.2)}$$

The odds ratio (OR), or the probability of success relative to failure can be calculated by:

$$\frac{P_i}{1-P_i} = \frac{1+e^{z_i}}{1+e^{-z_i}} = e^{z_i}, \qquad \text{(Eq. 1.3)}$$

Unlike probabilities, the OR reports the constant effect of a change in an independent variable (X_i) on the dichotomous dependent variable (Y_i). An OR >1 is indicative that a change in X increases the odds of success (Y_i=1), 0 < OR < 1 indicate decreasing odds, and OR=1 indicates no change in odds given a change in X. For example, if P_i = 0.75 then the odds ratio will be 3. This means the odds are three-to-one for the i_{th} observation exhibiting success (Y_i=1). Taking the natural log of equation (1.3) will give the value of the logit (L_i) as illustrated in equation (4):

$$L_i = \ln\left[\frac{P_i}{1-P_i}\right] = \ln(e^{z_i}) = z_i = \beta_0 + \beta_1 X_i + u_i\ , \quad \text{(Eq. 1.4)}$$

Where u_i is a stochastic error term and the β coefficients for the logit model are estimated using maximum likelihood techniques.

Following the estimation of the β coefficients, the probability of a given observation exhibiting success is calculated by substituting in specific values for the independent variables (X_i). Probabilities are usually evaluated at the mean values of the independent variables ($\bar{x}$); or they can be evaluated at specific values of interest (i.e., representative values, max/min values, etc.). It is necessary to fix other independent variables at a given value when calculating marginal effects because the logistic model is non-linear – that is, the β coefficients are not scalar in nature and thus have varying effects over values of X_i.

When evaluating logit models, the standard R^2 measure commonly used in linear regression models is of dubious value (Gujarati, 2009). Alternative measures of goodness-of-fit used when evaluating this model will be hit-or-miss analysis, McFadden's pseudo-R^2, and a likelihood ratio test with a χ^2 - statistic. Hit-or-miss analysis compares the number of accurate and inaccurate predicted outcomes to the actual in-sample outcomes. Higher proportions of successful in-sample prediction are associated with better goodness-of-fit. Veall and Zimmerman (1996) give McFadden's pseudo-R^2 as follows:

$$\text{McFadden pseudo} - \text{R2} \ = \ 1 - \left(\frac{\text{LL}_f}{\text{LL}_C}\right),, \quad \text{(Eq. 1.5)}$$

where LL_f is the log-likelihood from the specified (unrestricted) model and the LL_c is the log-likelihood of the (restricted) model containing only a constant term. The likelihood ratio test is the most frequently used validity test for logistic models. It tests the null hypothesis that a restricted model is better-fitting than an unrestricted model including additional explanatory regressors. The test statistic follows a χ^2 distribution with k degrees-of-freedom, where k is the number of independent variables in the model. Veall and Zimmerman (1996) give the test as:

$$D = -2(\mathrm{LL}_c - \mathrm{LL}_f), \qquad \text{(Eq. 1.6)}$$

If D exceeds the table value at a chosen level of significance, the null hypothesis is rejected and it is concluded that the fitted model is no better than a restricted model.

4.2. Propensity Score Matching

For the second research question, we are interested in establishing the treatment effect of SMS-utilization on perception-related outcomes of interest for agricultural irrigators. Given dichotomous treatment options (e.g., SMS utilization vs. SMS non-utilization), each respondent has a pair of outcomes represented as $\mathrm{Y}_i(0)$, the outcome without treatment, and $\mathrm{Y}_i(1)$, the outcome with treatment. The following is generally derived from Rubin (1974). He begins by defining the true causal effect of a treatment (α) as:

$$\alpha = [\mathrm{Y}_i(1) - \mathrm{Y}_i(0)]\,, \qquad \text{(Eq. 2.1)}$$

which is also called the "treatment effect". However, it should be apparent that the fundamental problem of estimating this effect is that units of observation are only observable as either $\mathrm{Y}_i(0)$ or $\mathrm{Y}_i(1)$ but never both. Y_i can be observed only under the actual treatment received, mathematically expressed as:

$$\mathrm{Y}_i = d_i Y_i(1) + (1 - d_i) Y_i(0)\,, \qquad \text{(Eq. 2.2)}$$

where d_i is an indicator equal to 1 in the presence of treatment. Resultantly, we can rewrite Equation 2.1 as:

$$\alpha = [\mathrm{Y}_i(1)|d_i = 1] - [\mathrm{Y}_i(0)|d_i = 1] + [\mathrm{Y}_i(1)|d_i = 0] - [\mathrm{Y}_i(0)|d_i = 0]\,. \qquad \text{(Eq. 2.3)}$$

Note how this expression highlights the counterfactual nature of causal effects – the estimated treatment effect relies on supposing untreated observations' outcomes had they been treated and vice versa for treated observations. Since these two counterfactual terms, $[\mathrm{Y}_i(0)|d_i = 1]$ and$[\mathrm{Y}_i(1)|d_i = 0]$, are not identifiable for any specific unit of observation, the observable difference between treated and untreated groups produces what Rubin calls an *average treatment effect* (ATE), written as:

$$\mathrm{ATE} = \mathrm{E}[\mathrm{Y}_i(1)|d_i = 1] - \mathrm{E}[\mathrm{Y}_i(0)|d_i = 0]\,. \qquad \text{(Eq. 2.4)}$$

Note that the ATE is fully identifiable for any treatment condition regardless of the data structure or experimental design; however, the interpretation of the ATE differs depending on the construction of treatment and control groups. When treatment and control conditions are assigned irrespective of measurable or immeasurable differences between observations, such as within a randomized control trial (RCT), the ATE generates what is known as the *average treatment on the treated*, which is intuitively defined as the average treatment effect for the subpopulation of observations who actually participate in treatment; written representatively as:

$$\mathrm{ATT} = \mathrm{E}[\mathrm{Y}_i(1)|d_i = 1] - \mathrm{E}[\mathrm{Y}_i(0)|d_i = 1]\,. \qquad \text{(Eq. 2.5)}$$

Under randomization, this ATT is recoverable from the observable ATE and is an unbiased estimator of the true causal effect (Rubin, 1974).

However, implementation of an RCT is not always practical for the social scientist. Firstly, random assignment of some treatment conditions may be questionable on ethical or moral grounds. For example, it may be unethical to randomly expose subjects to negative treatment conditions (i.e., incarceration, illness, homelessness, etc.) as a way to estimate their effects on life expectancy or earnings. Moreover, large-scale RCTs are further limited due to often being prohibitively expensive or complicated. To compensate, social scientists will sometimes rely on what is called a *natural experiment*. In natural experiments the underlying mechanism of treatment assignment is random despite being beyond the researcher's control. For example, an agricultural economist wanting to study the impact of annual flooding on the profitability of small-holding farms in a developing country may take advantage of the fact that the selection of plots that floods from year-to-year within a fixed geographic area is random. However, true natural experiments are difficult to identify in the social sciences due to the problem of *selection bias*. Selection bias occurs when observations' probabilities of receiving or adhering to treatment are functions of other observable or unobservable characteristics (i.e., not random). To understand the effects of selection bias for causal inference, let us once again consider the observable ATE:

$$\mathrm{ATE} = \mathrm{E}[\mathrm{Y}_i(1)|d_i = 1] - \mathrm{E}[\mathrm{Y}_i(0)|d_i = 0]\,. \qquad \text{(Eq. 2.4)}$$

Adding and subtracting the counterfactual term to the ATE (so that the expression is unchanged) yields:

$$\mathrm{ATE} = \mathrm{E}[\mathrm{Y}_i(1)|d_i = 1] - [\mathrm{Y}_i(0)|d_i = 0] + \mathrm{E}[Y_i(0)|d_i = 1] - \mathrm{E}[Y_i(0)|d_i = 1], \quad \text{(Eq. 2.6)}$$

which can be reordered as:

$$\mathrm{ATE} = \{\mathrm{E}[\mathrm{Y}_i(1)|d_i = 1] - \mathrm{E}[\mathrm{Y}_i(0)|d_i = 1]\} + \{\mathrm{E}[\mathrm{Y}_i(0)|d_i = 1] - \mathrm{E}[Y_i(0)|d_i = 0]\}\,. \qquad \text{(Eq. 2.7)}$$

It should be apparent that the first bracketed expression is equal to the ATE (from equation 2.5); the second bracketed expression represents the selection bias, denoted by δ. Note that since this term includes a counterfactual, it cannot be identified. Equation 2.7 can be rewritten as:

$$\mathrm{ATE} = \mathrm{ATT} + \delta$$

This demonstrates that, in the presence of selection bias, the observable ATE will recover ATT plus selection bias. This means that ATE is not an unbiased estimator of the true causal effect (α) when selection bias is present.

