Willingness to Pay for Sensor-Controlled Irrigation

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Abstract. Water scarcity is likely to increase in the coming years, making improvements in irrigation efficiency increasingly important. An emerging technology that promises to increase irrigation efficiency substantially is a wireless irrigation sensor network that uploads sensor data into irrigation management software, creating an integrated system that allows real-time monitoring and control of moisture status that has been shown in experimental settings to reduce irrigation costs, lower plant loss rates, shorten production times, decrease pesticide application, and increase yield, quality, and profit. We use an original survey to investigate likely initial acceptance, ceiling adoption rates, and profitability of this new sensor network technology in the nursery and greenhouse industry. We find that adoption rates for a base system and demand for expansion components are decreasing in price, as expected. The price elasticity of the probability of adoption suggests that sensor networks are likely to diffuse at a rate somewhat greater than that of drip irrigation. Adoption rates for a base system and demand for expansion components are increasing in specialization in ornamental production: Growers earning greater shares of revenue from greenhouse and nursery operations are willing to pay more for a base system and willing to purchase larger numbers of expansion components at any given price. We estimate that growers who are willing to purchase a sensor network expect investment in this technology to generate significant profit, consistent with findings from experimental studies.

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Introduction

Current trends on water supply and demand indicate that the importance of greater water use efficiency is likely to grow, especially for agricultural uses, which account for 80 percent or more of consumptive use in the US as a whole and over 90 percent in many western states (Schaible and Aillery, 2012). Population growth is increasing water demand for urban uses and for energy production (Sauer et al., 2010; Schaible and Aillery, 2012; Gleick, 2013). Expansion of irrigated acreage in the High Plains combined with depletion of groundwater supplies from the Ogallala Aquifer has intensified competition among agricultural users, between agricultural and other user, and between states (Evans and Sadler, 2008; Gleick, 2013; Kuwayama and Brozovic, 2013). Climate change is expected to reduce average snowpack accumulation in the Sierra Nevada and Rocky Mountains, shrinking available supplies throughout much of the western US (Mote et al., 2005).

Growing water scarcity can be mitigated by increases in irrigation efficiency by combining more precise application equipment and decision support systems (Evans and Sadler, 2008). Wireless sensor networks, an emerging technology on the verge of commercial introduction, offer this kind of decision support. These systems upload data wirelessly into irrigation management software, allowing irrigation managers to monitor moisture status and match water application with plant uptake needs in real time. This technology differs from moisture sensors currently on the market in its integration of user-friendly software and control capabilities that permit real time information access and irrigation control. Research studies conducted in actual production environments indicate that these systems can reduce irrigation costs—including labor and energy in addition to water—substantially (Belayneh et al., 2013).

Other documented benefits include lower plant loss rates, shorter production times, less need for pesticide application, and higher yield and quality (Lichtenberg et al., 2013; Saavoss et al., 2014). These research studies all indicate that adoption can be extremely profitable.

This paper uses an original survey of nursery and greenhouse farmers nation-wide to investigate likely initial acceptance, diffusion rates, and ultimate ceiling adoption rates of this new sensor network technology. We focus on the greenhouse, nursery, and floriculture industry, a large and growing segment of US agriculture. Sales of this sector totaled almost $17 billion in 2007, more than vegetables ($15 billion), wheat ($11 billion), cotton ($5 billion), and almost as much as fruits, nuts, and berries ($19 billion) or soybeans ($20 billion) (US Department of Agriculture, 2009). The value of each acre-foot of water used for greenhouse and nursery products is 2-3 orders of magnitude greater than other crops (Ackerman and Stanton, 2011). States in the water-scarce Pacific, Mountain, and South Central regions account for 37 percent of greenhouse and nursery sales, suggesting that water savings are likely extremely important for this industry (Hall, Hodges and Palma, 2011). The high market value of ornamental crops combined with their large footprint in water-scarce, high water cost regions makes them a likely market for sensor networks.

We investigate two dimensions of demand for these sensor networks with an eye toward gauging likely initial grower acceptance of this technology, how rapidly it is likely to disseminate, and the ultimate size of market for wireless sensor networks. We begin by estimating willingness to pay for a base system consisting of 5 sensors connected to a single transmission node plus software. We use the willingness to pay estimates to discuss characteristics of likely base system adopters and to explore likely effects of changes in system prices and grower perceptions of system benefits on the speed at which this technology is likely to diffuse. We then investigate potential system scale by estimating demand for additional transmission nodes, with each node holding up to 5 sensors. We use this estimated demand relationship to investigate characteristics associated with demand for additional nodes.