In the absence of randomization achieved through a controlled or natural experiment, it has been demonstrated that selection bias prevents researchers from using ATE estimates to recover the true causal effects of a treatment or intervention. This is an especially potent concern for the second question of this research, because SMS is not randomly distributed within the population. The previous literature review section succinctly lists sources of non-randomness (i.e, selection) for irrigation technology utilization, including producer age, farm income, location, and Theory of Planned Behavior (TPB) attribute variables. Therefore, when assessing the impact of SMS-utilization on potential outcome variables of interest, simple comparisons between the treatment and control groups will generate biased results. Thankfully, multiple quasi-experimental approaches for social science research have been formulated to address this issue of selection.

Matching techniques for statistical inference attempt to account for selection bias by conditioning each unit's outcome on its likelihood of selecting treatment. Matching assumes that observations with the same set of pretreatment covariates, X_i, have identical probabilities of being exposed to the treatment condition, thus mimicking the property of random assignment found in experimental studies. It should be apparent that matching techniques rely on a *conditional independence assumption* that practically imposes that treatment selection is a function of measurable observable characteristics rather than unobservables. High dimensionality in X can make matching difficult. To account for this, Rosenbaum and Rubin (1983) suggest matching on a generated propensity score, *p(x)*, defined as:

$$p(x) \equiv \Pr(d_i = 1 | X = x_i) \ , \qquad \text{(Eq. 2.8)}$$

where, given the assumption of conditional independence holds:

$$Y_i(0), Y_i(1) \perp d_i | p(x) \ , \qquad \text{(Eq. 2.9)}$$

where $\perp$ is an operator representing statistical independence. Note that the propensity score is equal to the predicted probability of treatment participation; thus, it is typically calculated through logistic or other binary regression.

Propensity score matching (PSM) matches each treated outcome to a most similar non-treated outcome based on similarity in the observations' generated propensity scores; it computes an ATE by averaging the difference in outcomes between matched treatment and control outcomes. The researcher-imposed choice of matching algorithm dictates which/how many observations are used to construct the counterfactual outcome for each observation. The most straightforward matching algorithm is *nearest neighbor* (NN) matching. The NN matching technique simply identifies for each observation which observation in the opposite treatment regimen has the closest propensity score. This matching occurs either with- or without *replacement*; in the latter case, an observation may only be used once for a match whereas matching with replacement allows for the same observation to be used to construct multiple counterfactual outcomes. Smith and Todd (2005) note that the choice of whether to match with- or without replacement imposes a bias–efficiency tradeoff; matching with replacement allows for the "best" counterfactual outcome to be evaluated for each observation (thus decreasing bias) but often limits the total number of observations used in matching (increasing variance). A compromise solution is to allow oversampling (NN-2, NN-3, etc.) to increase the number of observations used to construct the counterfactual outcome; however, simple multiple-NN matching introduces unnecessary bias because each counterfactual outcome is uniformly weighted regardless of the difference between its and the treated observation's propensity scores (Smith, 1997). Kernel matching (KM) represents an improvement over simple multiple-NN matching in that treated units are matched with a weighted average of all control units, with weights being inversely proportional to the distance between the propensity scores of the treated and control groups. As Smith and Todd (2005) note, higher weight will be placed on observations close in terms of the propensity score and more distant observations will receive lower weights. In situations where the distribution of propensity scores between treatment and control groups is very different (for example, when there are many treated individuals with high propensity scores but few in the control group) it is recommended to limit kernel matching to the region within common support in order to reduce unnecessary bias from incorporating suboptimal matches (Caliendo & Kopeining, 2008). Therefore, our results will present treatment effects from both a Gaussian kernel matching algorithm within the region of common support and nearest neighbor matching (NN-1).

4.3. Hypotheses and Variable Selection

Firstly, the farm technology literature summarized above was consulted. Based on a review of this research, variables such as producer age, farm size, farm income, and information sources were hypothesized as variables that could help predict SMS-utilization. Moreover, through iterative consultations with the AgWET project team other variables were considered for inclusion based on strong observational evidence suggesting them as predictors of SMS-utilization: namely, these variables included crop mix, subjective producer assessments of risks and farm technology, broadband connectivity, and farm location. Univariate analysis of these relevant survey variables was initially undertaken in Stata/IC 14.1 to test for significance for SMS-utilization and observe correlations with other potential independent variables.

Researchers participating in the inter-disciplinary AgWET project team and industry vendors (see Table 1) expressed many hypotheses as to why producers either do or do not use SMS technology. They stated that the relative high costs of SMS technology often made adoption prohibitively expensive for smaller, low-value farms. SMS-utilization was observationally correlated with fruit or vegetable production, presumably due to some high-value crops in this production class having high total water requirements. For example watermelon, of which 23,000 acres were in production in Georgia in 2018, can have irrigation intervals as short as seven to ten days under dry conditions (University of Georgia, 2017). Additionally, typically late planting dates (May) for southwestern Georgia's substantial peanut crop creates the potential for short-season double-cropping with high-value, cool-season vegetables such as spinach or lettuce in the early spring. Producers who elect to double-crop may see increased benefits from improved irrigation scheduling, therefore suggesting a potentially positive impact on SMS-utilization.

During the time the survey responses were being collected (winter 2017/18), many producers in the region would have still been recovering from the widespread effects of the 2016 southeastern United States drought. The severity of the drought peaked in November 2016 with 75 percent the area within Georgia in a state of "severe drought" or worse[7], a major degradation of pasture and rangeland, wildfires, and elevated levels of evaporative stress (Williams et al., 2017). It would be expected that increased drought-consciousness at the time of the survey

[7] Georgia, 2016-29-11. United States Drought Monitor. National Drought Mitigation Center, University of Nebraska–Lincoln. Retrieved from: https://droughtmonitor.unl.edu/Maps/MapArchive.aspx

resulting from the residual effects from the 2016 southeastern drought could have heighted producer awareness of environmental risk, agricultural water use, and drought-mitigating production behavior (i.e., SMS-utilization). This hypothesis would suggest a positive impact from high levels of drought-related concern for SMS utilization.

The survey instrument measured respondents' general perceptions of irrigation scheduling technology. These questions assessed producer perceptions consistent with Davis' Technology Acceptance Model (1989), attitudinal assessments of behavior (ATB), and perceived behavioral control (PBC). The AgWET project team was also interesting in assessing the impact of Extension-provided information on SMS-utilization given recent programming efforts stressing improved irrigation efficiency. Knowledge of the predicted impact of these variables on SMS-utilization is limited due to limited previous research; however, the Theory of Planned Behavior (TPB) supports the hypothesize that positive ATB assessments will increase technology utilization.

Previous research has shown that the use of computers in farm management decisions is associated with higher rates of technology utilization (Paxon et al., 2011). Additionally, many SMS-related data platforms rely on a reliable Internet connection (see Table 1). Therefore, the logistic regression specification will test the hypothesis that the number of available county broadband service providers is a predictor of SMS-utilization.

An additional hypothesis examined during variable testing and selection concerned the location of SMS-utilizing producers who responded to the survey instrument. Sixty-one percent of irrigation-using respondents were located in the southwestern Georgia production region as defined by the UGA Cooperative Extension service. Irrigated operations within this region lie almost exclusively within the Apalachicola-Flint-Chattahoochee (AFC) River Basin, for which there is increasing regulatory and legal risk due to ongoing Supreme Court litigation between the U.S. states of Florida and Georgia concerning irrigation withdrawal limits. Therefore, it would be expected that producers in the region would have a strong incentive to make investments in improved irrigation scheduling technology as a way to maximize water-use efficiency. Additionally, there is little urbanization and lower rates of population growth in this region. These factors limit farmland conversion pressure in the region, thus encouraging producers to consider longer-range planning horizons that can improve technology adoption (Adelaja et al., 2011).

Logistic regression results will be informative for PSM model specification. However, the PSM literature is not without suggestions for optimizing variable selection. The literature suggests a strong assumption of causality among the covariates, outcomes, and treatment variables should be derived from economic theory and previous research (Smith and Todd, 2005). Austin et al. (2007) use a series of Monte Carlo simulations to suggest that variables should be included based on their ability to predict treatment assignment and potential causal relationship to the outcome variable of interest. Furthermore, we want to omit any covariates possibly influenced by treatment assignment.

V. RESULTS

Predictive models were estimated using the data and methods described in Sections III and IV. The dependent variable was whether or not a producer indicated using soil-moisture sensors (SMS) to schedule irrigation in 2017 (Y_i = 1 if yes, Y_i; = 0 if no). Numerous explanatory variables and their transformations were tested during the model development stage. Estimates reported here are chosen based on estimated coefficients' levels of significance and the overall predictive ability of the model. Estimated models 2 and 3 are used as the basis for propensity score matching results.

Summary statistics for the estimation sample are presented in Table 4. Coefficient estimates and variable significance for the three estimated models are shown in Table 5. Predicted values of the dependent variable are given in Table 6. Measures of goodness-of-fit are shown in Table 7, and treatment effects from propensity score matching are shown in Table 8.

Section 5.1. Estimated model 1

The survey respondents who indicated using irrigation on their farm in 2017 were divided into two groups: those who reporting using SMS to schedule irrigation (29 percent) and those who did not (71 percent). The results for estimated model 1 (Table 5) indicate that as age increases, the probability of a producer using SMS decreases before reaching a minimum and then subsequently increasing. Consistent with established literature, the probability of a producer using SMS to schedule irrigation increases with gross farm sales. Row crop and fruit/vegetable producers had higher probabilities of SMS-utilization, while producers with pasturelands had decreased probabilities of SMS-utilization. Producers relying on Extension meetings or county agents as their preferred sources of farm technology information had decreased probabilities of SMS-utilization. Increasing the number of broadband internet service providers in a respondent's county decreased the probability of SMS-utilization, and respondents in northwestern Georgia likewise had lower probabilities of SMS-utilization compared to the other regions. The probability of SMS-utilization increased as respondents gave more positive Likert responses to an attitude toward-behavior *(*ATB) statement about irrigation scheduling technology. Respondents who indicated high-levels of concern about water-use on their farms were more likely to use SMS, but perceiving high risk from environmental group opposition or drought/future water availability negatively influenced SMS-utilization.

The results from model 1 suggestively communicate that producer socioeconomic characteristics, farm characteristics, and some producer perceptions are significantly related to SMS-utilization. However, interpretation of some individual parameter coefficients is challenging due to issues concerning causality. For example, though the results suggest a statistically significant, positive effect on SMS-utilization from a survey respondent perceiving a high-level of concern about on-farm water use the true causal direction of the relationship cannot be inferred. This estimation specification assumes that a producer's perceptions of his on-farm water-use precede SMS-utilization. However, if a potentially-reversed causal direction is assumed the significant result could be explained as SMS-utilization affecting producer perceptions. Due to the observational nature of the data it cannot be established which the causal precedent is: perception or utilization. This issue of causal unidentification gives new relevancy to a PSM estimation technique. By conditioning on the utilization of SMS, PSM will recover the average treatment effect of the technology on subjective producer perceptions of their farm water-use and water-risk. These results will be presented in Section 5.5.

Section 5.2. Estimated models 2 and 3

While Model 1 establishes the significance and sign of several theoretically-relevant variables for SMS-utilization, it is not appropriate for generating PSM results. PSM literature suggests that a clear causal relationship based in economic theory or previous research should be identified between the independent variables, treatment assignment, and outcomes when creating the matching estimator (Smith & Todd, 2005). Given the inclusion of several causally unidentified variables, model 1 fails to meet this requirement.

In response to this issue, the researchers devised two alternate logistic model specifications (see model 2 and model 3). Model 2 omits all possibly causally ambiguous covariates from the model 1 specification. These variables include attitudinal assessments of farm technology and on farm water-use, drought-risk, and future water availability. It is not immediately clear, either from economic intuition or established literature, if changes in these variables would precede SMS-utilization (insinuating they are predictors of adoption) or come about as a result of SMS-use (suggesting a technological treatment effect from SMS on perceptions). Model 3 is identical to model 2 except that it contains two additional covariates =1 if a survey respondent indicated a high-level concern about water use at the statewide or national level. These covariates are included because they can be reasonably assumed to be correlated with subjective producer perceptions of water-use and water-risk; however, we would not expect them to be related to an individual producer's SMS-behavior. Since they are likely correlated with the outcomes of interest but not treatment assignment, we refer to them as "outcome controls". This difference between model 2 and model 3 will allow for use to empirically evaluate the usefulness of these types of controls in PSM estimation.

Signs and significances for models 2 and 3 when compared to model 1 are generally consistent. Some variables associated with crop mix and broadband Internet service lost statistical significance in the restricted models (see Table 5). However, the general consistency in results for other variables across the three model specifications may be seen as an indication of robustness of results.

5.3. Predicted probabilities

Table 6 expands on the directions of effect for each estimated model's independent variables by showing calculated probabilities over a range of possible covariate levels. This information provides a sensitivity analysis of the models' results. Given the large number of binary cofounders in the estimated models, predicted probabilities at mean covariate levels are nonsensical. Therefore, the predicted probabilities are generated for the covariate levels observed; more intuitively, the predicted probabilities represent the mean predicted probability for each independent variable level if the other covariates are allowed to vary as they do within the data. Across the three models, respondents who were 25 years of age had a 42 percent probability of using SMS in 2017. The predicted probabilities all reach a minimum between ages 45–55, and then increase to 47 percent predicted probability by age 75. This pattern of SMS-utilization could be due to the influence of farm successors. As the primary farm operator ages, younger farm successors (i.e., children of the primary operator) typically assume more agency and responsibility in making production and investment decisions for the operation (Potter & Lobley

1992, Mishra et al., 2010; Karali et al., 2013). The influence of these younger decision-makers may be positively influencing SMS-utilization.

Respondents with land in pastures averaged across the three models a 12 percent predicted probability of SMS-utilization. Respondents without any land in pastures had a 41 percent predicted probability of using SMS. This negative effect of pastureland on SMS-utilization seems unsurprising, as pasturelands used for livestock grazing or browsing are unlikely to benefit from active water management in the same way as croplands. Fruit or vegetables producers have an average 43 percent predicted probability of SMS-utilization. This is compared with a 24 percent predicted probability for non-fruit/vegetable producers. This finding appears to confirm the research hypothesis that higher-value, water-intensive crops and potential opportunities for short season double-cropping increase producer benefits from SMS.

Predicted probabilities related to a respondent's preferred source of farm technology information indicated lower predicted probabilities for those producers preferring extension meetings or agents. Respondents preferring farm technology information from extension meetings had a predicted probability of SMS-utilization of 25 percent, compared to 18 percent for those preferring meetings with county agents. Respondents with consultants as their preferred source of information averaged 51 percent utilization of SMS. The omitted "other" category included information from farm commodity groups and equipment dealers and had a predicted probability of SMS-utilization of 48 percent. Information from consultants and these other sources may be more-specific to SMS than more generally-communicated Extension information.

Predicted probabilities of SMS-utilization were the highest for producers in the northeastern and southwestern regions of the state. While the predicted probability of

SMS utilization in the northeastern region of the state was 41 percent in model 1, it averaged much lower (21 and 24 percent) in model specifications 2 and 3. Lower-predicted probabilities for SMS utilization in northwest Georgia are intuitive given the relative urbanity of the region. Similarly, decreasing probabilities of SMS-utilization given increases in the number of broadband internet service providers may be attributable to telecommunications penetration being a rough measure of urbanity. A decrease in SMS-utilization in urban fringe areas is intuitive given the negative influence of farmland conversion pressure on long-range investments in productive capacity (Adelaja et al., 2011). Additionally, these regional variations in SMS-utilization even after controlling for crop mix and farm size may indicate that the relative small number of SMS vendors or powerful unobserved social network effects limits the geographic extent of the technology's diffusion.

Lastly, producers indicating a high-level of perceived risk from environmental group opposition had a 22 percent predicted probability of SMS-utilization compared to 60 percent of those who did not. This variable was highly significant across the three model specifications. While speculative, the negative effect of perceiving high-risk from environmental group opposition on SMS-utilization may be related to the role of these groups in ongoing ACF River Basin dispute. However, another possible interpretation is antagonism towards the environmentalist community may be negatively correlated with education, and education may in turn positively affect SMS-utilization. Previous research has shown that producers with less education are more skeptical of environmental group activities and climate change (Deressa et al., 2009; Rejesus et al., 2013).

Section 5.4. Model evaluation

Table 7 shows several measures of goodness-of-fit for the three estimated models. Model 1 has the best hit-to-miss ratio (93.6 percent), while models 2 (78.1 percent) and 3 (81.0 percent) hit less frequently. The mean predicted probabilities suggest that model 2 may have under-predicted SMS utilization. All predicted models were statistically significant at a 5 percent level based on the χ^2–statistic. While all models possess sufficient goodness-of-fit, estimated model 1 excels in terms of predictive power due to the inclusion of additional independent variables accounting for the effect of locally-idiosyncratic factors for SMS-utilization. Given this possible over-parameterization and earlier stated concerns about the presence of unidentified causal relationships, we are unsure of the model's inferential value and consider it more of a predictive model. Estimated models 2 and 3 have been designed to not suffer such causal non-identification; as such, they are the models used for PSM results.

Section 5.5. SMS technology effects

Table 8 presents results from the propensity score matching (PSM) technique. We test for the effect of SMS technology on two dependent variables. The first was dependent variable was whether or not a respondent indicated a high-level of concern about his on-farm water-use (Y_i= 1 if yes, Y_i= 0 if no); the second was whether or not a respondent indicated that drought or water unavailability was a significant risk to future agriculture (Y_i;= 1 if yes, Y_i = 0 if no). These two outcomes of interest are self-reported measures of producers' attitudes and perceptions. The outcomes are conditioned on the predicted probability (i.e., propensity) of each observation having utilized SMS to schedule irrigation events in 2017.