Briefly, the estimated coefficients of the base system willingness to purchase model indicate that as many one-fifth of nursery and greenhouse operators might purchase a base system when it becomes commercially available while about 30% are unlikely to purchase a base system at any price. The estimated price elasticity of demand for a base system suggests that this technology is likely to diffuse more rapidly than drip irrigation. Our estimates of base system willingness to pay combined with our estimates of demand for additional nodes, indicate an average expected profit from adoption of about $11,000 annually, with substantial variation around that figure.

We proceed as follows. We begin with a review of the literature on adoption of irrigation technologies. We then describe our survey of nursery and greenhouse operators and the data obtained from that survey. The subsequent section discusses the specification and estimation of models of willingness to pay for a base system and demand for additional nodes. We then discuss estimation results, followed by a discussion of implications for the initial adoption and subsequent diffusion of this technology. A final section concludes.

Economics of Precision Irrigation Adoption

Traditional gravity-fed irrigation systems rely on soils to hold a reservoir of water available for plant uptake. The efficiency of these systems is limited: Some of the water applied is lost via surface runoff, some percolates through the root zone into groundwater, and some groundwater drains into nearby streams and ditches. Improving uniformity of application by leveling can reduce—but not eliminate—these losses (Feinerman et al., 1983).

Sprinkler and drip systems increase irrigation efficiency by substituting capital and energy for soil water holding capacity (Caswell and Zilberman, 1986; Lichtenberg, 1989). Farmers cultivating lower quality soils or land with greater slope are thus more likely to adopt more precise irrigation technologies than farmers cultivating better soils on level land, where the gains from increasing irrigation precision are lower (Lichtenberg, 1989; Dinar and Yaron, 1990; Negri and Brooks, 1990; Shrestha and Gopalakrishnan, 1993; Green et al., 1996; Green and Sunding, 1997; Moreno and Sunding, 2005; Koundouri et al., 2006; Schoengold et al., 2006). Larger farm operations, which presumably have greater capacity to finance investment in irrigation equipment, are also more likely to adopt drip and sprinkler systems (Dinar et al., 1992; Shrestha and Gopalakrishnan, 1993; Green et al., 1996). The gains from increasing irrigation precision—and thus the likelihood of adoption of more efficient irrigation technologies—have also been shown to be greater when water is more expensive (Dinar and Yaron, 1990; Green et al., 1996; Pfeiffer and Lin, 2014) and when the marginal value of water is greater (Caswell and Zilberman, 1985; Lichtenberg, 1989; Dinar et al., 1992; Shrestha and Gopalakrishnan, 1993; Schoengold et al., 2006).

As noted above, irrigation efficiency is lower—and thus investments in more efficient irrigation equipment are more profitable—on farms whose soils vary more in terms of soil permeability, slope, and similar factors (Feinerman et al., 1983). The same holds for investments in precision agriculture technologies more generally. For instance, variable rate fertilizer application is more profitable on fields whose soils vary more in terms of natural fertility (Babcock and Pautsch, 1998; Pautsch et al., 1999; Griffin et al., 2000; Oriade and Popp, 2000; Bullock et al., 2005) and correspondingly less profitable on farms with more uniform soils (Hudson and Hite, 2003).

The key advantage of sensor networks is that they provide more accurate information about substrate moisture status in real time, allowing growers to make real time adjustments to irrigation water applications. The potential value of more accurate information about the production environment has been demonstrated for variable rate fertilizer application (Pautsch et al., 1999; Bullock et al., 2005) as well as for sensor networks (Belayneh et al., 2013; Lichtenberg et al., 2013; Saavoss et al., 2014).