Unmatched results indicate some observable differences in outcomes for treatment and control groups prior to matching. SMS-users indicate perceiving less risk from drought or future water unavailability than SMS non-users; however, SMS-users indicate more concern about on farm water-use than SMS non-users in the unmatched results. These divergent outcomes seem unintuitive. The differences between model 2 and model 3 for the unmatched estimates are because some observations fall out due to incomplete cases of the independent variables used in estimation.

Once conditioning each observation on its propensity of selecting SMS, model 2 finds no observable differences in the dependent variables for SMS-using and non-using regimes. There are no differences between nearest-neighbor and Gaussian Kernel matching algorithms. The inability of the matching estimator to identify an effect is indicative of the observed difference in the unmatched sample being due to selection bias; the PSM estimator has in theory eliminated any observable selection bias, thus generating pseudo-randomized treatment and control groups. This conclusion is supported by model 2's ability to balance the treatment and control groups' covariate levels after matching.

Model 3 differs from model 2 in that it includes two dummy variables which function as control variables for the outcomes of interest (see Section 5.2.) Like model 2, model 3 eliminates the significant difference between SMS users and non-users in terms of drought- and water-risk perception. However, model 3 augments treatment effects for respondent concern about their individual farm water-use. Before matching there is a 16.8 percentage point increase in a producer’s concern for his on-farm water-use when utilizing SMS; after matching this difference grows to over 50 percentage points and is highly significant. Although a large number of treated observations (n=10) are omitted due to the common support requirement imposed by Gaussian kernel matching, the results are robust to an alternate NN-1 matching algorithm. These findings suggest a causal effect of SMS-utilization on producer perception of on-farm water-use.

We hypothesize that the mechanism for this difference is an information treatment effect. As technology improvements have made SMS information more accurate and new web and mobile platforms have been launched to incorporate this information for agricultural decision making, producers have been able to more clearly observe their irrigation's impact on soil-moisture levels. This has increased producer awareness of on-farm water-use, and this awareness has motivated additional concern about on-farm water management. This theory also explains the divergence in SMS' effects across the two dependent variables: additional information about on-farm water-usage seems likely to alter perceptions of on-farm water management, but it is not clear what utility this information would have in assessing future drought or water availability risk.

Supporting this theory of information treatment is an alternate PSM estimation (Table 9) where we used hired consultants for irrigation scheduling as the treatment variable. While both SMS and irrigation consultants represent advanced irrigation scheduling methods, the supposed information effect would be unique to SMS treatment. These results indicate no significant difference between producer perceptions based on the use of hired consultants for irrigation scheduling.

Table 4. Summary statistics for estimation sample

Independent variable *N = 81*	Mean (SD)	Min	Max
Respondent age (years)	46.6 (16.4)	21	80
Gross farm sales:			
Low (less than 100k)	0.29	0	1
Medium (100k-1 mil.)	0.47	0	1
High (>$ 1 mil.)	0.24	0	1
Row crop producer (Yes = 1, No = 0)	0.82	0	1
Fruit or vegetable producer (Yes= l,No = 0)	0.29	0	1
Has land in pasture (Yes = 1, No = 0)	0.32	0	1
Preferred source of farm technology information:			
Extension meetings	0.31	0	1
County agents	0.33	0	1
Consultants	0.15	0	1
Other	0.21	0	1
Number of broadband internet service providers in county	0.97 (0.48)	0.11	2.57
Respondent agreement that farmers should use irrigation scheduling technology (5-point Likert scale)	3.79 (1.08)	0	5
Respondent perception of irrigation scheduling technology ease of use (5-point Likert scale)	3.49 (1.15)	0	5
Respondent willingness to learn more about irrigation scheduling technology (5-point Likert scale)	3.92 (1.21)	0	5
Respondent rates “environmental group opposition” as major threat to future agriculture (Yes= l,No = 0)	0.82	0	1
Respondent rates “increased government regulation” as major threat to future agricultme (Yes= l,No = 0)	0.85	0	1
Respondent rates “drought” or “future water availability” as major threat to future agriculture (Yes= l,No = 0)	0.77	0	1
Respondent has “high concern” about water use on their farm (Yes = 1, No = 0)	0.58	0	1
Respondent has “high concern” about water use in Georgia (Yes = 1, No =0)	0.68	0	1
Respondent has “high concern” about water use in the United States (Yes = 1, No = 0)	0.77	0	1
Farm location:			
Northeastern	0.10	0	1
Northwestern	0.10	0	1
Southeastern	0.17	0	1
Southwestern	0.63	0	1

Table 5. Estimated model coefficients.

		Estimated model 1[a]	Estimated model 2[b]	Estimated model 3[c]
Intercept		–11.02	–8.31**	–8.70**
		(8.20)	(3.56)	(3.63)
Respondent age		–0.68**	–0.40**	–0.37**
(years)		(0.29)	(0.16)	(0.16)
Respondent age		0.007**	0.004**	–0.003**
(years squared)		(0.003)	(0.001)	(0.002)
Gross farm sales category:	$100k-$l mil.	2.05	0.38	0.60
		(1.71)	(1.04)	(1.08)
	> $1 mil.	6.81*	3.17**	3.74**
		(3.62)	(1.45)	(1.59)
Row crop producer		6.12*	0.17	–0.31
(Yes = 1, No = 0)		(3.28)	(1.17)	(1.28)
Fruit or vegetable producer		7.14**	1.21	0.86
(Yes= 1, No = 0)		(2.85)	(0.85)	(0.91)
Has land in pasture		–10.59**	–2.04**	–2.40**
(Yes= 1, No = 0)		(4.45)	(0.86)	(0.96)
Preferred source of farm technology info:				
Extension meetings		–7.04**	–1.60*	–2.19*
		(3.32)	(1.11)	(1.28)
County agents		–8.99**	–2.35**	–2.69**
		(3.86)	(1.07)	(1.17)
Consultants		0.05	0.91	0.08
		(2.43)	(1.25)	(1.37)
# of broadband ISPs in county		–3.58*	–1.30	–1.43
		(2.03)	(0.95)	(0.97)
5-point Likert assessments:				
Farmers should use technology to schedule irrigation		2.75**		
		(1.19)		
Irrigation scheduling technology is easy-to-use		0.24		
		(0.38)		
I am willing to learn more about irrigation scheduling technology		0.29		
		(0.35)		
Farm location:				
Northwestern		–8.21*	–1.37*	–0.78
		(4.31)	(0.86)	(1.92)
Southeastern		–5.22	–0.19	–0.85
		(3.67)	(1.69)	(1.87)
Southwestern		–1.01	1.34	1.10
		(2.31)	(1.58)	(1.70)
Respondent indicated "high concern" about on-farm water-use: (Yes = l, No = 0)		3.98*		
		(2.06)		
Respondent perceives high risk from:				
Environmental group opposition		–7.04**	–2.51***	–2.99
		(2.85)	(0.93)	(1.10)
Increased government regulation		3.71	1.61	1.82
		(2.95)	(1.10)	(1.29)
Drought or future water availability		–4.86**		
		(2.23)		
Respondent indicated "high concern" about water-use in Georgia (Yes = 1, No = 0)				–1.86
				(1.33)
Respondent indicated "high concern" about water- use in the United States (Yes = l, No = 0)				2.37*
				(1.38)

Dependent variable = 1 if SMS was utilized for irrigation scheduling in 2017
* p < 0.1, ** p< 0.05, ***p< 0.01
[a]Full specification
[b]Restricted specification, causally unidentified covariates omitted
[c]Restricted specification, causally unidentified covariates omitted + outcome controls for farm-level water-use concern

Table 6. Predicted probabilities

		Estimated model 1[a]	Estimated model 2[b]	Estimated model 3[c]
Respondent age				
25		0.39	0.46	0.42
35		0.22	0.27	0.25
45		0.17	0.19	0.18
55		0.19	0.19	0.19
65		0.28	0.28	0.28
75		0.49	0.49	0.45
Gross farm sales:				
<$100k		0.16	0.18	0.17
$100k-$l mil.		0.27	0.22	0.21
> $1 mil.		0.50	0.60	0.61
Row crop producer;	Yes	0.34	0.30	0.29
	No	0.11	0.28	0.28
Fruit or vegetable producer:	Yes	0.53	0.40	0.36
	No	0.22	0.25	0.26
Has land in pasture:	Yes	0.10	0.15	0.12
	No	0.44	0.39	0.40
Preferred source of farm technology info:				
Extension meetings		0.25	0.25	0.22
County agents		0.18	0.17	0.19
Consultants		0.49	0.57	0.47
Other		0.49	0.45	0.48
# of broadband ISPs in county				
0		0.51	0.47	0.45
1		0.31	0.30	0.29
2		0.12	0.16	0.15
3		0.06	0.07	0.07
Response: "Farmers should use technology to schedule irrigation"	Agree	0.23		
	Disagree	0.02		
Response: "Irrigation scheduling technology is easy-to-use"	Agree	0.31		
	Disagree	0.23		
Response: "I am learning to learn more about irrigation scheduling technology"	Agree	0.30		
	Disagree	0.40		
Farm location:				
Northwestern Extension district		0.09	0.18	0.17
Northeastern Extension district		0.41	0.21	0.24
Southeastern Extension district		0.20	0.19	0.18
Southwestern Extension district		0.36	0.37	0.37
"High concern" about on-farm water-use:	Yes	0.36		
	No	0.19		
Respondent perceives high risk from;				
Environmental group opposition:	Yes	0.21	0.23	0.21
	No	0.56	0.61	0.62
Increased government regulation	Yes	0.32	0.33	0.32
	No	0.15	0.16	0.17
Drought or future water availability	Yes	0.22		
	No	0.47		
"High concern" about water-use in Georgia	Yes			0.22
	No			0.44
"High concern" about water-use in the United States	Yes			0.35
	No			0.14

Dependent variable = 1 if SMS was utilized for irrigation scheduling in 2017

[a]Full specification

[b]Restricted specification, causally unidentified covariates omitted

[c]Restricted specification, causally unidentified covariates omitted + outcome controls for farm-level water-use concern

Table 7. Measures of goodness-of-fit.

	Actual responses from survey instrument (%)	Mean predicted probabilities from model results (%)	Percentage of accurate predictions (hit-or-miss ratios)	Log of the likelihood function	χ^2- statistic	McFadden pseudo-R^2	*N*
Estimated model 1[a]							
Respondent uses SMS (Yi = 1)	29	76	93.6	-16.92	60.77	0.64	78
Respondent does not use SMS (Yi = 0)	71	10					
Estimated model 2[b]							
Respondent uses SMS (Yi = 1)	28	47	78.1	-32.20	22.13	0.24	81
Respondent does not use SMS (Yi = 0)	72	20					
Estimated model 3[c]							
Respondent uses SMS (Yi = 1)	29	56	81.0	-31.24	32.83	0.34	79
Respondent does not use SMS (Yi = 0)	71	10					

[a]Full specification
[b]Restricted specification, causally unidentified covariates omitted
[c]Restricted specification, causally unidentified covariates omitted + outcome controls for farm-level water-use concern

Table 8. SMS-utilization effect on producers' perceptions matching results

Dependent variable	Estimated model 2[b]			Estimated model 3[c]		
	UM	NN-1	GKM	UM	NN-1	GKM
"High concern" about water-use on their farm (Yes = 1, No = 0)	0.161 (0.12)	0.131 (0.08)	0.20 (0.17)	0.168* (0.08)	0.522** (0.24)	0.538*** (0.19)
"High risk" from drought or future water availability (Yes = 1, No = 0)	–0.150* (0.08)	–0.04 (0.13)	0.0 (0.14)	–0.164** (0.07)	–0.174 (0.17)	–0.154 (0.16)
Balancing property satisfied	No	Yes	Yes	No	Yes	Yes
Common support imposed	No	No	Yes	No	No	Yes
Observations						
Treated	23	23	20	23	23	13
Control	58	58	58	56	56	56

*p< 0.1, **p< 0.05, *** p < 0.01, standard errors (S.E.) reported in parentheses

[b]Restricted specification, causally unidentified covariates omitted

[c]Restricted specification, causally unidentified covariates omitted + outcome controls for farm-level water-use concern

UM – unmatched, NN-1 – nearest neighbor (1) with replacement, GKM – Gaussian kernel matching

Table 9. Irrigation consultants effect on producers' perceptions matching results

Dependent variable	Estimated model 2[b]			Estimated model 3[c]		
	UM	NN-1	GKM	UM	NN-1	GKM
"High concern" about water-use on their farm (Yes = 1, No = 0)	–0.10 (0.15)	–0.07 (0.23)	–0.08 (0.25)	–0.10 (0.15)	–0.14 (0.24)	0.15 (0.26)
"High risk" from drought or future water availability (Yes = 1, No = 0)	–0.028 (0.09)	–0.14* (0.10)	–0.14* (0.10)	–0.024 (0.99)	–0.07 (0.15)	–0.09 (0.16)
Balancing property satisfied	No	Yes	Yes	No	Yes	Yes
Common support imposed	No	No	Yes	No	No	Yes
Observations						
Treated	14	14	13	14	14	13
Control	60	60	60	60	60	56

*p< 0.1, **p< 0.05, *** p < 0.01, standard errors (S.E.) reported in parentheses

[b]Restricted specification, causally unidentified covariates omitted

[c]Restricted specification, causally unidentified covariates omitted + outcome controls for farm-level water-use concern

VI. CONCLUSION

SMS-utilization has the potential to significantly mitigate production risk in agriculture by improving water-use efficiency (WUE), and decreasing environmental risk in the Apalachicola Chattahoochee-Flint (ACF) River Basin. However, logistic regression results suggest the utilization of SMS technology in irrigated agriculture remains inconsistent across a vector of farm and operator characteristics, namely: operator age, farm size, crop mixture, preferred information sources, and subjective producer assessments of water-use and water-risk. These findings are indicative of how the high financial costs and intensified management practices required by SMS adoption might present a technological barrier to older, less well-off agricultural irrigators.

Using data on SMS-utilization, producer-level assessments of concern for on-farm water use, and a propensity score matching (PSM) estimator, there is suggestive evidence that SMS utilization motivates increased producer concern about on-farm water use. The quantitative effect of SMS-utilization on these concerns appears to be quite large – there is an over 50 percentage point increase in producer concern for water-use on his farm when using SMS compared to similar non-utilizing producers using both nearest-neighbor and Gaussian kernel matching algorithms. We hypothesize this results from SMS ability to combine and visualize soil-moisture information for producers. Information treatment being the primary causal effect is supported by additional PSM estimates suggesting no effect from the use of hired irrigation consultants on producer concern for his farm's water-use.

These two findings are valuable for extension programming aimed at increasing the efficiency of irrigated agriculture and improving water-use efficiency (WUE). In addition to demonstrating which categories of producers may be more apt to utilize SMS, this research also suggests that SMS-utilization could impact producer behavior through its effect on motivating increased concern for on-farm water usage, and that this increase in concern could potentially manifest in other WUE-improving production decisions or practices.

Section 6.1. Research limitations

However, we must concede that this research is not without practical or theoretical limitations. Firstly, it is unfortunate that the survey data did not include a question about the respondent's education level.[8] Farmer education has previously been shown as a significant predictor of irrigation technology choice (Negri & Brooks, 1990; Pokhrel et al., 2018) and increased producer environmental awareness (Deressa et al., 2009; Rejesus et al., 2011). These two variables were the main objects of interest in this study. Secondly, the observational structure of the survey dataset limits this research to discussion of irrigation technology utilization rather than the more commonly evoked process of technology adoption. Utilization is simply the use or non-use of a technology or other production practice. Technology adoption is sociological process of transitioning from a state of non-use to use; although several theories of technology adoption have been presented across multiple disciplines, they commonly involve complex interactions between user characteristics, technical attributes, social networks, perceptions, and environmental factors that are temporally and/or spatially distributed. This research made an attempt to model dynamics with survey questions included based on Davis' Technology Acceptance Model (1989) and Ajzen's Theory of Planned Behavior (1991); however, the instrument was likely

[8] We chose to ask for the number of years the respondent has been engaged in farming since the age of 18 to represent experience rather than ask about respondent education level. This, however, was highly correlated with overall age and thus did not provide an adequate proxy for education.

insufficient in capturing these modalities of technology adoption. However, the comparisons between SMS-users and non-users possess some value in at least partially assessing underlying dynamics of adoption by relating an emergent technology's use to producer and farm characteristics.

More theoretical concerns include questions about construct validity and the limitations of the PSM method. Firstly, some dependent variables used in the PSM estimations may not be sufficient in truly assessing producer attitudes about on-farm water management. A producer's "concern" about water-use on his farm does not necessarily translate into willingness to alter production behavior, especially when there are significant financial and management risks involved. Respondents to the survey instrument may be interpreting "concern" as simple awareness or knowledge of water use on their farm rather than indicating some inclination to alter management behavior. Nonetheless, we believe these results still possess value if one interprets producer concern about his personal water-use as a necessary (albeit insufficient) condition for WUE-improving investments. This assumption seems reasonable to the researchers. Secondly, while Rosenbaum and Rubin (1983) contend that the main advantage of their PSM estimation method is its ability to simplify highly-dimensional interactions predicting treatment assignment into a comprehendible, easily matched propensity score, this is only advantageous if the underlying treatment selection process is known to the researcher. Otherwise, he is left having to model the exact, highly-dimensional interactions for which PSM is supposed to provide a workaround. Given this necessary limitation for PSM estimators, the method appears of questionable value when trying to predict the effects of emergent technologies whose diffusion dynamics may not be completely understood.