Data

We investigate potential willingness to pay for sensor networks using data from an original survey of greenhouse and nursery operations conducted from January 2012 through March 2013. The survey was administered in person to growers at the Mid-Atlantic Nursery Trade Show and the Georgia Green Industry Association annual meeting and online via invitations circulated through extension networks. Incomplete surveys were followed-up with phone calls or emails. Growers attending the Mid-Atlantic Nursery Trade Show and Georgia Green Industry Association annual meeting numbered 541 and 80, respectively. The extension networks through which invitations were circulated have a potential reach of about 9,100 commercial greenhouse and nursery operations. A total of 268 surveys were completed, 35% of which were filled out at trade shows and 65% of which were completed online. The sample is more representative of commercial operations—and thus likely purchasers of the wireless sensor systems we study—than of the greenhouse and nursery industry as a whole. For example, the revenue distribution of the respondents in our sample is skewed towards operations with high gross revenues compared with the national revenue distribution of the nursery and greenhouse growers as reported in the U.S. Census of Agriculture (Table 1). The 47% of operations surveyed by the Census of Agriculture that gross less than $25,000 per year are unlikely to profit from wireless sensor networks since their profit margins are unlikely to justify the cost of system purchase and maintenance. The sample is also skewed towards larger operations in terms of acreage. Operations in Appalachia and the Southeast were over-represented relative to the share of operations reported by the Census of Agriculture while operations located in the Midwest were under-represented.

The survey focused on general characteristics of the operation and the respondent, as well as questions that were directed specifically towards water use practices such as water sources. Questions concerning general characteristics of the operation included income, total costs, size, zip code, and revenue sources. Respondents were also asked to list the percent of total water used from surface, deep wells, shallow wells, recycled water, rain, municipal water, and other water sources. Questions concerning characteristics of the respondent included age, education level, and position in the company.

Information about growers' willingness to pay for a base system and for additional nodes was elicited in the following series of steps. First, respondents were given the following background information:

> "As part of this project, we are developing and testing sensor networks that can monitor root zone moisture, weather and many other variables for precision irrigation and nutrient management. These more advanced sensor networks can automatically turn irrigation on and off as needed, reducing or eliminating the need for manual irrigation control. The sensors decide when, where, and how much to irrigate based on set-points you determine. Answering the questions below will help us to better understand

the extent of technology adoption in the nursery and greenhouse industry."

Respondents were then asked for their perceptions of potential benefits and limitations of sensor networks (Table 2). Next, respondents were asked to look at a schematic of a base sensor network system (Figure 1) and asked the following question:

> "A basic sensor system contains a base station, software, and a single node (with up to 5 sensors), which monitors and controls irrigation in a single production area/irrigation zone. Would you purchase a basic sensor system if the price was $X?"

The system price X was randomized across participants with values of $500, $1,000, $2,000, $3,000, $4,000, or $5,000."[1] Every price bin had nearly the same number of growers assigned to it (Table 3).

To determine how extensive a sensor network respondents might be willing to purchase, respondents were again shown the sensor network schematic in Figure 1 and asked the following question:

> "A basic sensor system is expandable, so you could buy additional nodes (5 sensors), and use the same base station and software package. Suppose you already purchased the basic system, how many additional nodes would you be willing to purchase for your operation if EACH node cost $X?"

The price of an additional node X was randomized with values of $500, $1,000, $1,500 or $2,000. Respondents were to select the number of additional nodes from the following list: 0, 1,

[1]An earlier version of the survey also included a $1,500 bin, and there is one response with that price level. That observation is treated like the other price levels in the probit model.

2, 3, 4, 5, 6-7, 8-10, 11-15, 16-20, and 21 or more. Prices were assigned close to evenly between the bins (Table 3). Note that the additional nodes question is framed in a way that assumes the respondent already owns the base system, allowing a respondent to report a willingness to buy additional nodes even if she was not willing to buy a base system at the price offered.

Thirty-nine percent of the growers included in the sample said they would be willing to buy a base system. Conditional on having purchased a base system, growers were willing to purchase an average of 3.5 additional nodes. The desired scale of a wireless sensor network varied substantially: Some growers were not willing to purchase any additional nodes while others were willing to purchase as many as 21. Both the share of growers willing to purchase a base system and the average number of additional nodes purchased are generally decreasing in price, albeit not monotonically (Table 3). Differences in size of operation are the most likely source of this non-monotonicity: Growers who were quoted a price of $3000 for a base system and $1500 for each additional node are substantially smaller on average than growers quoted prices of $2000 or $4000 for a base system and $1000 or $2000 for each additional node.

Descriptive statistics of the variables used in the econometric analysis are shown in Table 4. The growers in the sample vary substantially in size as measured by both revenue and spatial extent of the operation. Most respondents specialized heavily in greenhouse and nursery production. About half of these growers had formal education at least through a bachelor's degree. Most growers had very positive perceptions of the capabilities of wireless sensor networks. Cost and reliability were the major concerns about the technology.