Section 6.2. Future research agenda

As a complement to this research, the UGA AgWET project developed a discrete choice experiment (DCE) for irrigation scheduling technology choice. Given the relative high-costs of SMS technology, new irrigation decision aides have been developed using public weather data and limited producer-entered data to calculate soil moisture in real time. Producer willingness-to-adopt (WTA) these technologies for use in irrigation scheduling is of interest to agricultural extension, industry, and environmental managers. Resultantly, this research team developed and piloted a fully-orthogonal DCE as a way to estimate producers' WTA for different variants of irrigation scheduling decision aides. The variables and attribute levels were set following iterative consultations with the AgWET project team, industry leaders, and producers. While the survey instrument was piloted in April 2019, limited response prevented any substantial analysis.

Appendix B is the text of the DCE. Given proper citation, the author hereby releases its text and design for use in research and educational applications.

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APPENDIX A

THE SURVEY INSTRUMENT

Farmers' Perceptions of Agricultural Water Use in Georgia

Start of Block: Consent

Q1 We are researchers in the College of Agricultural and Environmental Sciences at The University of Georgia. We invite you to participate in a research study titled **Farmers' Perceptions of Agricultural Water Use in Georgia** that is being conducted under the auspices of the Office of the Associate Dean for Extension. The purpose of this study is to identify farmers' thoughts on water use by farmers in the state of Georgia. Your participation will involve taking an online survey and should only take about 5 - 10 minutes. Your involvement in the study is voluntary, and you may choose not to participate or to stop at any time without penalty or loss of benefits to which you are otherwise entitled. If you decide to withdraw from the study, the information that can be identified as yours will be kept as part of the study and may continue to be analyzed, unless you make a written request to remove, return, or destroy the information. Your responses will be kept anonymous. The results of the research study may be published, but your name or any identifying information will not be used. In fact, the published results will be presented in summary form only. Your name will only be used to enter you into the drawing for the Yeti cooler. Your name will not be kept with your responses. The findings from this project may provide information for future communication, marketing, technology development, and/or workshops for Georgia farmers related to agricultural water use. There are no known risks or discomforts associated with this research. As an incentive, your name will be entered into a drawing for a Yeti cooler. **The drawing will take place at the end of the farm**

show. The winner will be contacted via phone. The cooler must be picked up at the exhibit booth. If you have any questions about this research project, please feel free to call me Jessica Holt at (706) 542-3521 or send an e-mail to jaholt@uga.edu. Questions or concerns about your rights as a research participant should be directed to The Chairperson, University of Georgia Institutional Review Board, 629 Boyd GSRC, Athens, Georgia 30602; telephone (706) 542-3199; email address irb@uga.edu. By selecting "Yes" below you are agreeing to participate in this research. Thank you for your consideration! Please keep a screenshot of this page for your documentation. Sincerely, Jessica Holt, Adam Rabinowitz, Abigail Borron, and Amanda Smith

○ I **agree** to participate in this research

○ I **do not agree** to participate in this research

Page Break

End of Block: Consent

Start of Block: Issue and General Info

Q2 Did you use irrigation on your farm in 2017?

○ Yes

○ No

Page Break

Q3 Do you use a cellphone, tablet, or computer to monitor, start, or stop your irrigation system?

○ Yes

○ No

Page Break

Q4 Rate the degree to which you feel agricultural water use is a topic that needs to be addressed in the following:

	A great deal	A lot	A moderate amount	A little	None at all
Your Farm	○	○	○	○	○
Your County	○	○	○	○	○
Your Water District	○	○	○	○	○
Georgia	○	○	○	○	○
United States	○	○	○	○	○

Page Break

Q5 Please select your preferred source for receiving information about farm technology.

- ◯ Talking to my county Extension agent
- ◯ Attending UGA Extension meetings
- ◯ Attending commodity meetings
- ◯ From an equipment dealer
- ◯ From a consultant
- ◯ Other (please specify): ____

Page Break

Q6 Rate your level of agreement or disagreement with the following statements.

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
Farmers should use technology to schedule irrigation.	○	○	○	○	○
The technology available today for scheduling irrigation is easy to use.	○	○	○	○	○
I would be willing to learn more about ways to use smart phones/devices to schedule irrigation.	○	○	○	○	○

Page Break

Q7 Please select each agricultural product that you produced during 2017. (select all that apply)

- ☐ Row Crops
- ☐ Vegetables
- ☐ Pasture
- ☐ Hay
- ☐ Orchard Crops
- ☐ Fruits
- ☐ Field nursery
- ☐ Greenhouses
- ☐ Turfgrass
- ☐ Livestock
- ☐ Other (please specify): ____

Page Break

Q8 What is the total size of your row crop farming operation?

- ○ Less than 250 acres
- ○ 250-499 acres
- ○ 500-749 acres
- ○ 750-999 acres
- ○ 1,000-1,499 acres
- ○ 1,500-1,999 acres
- ○ 2,000-2,499 acres
- ○ 2,500 acres or more

Page Break

Q9 How much do you feel the following are a risk to future agricultural production?

	A great deal	A lot	A moderate amount	A little	None at all
Increased government regulations	○	○	○	○	○
Climate change	○	○	○	○	○
Changing weather patterns	○	○	○	○	○
Urban population growth	○	○	○	○	○
Drought	○	○	○	○	○
Future water availability	○	○	○	○	○
Environmental group opposition	○	○	○	○	○

Page Break

End of Block: Issue and General Info

Start of Block: Current irrigation techniques

Q10 Which of the following do you **currently** use to assist you in scheduling irrigation on your farm? (select all that apply)

- ☐ Irrigation scheduling service (not web-based)
- ☐ Soil moisture sensors
- ☐ Plant moisture sensors
- ☐ Irrigation scheduling website
- ☐ Irrigation scheduling app on a smartphone or tablet
- ☐ Extension recommendations
- ☐ Plant growth curve
- ☐ Evapotranspiration
- ☐ Paid crop/irrigation consultant
- ☐ Weather stations or weather reports
- ☐ Calendar (days after planting)
- ☐ Irrigate when neighbors/other farmers irrigate
- ☐ Appearance/condition of the soil
- ☐ Appearance/condition of the crop
- ☐ None of these
- ☐ Other (please specify): ____

Page Break

End of Block: Current irrigation techniques

Start of Block: Barriers

Q11 What do you feel are the reasons you are **unlikely** to adopt **new irrigation scheduling tools** for your farm? (select all that apply)

- ▢ Installation, maintenance, and/or operating costs are too high
- ▢ I don't make the irrigation decisions for my farm
- ▢ I plan to quit farming soon
- ▢ New methods are not reliable
- ▢ I don't know how it will affect my water use
- ▢ I don't know how it will affect my yields or crop quality
- ▢ It takes too much time to manage
- ▢ I don't know enough about what is available
- ▢ My current irrigation methods are sufficient for my farm
- ▢ Other (please specify): ____

Page Break

Q12 What are the reasons you choose not to irrigate on your farm? (select all that apply)

- ▢ Installation and/or maintenance costs are too high
- ▢ Energy costs are too high
- ▢ I don't make the irrigation decisions for my farm
- ▢ I don't have a reliable source of water
- ▢ I plan to quit farming soon
- ▢ I don't know how it will affect my water use
- ▢ I don't know how it will affect my yields or crop quality
- ▢ It takes too much time to manage
- ▢ I don't know enough about what is available
- ▢ I already have sufficient soil moisture without irrigation
- ▢ Other (please specify): ____

Page Break

End of Block: Barriers

Start of Block: Decisionmaking

Q13 Who is primarily responsible for making the irrigation decisions on your farm?

- ○ Myself or unpaid family member
- ○ Paid farm manager/worker or paid family member
- ○ Paid farm/irrigation consultant
- ○ Renter
- ○ Other (please specify): ____

Page Break

Q14 What sources do you rely on for irrigation management information? (select all that apply)

- ▢ NRCS or other government agency including conservation districts
- ▢ County Extension agent or Extension specialists
- ▢ Other farmers
- ▢ Media or internet searches
- ▢ Farm or irrigation consultant
- ▢ Other (please specify): ____

Page Break

End of Block: Decisionmaking

Start of Block: Farmer Information

Q15 In what zip code is your primary farm operation located?

____

Page Break

Q16 Please choose your gender.

○ Male

○ Female

Page Break

Q17 Please choose your age range.

- ○ Under 18
- ○ 18 - 24
- ○ 25 - 34
- ○ 35 - 44
- ○ 45 - 54
- ○ 55 - 64
- ○ 65 - 74
- ○ 75 - 84
- ○ 85 or older

Page Break

Q18 How many years have you been farming since age 18?

____

Page Break

Q19 Which of the following categories best describes your gross farm sales for 2017?

- ○ Under $50,000
- ○ $50,000 - $99,999
- ○ $100,000 – 349,999
- ○ $350,000 - $749,999
- ○ $750,000 - $999,999
- ○ $1 million - $4,999,999
- ○ $5 million - $9,999,999
- ○ $10 million or Greater
- ○ Prefer not to answer

Page Break

Q20 May the University of Georgia contact you in the future about potential workshops or further research regarding irrigation scheduling tools?

- ○ Yes (please provide your email in the box below) ____
- ○ No

Page Break

End of Block: Farmer Information

Start of Block: Incentive Information

Q21 Thank you for your time. **To be entered into the drawing for the Yeti Cooler please provide us with your cell phone number below.** The winner will be contacted at the end of the farm show and will need to arrange to pick up the cooler at the exhibit booth. If you answered No on the previous question you will not be contacted unless you are the winner of the cooler. (If you do not wish to give us your phone number, hit the next button, but you will not be entered into the drawing.)

Enter your phone number in this format: XXX-XXX-XXXX

____

End of Block: Incentive Information

APPENDIX B

DISCRETE CHOICE EXPERIMENT

Start of Block: Consent

Q1 We are researchers in the College of Agricultural and Environmental Sciences at The University of Georgia. We invite you to participate in a research study titled **Farmers' Preferences for Irrigation Management Technology** that is being conducted under the auspices of the Office of the Associate Dean for Extension. The purpose of this study is to identify farmers' decision process related to irrigation management systems/technology. Your participation will involve taking an online survey and should only take about 10 - 15 minutes. Your involvement in the study is voluntary, and you may choose not to participate or to stop at any time without penalty or loss of benefits to which you are otherwise entitled. If you decide to withdraw from the study, the information that can be identified as yours will be kept as part of the study and may continue to be analyzed, unless you make a written request to remove, return, or destroy the information. Your responses will be kept anonymous. The results of the research study may be published, but your name or any identifying information will not be used. The published results will be presented in summary form only. Your name will not be kept with your responses. After any identifiers have been removed, information may be shared with other researchers without additional consent. The findings from this project may provide information for future communication, marketing, technology development, and/or workshops for Georgia farmers related to irrigation management technology. There are no known risks or discomforts associated with this research. Your confidentiality will be maintained to the degree permitted by the technology used. Specifically, no guarantees can be made regarding the interception of data sent via the Internet by any third parties. If you have any questions about this research project, please feel free to call me, Ethan Cartwright, at (662) 312-0498 or send an e-mail to ecartwright@uga.edu or you may contact my research advisor, Dr. Adam N. Rabinowitz, at (229)386-3512 or via e-mail at adam.rabinowitz@uga.edu. Questions or concerns about your rights as a research participant should be directed to the University of Georgia Institutional Review Board at (706) 542-3199 or irb@uga.edu. By selecting "I Agree" below you are agreeing to participate in this research. Thank you for your consideration. Please keep a screenshot of this page for your documentation. Sincerely, Ethan Cartwright, Graduate Research Assistantand Adam N. Rabinowitz, Ph.D., Assistant Professor

○ Yes, **I agree** to participate in this research

○ No, **I do not agree** to participate in this research

Skip To: End of Survey If Q1 = No, I do not agree to participate in this research

End of Block: Consent

Start of Block: Screening

Q39 Please enter the total number of **irrigated crop acres** you planted in 2018

____

Skip To: End of Survey If Q39 = 0

Page Break

Display This Question:

If If Please enter the total number of irrigated crop acres you planted in 2018 Text Response Is Not Equal to 0

Q38 For the following crops, please enter the number of **irrigated acres** you planted in 2018

	Irrigated acres in 2018
Row Crops (i.e., cotton, peanut, soybean, corn, etc.)	
Fruits, vegetables, or tree nuts	
All other crops	

Page Break

Q4 What is your age?

- Under 18
- 18 - 24
- 25 - 34
- 35 - 44
- 45 - 54
- 55 - 64
- 65 - 74
- 75 - 84
- 85 or older

Skip To: End of Survey If Q4 = Under 18

Page Break

Q10 Are you primarily responsible for making the irrigation decisions on your farm?

- ○ Yes
- ○ No

Page Break

End of Block: Screening

Start of Block: Choice Sets

Q6 In the following section you will be asked to evaluate several alternatives.

For each question, you will be presented with systems for managing irrigation on your farm. The systems are similar in that they all produce a recommendation telling you the best time/how much to irrigate. The systems vary in what information they use to generate the recommendation, their costs, an expected change in yields, and if they're eligible for a cost-share program.

In each question, you will be presented with 3 potential systems. In all of these systems you will be asked to evaluate on the basis of maknig a 4-year committtment. Please select the system you would choose as if you were making a real purchasing/management decision. If you would not choose any of the systems, there is a "none of the above" option for you to select.

For more information about the types of systems you will be presented, please click the **next** button.

Page Break

Q40 The systems you will be presented with today are in three general categories. The categories are as follows:

Soil Moisture Sensors are installed pieces of equipment that directly measure the soil moisture level in a field. You purchase the equipment from a dealer who installs it after planting and removes it just prior to harvest. The sensors will use wireless telemetry to transmit your soil moisture data to the manufacturer, who then makes the data available to you via an app or website. You will need to set a threshold for when to irrigate and you will be notified via email and/or text messaging when the sensor measures soil moisture below the level you have set. You will purchase this equipment the first year and then in subsequent years you will only pay for maintenance and data processing. The sensors will last four (4) years before they will need to be replaced.

A **Scheduling App or Website** relies on public weather data and user-generated information to estimate a soil water balance model. You select your crop type, seed variety, soil type, and field location when setting-up the app/website. The app/website then collects information from the closest public weather station (within 20 miles from your field) to calculate the field's soil water balance given rainfall amounts and evapotranspiration. When the calculated soil water balance falls below a specified level, you receive a text and/or email alert recommending you irrigate. You must manually enter each of your irrigation events (inches) into the app/website for the recommendations to be accurate. The app/website does not require you to purchase any additional equipment or services.

<u>Irrigation Consultants</u> are hired professionals a farmer pays to manage their irrigation and make recommendations. The consultant combines information from multiple sources including installed soil moisture sensors, weather reports, and soil water balance models to determine the best time for you to irrigate. Additionally, the consultant visits your farm at least once a week to assess crop progression and soil conditions. They send recommendations to you on when to irrigate either in-person, over the telephone, or through email. They are also able and willing to discuss any irrigation-related concerns with you in a timely manner. Hiring a consultant does not require you to purchase any additional equipment or services.

If at any point during the survey you want to review these descriptions, please click on the link provided.

Page Break

S1 Which of the following systems would you select:

To review the descriptions of these systems in a new tab, please click here.

○ System 1: A **free** scheduling app or website You can expect a **10% increase** in yields There will be a **25% improvement** in your water-use efficiency

○ System 2: An **irrigation consultant** at **$12/acre** per year You can expect **no change** in yields There will be **no change** in your water-use efficiency **75%** of the costs will be covered by a cost-share program

○ System 3: **Soil moisture sensors** costing **$25/acre** for the first year and **$5/acre** for each of the next 3 years for an average annual cost of **$10/acre** You can expect a **5% increase** in yields There will be **10% improvement** in your water-use efficiency **50%** of the costs will be covered by a cost-share program

○ None of the Above

Page Break

S2 Which of the following systems would you select:

To review the descriptions of these systems in a new tab, please click here.

- ○ System 1: **Soil moisture sen**sors costing **$25/acre** for the first year and **$5/acre** for each of the next 3 years for an average annual cost of **$10/acre** You can expect a **10% improvement** in yields There will be **no change** in your water-use efficiency **50%** of the costs will be covered by a cost-share program

- ○ System 2: A **free scheduling app or website** You can expect **no change** in yields There will be a **10% improvement** in your water-use efficiency

- ○ System 3: An **irrigation c**onsultant at **$12/acre** per year You can expect a **5% improvement** in yields There will be a **25% improvement** in your water use-efficiency No cost-share program is available

- ○ None of the Above

Page Break

S3 Which of the following systems would you select:

To review the descriptions of these systems in a new tab, please click here.

- ○ System 1: An **irrigation co**nsultant at **$12/acre** per year You can expect a **5% increase** in yields There will be **no change** in your water-use efficiency **75%** of the costs will be covered by a cost-share program

- ○ System 2: A **free scheduling app or website** You can expect a **10% increase** in yields There will be a **25% improvement** in your water-use efficiency

- ○ System 3: **Soil moisture sensors** costing **$25/acre** for the first year and **$5/acre** for each of the next 3 years for an average annual cost of **$10/acre** You can expect **no change** in yields There will be a **10% improvement** in your water-use effciency No cost-share program is available

- ○ None of the Above

Page Break

S4 Which of the following systems would you select:

To review the descriptions of these systems in a new tab, please click here.

○ System 1: A **free scheduling app or website** You can expect a **5% increase** in yields There will be a **25% improvement** in your water-use efficiency

○ System 2: **Soil moisture sensors** costing **$25/acre** for the first year and **$5/acre** for each of the next 3 years for an average annual cost of **$10/acre** You can expect a **10% increase** in yields There will be a **10% improvement** in your water-use efficiency **75%** of the costs will be covered by a cost-share program

○ System 3: An **irrigation consultant** at **$12/acre** per year You can expect a **5% increase** in yields There will be **no improvement** in your water-use efficiency No cost-share program is available

○ None of the Above

Page Break

S5 Which of the following systems would you select:

To review the descriptions of these systems in a new tab, please click here.