Specification and Estimation

A probit model was used to estimate the willingness to purchase the base system. A tobit model was used to estimate demand for additional nodes.

Estimating Willingness to Pay for a Base System

Growers presumably answer the question of whether they are willing to buy the sensor system affirmatively if and only if they expect that using a sensor network to control irrigation would increase profit relative to their current irrigation methods. The expected increase in profit from investing in a sensor network $\Delta\pi^*$ was not observed; instead, we observe the binary response of whether or not the grower would buy the system at the price quoted. We assume that growers would buy the system if they expect the investment to be profitable:

$$\Delta\pi^* = \alpha X + Z'\beta + \varepsilon$$

$$y = 1 \; if \; \Delta\pi^* \geq 0$$

$$y = 0 \; if \; \Delta\pi^* < 0$$

Here X is the randomized price assigned to each respondent, **Z** is a vector of controls and ε is a mean zero random error capturing the influence of all unobserved factors that enter into the grower's adoption decision. The probability that a grower would buy a base system is thus:

$$\Pr(Y = 1 | X_0, Z) = \Phi(\alpha X + \boldsymbol{Z}'\boldsymbol{\beta})$$

where Y =1 if the respondent answers affirmatively and Y=0 otherwise and $\Phi(\cdot)$denotes the cumulative distribution of ε. We assume that ε is distributed normally and thus estimate the parameters α and β using probit.

The set of characteristics **Z** used in the probit model included measures of operation size, the share of ornamental production in the firm's total revenue, the grower's education level, the grower's perception of the benefits and limitations of wireless sensor systems, and indicators for the operation's water sources and the region in which the operation is located.

There are three main types of ornamental production environments: greenhouse, container, and field. Greenhouse production is labor and energy intensive but has the highest profit per area. Typical operation size ranges are 0.1 to 10 acres of production area. Container production is less intensive, and can be more easily managed on a larger scale, with typical sizes of 0.5 to 50 acres of production area. Field operations tend to be the least intensive, with operation sizes typically in the range of 5 to 500 acres. Operations often have more than one production method being used at the same time (i.e. greenhouse and container production).

We use two measures of size, gross income and acreage. Gross income of the operation was included to account for differences in available funds to purchase any given technology. Higher grossing operations are also more likely to hire labor that specializes in managing their irrigation systems, so sensor networks may provide a relatively larger labor cost savings for them. Size in acres was included to measure the ability of a firm to take advantage of economies of scale in sensor placement. Similarly, larger operations of any given type tend to have more irrigation zones, which make the irrigation systems more complex and therefore costly to manage. Since the sensor systems simplify irrigation systems by enabling automation of irrigation management, larger firms may expect to experience greater increases in profit than smaller firms. We expect that both the gross income and size in acres will be positively correlated with a respondent’s willingness to buy a sensor network.

The percent of all revenue from ornamental production was included because ornamental crops typically irrigate more frequently than agronomic producers, and therefore operations with high portions of their revenues coming from ornamental crops may see the benefits of investing in sensor networks more quickly, particularly for greenhouse and container production. Operations that specialize more in ornamental production may also be more aware of new technological developments. For example, producers specializing in ornamentals are likely to have more involvement in industry-specific information networks through trade-shows and targeted advertising. A sharper focus on the greenhouse and nursery industry also likely translates to more inputs focused on greenhouse and nursery production, including water, labor, and disease control measures. Sensor networks may reduce the cost of all these inputs, so we expect that willingness to buy a sensor network will increase with the percentage of revenue from greenhouse and nursery operations.

Growers with more formal education levels likely have both greater human capital and greater technological sophistication. Thus, higher educational attainment is likely correlated with both greater expected productivity increases and lower expected transition costs. Previous studies have indicated that individuals with higher levels of education are more willing to adopt new agricultural technologies (Feder et al., 1985; Dinar and Yaron, 1990; Koundouri et al., 2006). We expect that higher levels of education will correlate with a higher willingness to buy a sensor network.

Previous studies also indicate that older growers are less likely to adopt new technologies, suggesting that willingness to adopt a sensor network should decrease as the age of the operator increases, a finding that has been attributed to a shorter time horizon and higher transition costs (Feder et al., 1985). Research to date suggests that the payback period for investments in sensor networks is quite short (Belayneh et al., 2013; Lichtenberg et al., 2013) suggesting that a shorter time horizon should not be an impediment to adoption. Once technological sophistication is taken into account (by controlling for education level, for instance), transition costs may not correlate with age. There are thus reasons to believe that age may not be a factor in growers' willingness to buy sensor networks. We include it in our base specification regardless, in keeping with previous literature on this topic.

We expect willingness to buy a sensor network to be greater for growers who express positive views of their benefits and lower for growers who express concerns about their cost, effectiveness, or reliability. We thus include indicators of whether respondents expressed beliefs about each potential advantage and limitation of wireless sensor networks.

Water sources differ in terms of cost, quantity available, and quality. We thus include indicators of whether growers obtained water from shallow wells, deep wells, surface sources, municipal water systems, or gray water as well as whether growers reused runoff water. These sources are not mutually exclusive, as growers may use water from more than one source. All else equal, water from deep wells and municipal sources tends to be more expensive than water from other sources. Growers using water from these sources are likely to obtain greater reductions in water expenditures than growers using water from cheaper sources; we thus expect growers getting water from deep wells or municipal sources to be willing to pay more for a sensor network. Operations using surface water, recycled water, or gray water face a higher risk of growth reduction or plant death due to disease, phytotoxicity, etc. Since sensor networks have been shown to reduce disease losses, we expect growers using these water sources to be willing to pay more for a sensor network. Conversely, operations that rely solely on rain water for irrigation stand to gain very little from using sensor networks, so we expect growers using rainfall to be willing to pay less for a sensor network.

Finally, we include regional dummy variables to control for unobserved factors such as climate conditions, information networks, and water scarcity. We expect growers located in regions with higher levels of water scarcity (e.g., the Pacific, and South Central regions) to be willing to pay more for a wireless sensor network compared to growers located in regions where water is less scarce (e.g., the Northeast).

Estimating Demand for Additional Nodes

A single node gives information about substrate moisture status for a limited area. Growers with more extensive operations or those growing a larger number of plant species with different water requirements would likely need to use a larger number of nodes in order to benefit from greater irrigation precision. We estimate demand for additional nodes—contingent on prior acquisition of a base system—in order to gauge variations in the scale at which sensor networks are likely to be used and in order to investigate operation characteristics correlated with those variations. We use a double censored tobit model to estimate this demand for additional nodes. Responses are censored at 0, while the number of additional nodes to be purchased are top coded at 21 or more. Choices of the number of additional nodes greater than 5 were presented as ranges: 6-7, 8-10, 11-15, and 16-20. We use the midpoint of each range (6.5, 9, 13, and 18) as the observed number of additional nodes y_i in our tobit model. We observe the latent demand for additional nodes by grower i, y_i*, only if it lies between 0 and 21, i.e., observed demand y_i is:

$$y_i = 21 \; if \; y_i * > 21$$

$$y_i = y_i * \; if \; 0 < y_i * < 21$$

$$y_i = 0 \; if \; y_i * < 0$$

$$y_i * = \gamma W + \boldsymbol{V}'\boldsymbol{\delta} + \eta$$

where W is the randomized price, **V** is a vector of operation and grower characteristics, and η is a random error capturing the influences of all unobserved factors affecting a grower's demand for additional nodes (which we assume to be distributed normally with mean zero).

We expect that the same factors that influence willingness to pay for a base system to affect demand for additional nodes. Those factors include size, share of income derived from ornamental production, water source, education, and perceptions of benefits and limitations of sensor networks.

Operations that are larger in terms of acreage are likely to have more irrigation zones, and thus have a higher demand for additional nodes. Larger grossing operations may also have more funds available and may thus experience fewer financial constraints in deciding how extensive a sensor network system to purchase.

Operations that earn a greater percentage of revenue from ornamental crops typically grow a wider variety of plant species and are thus also likely to have a larger number of irrigation zones. For that reason, we expect the share of revenue from nursery and greenhouse operations to be positively correlated with the number of nodes demanded.

We expect that growers using more costly water sources such as deep wells and municipal water systems to be willing to buy more extensive sensor network systems as well, since their potential gains from irrigation cost savings are likely to be greater. The same reasoning leads us to expect that operations in more water scarce regions such as the Pacific and the Southeast, where the costs of water are higher due to constraints on availability as well as direct acquisition expenses, will be willing to purchase larger numbers of nodes than growers in less water scarce regions such as the Northeast.

We investigate the effect of human capital on sensor network system scale by including grower education levels in the additional node demand equation.