◯ System 1: **Soil moisture sensors** costing **$25/acre** for the first year and **$5/acre** for each of the next 3 years for an average annual cost of **$10/acre** You can expect a **no change** in yields There will be a **25% improvement** in your water-use efficiency **75%** of costs will be covered by a cost-share program

◯ System 2: A **free scheduling app or website** You can expect a **10% increase** in yields There will be a **no change** in your water-use efficiency

◯ System 3: An **irrigation consultant** at **$12/acre** per year You can expect a **5% increase** in yields There will be a **10% improvement** in your water-use efficiency **50%** of the costs will be covered by a cost-share program

◯ None of the Above

Page Break

S6 Which of the following systems would you select:

To review the descriptions of these systems in a new tab, please click here.

○ System 1: A **free scheduling app or website** You can expect a **5% increase** in yields There will be **no change** in your water-use efficiency

○ System 2: **Soil moisture sensors** costing **$25/acre** for the first year and **$5/acre** for each of the next 3 years for an average annual cost of **$10/acre** You can expect **no change** in yields There will be a **25% improvement** in your water-use efficiency No cost-share program is available

○ System 3: An **irrigation con**sultant at **$12/acre** per year You can expect a **10% improvement** in yields There will be a **10% improvement** in your water-use efficiency **50%** of the costs will be covered by a cost-share program

○ None of the Above

Page Break

S7 Which of the following systems would you select:

To review the descriptions of these systems in a new tab, please click here.

- ○ System 1: **Soil moisture sensors** costing **$25/acre** for the first year and **$5/acre** for each of the next 3 years for an average annual cost of **$10/acre** You can expect a **5% increase** in yields There will be a **25% improvement** in your water-use efficiency **75%** of the cost will be covered by a cost-share program

- ○ System 2: An **irrigation consultant** at **$12/hour** per year You can expect a **10% increase** in yields There will be a **10% improvement** in your water-use efficiency No cost-share program is available

- ○ System 3: A **free scheduling app or website** You can expect **no change** in yields There will be a **no improvement** in your water-use efficiency

- ○ None of the Above

Page Break

S8 Which of the following systems would you select:

To review the descriptions of these systems in a new tab, please click here.

○ System 1: A **free scheduling app or website** You can expect a **5% increase** in yields There will be a **10% improvement** in your water-use efficiency

○ System 2: **Soil moisture sensors** costing **$25/acre** for the first year and **$5/acre** for each of the next 3 years for an average annual cost of **$10/acre** You can expect a **10% increase** in yields There will be **no** improvement in your water-use efficiency **75%** of the costs will be covered by a cost-share program

○ System 3: An **irrigation consultant** at **$12/hour** per year You can expect **no change** in yields There will be a **25% improvement** in your water-use efficiency **50%** of the costs will be covered by a cost-share program

○ None of the Above

Page Break

S9 Which of the following systems would you select:

To review the descriptions of these systems in a new tab, please click here.

○ System 1: **Soil moisture sensors** costing **$25/acre** for the first year and **$5/acre** for each of the next 3 years for an average annual cost of **$10/acre** You can expect a **5% increase** in yields There will be **no improvement** in your water-use efficiency No cost-share program is available

○ System 2: An **irrigation consultant** at **$12/hour** per year You can expect a **10% improvement** in yields There will be a **25% improvement** in your water-use efficiency **75%** of the costs will be covered by a cost-share program

○ System 3: A **free scheduling app or website** You can expect **no change** in yields There will be a **10% improvement** in your water-use efficiency

○ None of the Above

Page Break

End of Block: Choice Sets

Start of Block: NOTA block

Display This Question:

If S1 = None of the Above

And S2 = None of the Above

And S3 = None of the Above

And S4 = None of the Above

And S5 = None of the Above

And S6 = None of the Above

And S7 = None of the Above

And S8 = None of the Above

And S9 = None of the Above

Q41 You indicated that you would not select any of the proposed irrigation management systems. What reason(s) best describes why you would not be interested in such a system at the present time? (select all that apply)

- ☐ These irrigation management methods are too expensive
- ☐ I don't make the irrigation decisions for my farm
- ☐ I plan to quit farming soon
- ☐ I don't trust these irrigation management methods
- ☐ I don't have enough time for these irrigation management methods
- ☐ My current methods for managing irrigation are sufficient
- ☐ I don't use irrigation on my farm
- ☐ Other (please explain): ____

End of Block: NOTA block

Start of Block: Mechanisms

Q32 How important would you describe each of the following factors when making a choice for an irrigation management system?

	Very important	Important	Somewhat important	Slightly important	Not important
What other farmers in my area are using	○	○	○	○	○
What Extension agents or Extension publications are recommending	○	○	○	○	○
What consultants or equipment dealers are reccomending	○	○	○	○	○
What commodity or farm groups are reccomending	○	○	○	○	○
Water-use efficiency	○	○	○	○	○
The cost of the system	○	○	○	○	○
The management time required	○	○	○	○	○
The presence of a cost-share program	○	○	○	○	○
The source of the information used to make recommendations	○	○	○	○	○

Page Break

Display This Question:

If Q32 [Very important] (Count) > 0

Carry Forward Selected Choices from "Q32"

Q33 Of the factors you selected as very important, which do you consider the **most important**?

- ○ What other farmers in my area are using
- ○ What Extension agents or Extension publications are recommending
- ○ What consultants or equipment dealers are reccomending
- ○ What commodity or farm groups are reccomending
- ○ Water-use efficiency
- ○ The cost of the system
- ○ The management time required
- ○ The presence of a cost-share program
- ○ The source of the information used to make recommendations

End of Block: Mechanisms

Start of Block: Technology

Q42 For how many years have you been using irrigation on your farm?

____

Page Break

Q43 Which of the following irrigation management systems or technologies have you used?

	Am currently using	Have used in the past	Have never used
Paid irrigation/crop consultants	○	○	○
Soil moisture sensors	○	○	○
Checkbook method	○	○	○
Calendar (days after planting) method	○	○	○
Irrigation scheduling app or website	○	○	○
Plant temperature sensors	○	○	○
Weather stations or weather reports	○	○	○
Appearance/condition of the soil	○	○	○
Appearance/condition of the crop	○	○	○

Page Break

Q44 Which of the following devices and technologies do you currently have access to? (select all that apply)

- ☐ Smartphone (i.e., iPhone, Samsung Galaxy, Google Pixel, etc.) with a data or internet connection
- ☐ Cell phone without a data or internet connection
- ☐ Tablet (i.e., iPad, Galaxy Tab, Microsoft Surface, etc.) with a data or internet connection
- ☐ Tablet without a data or internet connection
- ☐ Desktop or laptop computer with an internet connection
- ☐ Desktop or laptop computer without an internet connection
- ☐ AM/FM or broadcast radio
- ☐ Satellite or subscription radio
- ☐ Television with cable or satellite subscription
- ☐ Television without cable or satellite subscription
- ☐ High speed broadband or wired internet connection at home

Page Break

End of Block: Technology

Start of Block: Demographics

Q55 Rate the degree to which you feel agricultural water use is a topic that needs to be addressed in the following:

	A great deal	A lot	A moderate amount	A little	None at all
Your Farm	○	○	○	○	○
Your County	○	○	○	○	○
Your Water District	○	○	○	○	○
Georgia	○	○	○	○	○
United States	○	○	○	○	○

Page Break

Q37 What is your gender?

- ○ Male
- ○ Female

Page Break

Q35 Which of the following best describes your highest level of education?

- ○ Less than a high school diploma
- ○ High school diploma or equivalent (i.e., GED)
- ○ Some college, including associate or two-year degrees (i.e., AA, AS, ABA, etc.)
- ○ College graduate (i.e., BA, BS, BBA, etc.)
- ○ Graduate or professional school (i.e., MA, MS, MBA, PhD, MD, DVM, etc.)
- ○ Prefer not to answer

Page Break

Q36 In what ZIP code is your primary farming operation located?

____

Page Break

Q39 Which of the following categories best describes your gross farm sales for 2018?

- ○ Less than $50,000
- ○ Between $50,000 and $249,999
- ○ Between $250,000 and $499,999
- ○ Between $500,000 and $749,999
- ○ Between $750,000 and $999,999
- ○ Between $1,000,000 and $4,999,999
- ○ Greater than $5 million
- ○ Prefer not to answer

End of Block: Demographics

Start of Block: Follow-up

Q40 Thank you for your participation.

May the University of Georgia contact you in the future about potential workshops or further research regarding irrigation scheduling tools and technology?

- ○ Yes (please enter your email address) ____
- ○ No

End of Block: Follow-up