The literature suggests that one mechanism for addressing uncertainty about the performance of a new agricultural technology is to experiment with it on a portion of the farm operation. Experience with the technology reduces uncertainty about its potential; if the technology is truly more profitable, the share of the operation on which it is used should expand over time (Feder, Just, and Zilberman 1985). We investigate the effects of uncertainty about performance by including indicator variables for whether a grower believed sensor networks to have the advantages and limitations presented in Table 1. Belief in each potential advantage should indicate less uncertainty about potential benefits and should thus be correlated with a larger number of additional nodes demanded. Belief in each potential limitation should indicate greater uncertainty about potential benefits and should thus be correlated with a smaller number of additional nodes demanded.

Estimation Results

Willingness to Purchase a Base System

We simplified our model for willingness to purchase a base system in two ways. First, we aggregated education into two levels: (i) high school and some college and (ii) a post-secondary degree (including associate, bachelors, masters, and doctoral degrees). Wald tests indicated that the coefficients of the post-secondary degree categories ($p = 0.549$) were jointly not significantly different from zero and that none of the post-secondary degree categories were significantly different from each other ($p = 0.082$). Aggregation of education levels had little or no effect on the remaining estimated coefficients. Second, Wald tests indicated that the perceptions of benefits were jointly significant ($p = 0.017$) but that perceptions of limitations ($p = 0.707$), water source ($p = 0.944$), age category ($p = 0.251$), and region ($p = 0.738$) were not. We thus dropped these sets of indicators from the main model. As a robustness check, we report estimated coefficients and marginal effects of the variables included in our main model from models including these additional controls (Table 5).

The coefficients of the variables included in the probit model used to determine willingness to pay for a base system model all have signs consistent with our expectations (Table 5). They are also robust with respect to the inclusion of the additional control variables.

The coefficient of price is negative and significantly different from zero, consistent with downward sloping demand. The base system demand is not very sensitive to changes in price: A $100 reduction in price would increase the share of respondents willing to purchase a base system by only about 0.007 percentage points, on average (Table 6).

The coefficient of the percentage of revenue from ornamental production is positive and significantly different from zero, consistent with our hypothesis that growers who rely on nursery and greenhouse crops more heavily are likely to benefit more from using sensor networks and are likely to be more aware of potential benefits of sensor networks as well. Base system demand is more sensitive to the degree of specialization in greenhouse and nursery crops than to price: A one percentage point increase in the percentage of revenue from ornamental production is associated with 0.5 percentage point in increase in the share of respondents willing to purchase a base system, on average.

The coefficient of no post-secondary degree is negative and significantly different from zero, consistent with the hypothesis that farmers with more formal education are more likely to adopt new agricultural technologies. The effect of formal schooling on willingness to purchase a base system is substantial: Respondents without a post-secondary degree are 23 percentage points less likely to be willing to purchase a base system than those with a post-secondary degree.

The estimated coefficients of size in terms of acres and in terms of revenue are both positive but neither is significantly different from zero and both are quite small in magnitude, indicating a lack of scale effects influencing likely adoption of a base system. The average semi-elasticity of the likelihood of purchasing a base system with respect to income is significantly different from zero. But it too, is quite small: on average, an increase in income of $100,000 is associated with only a 0.05 percentage point increase in the probability of a respondent being willing to purchase a base system.

Willingness to purchase a base system was associated with some, but not all perceived benefits of sensor networks. Growers who believe that sensor networks can increase irrigation efficiency, reduce irrigation management costs, and improve product quality are more likely to be willing to buy a sensor network at the quoted price than those who did not. These beliefs are associated with substantial differences in base system demand. Those who believe that sensor networks can increase irrigation efficiency, reduce irrigation management costs, and improve quality are 12-15 percentage points more likely to be willing to purchase a base system. The coefficients of believing that sensor networks can reduce management costs and lower product losses were both positive, as expected, but not significantly different from zero. Somewhat surprisingly though, growers who believe that sensor networks can reduce disease are 15 percentage points less likely to be willing to buy a sensor network at the quoted price. The coefficient of believing that sensor networks can increase ability to manage growth rates was also negative but was not significantly different from zero.

Estimated Demand for Additional Nodes

As with the probit model of willingness to purchase a base system, we simplified the tobit model of demand for additional nodes by dropping variables that were not significantly different from zero. Wald tests indicated that education levels ($p = 0.636$), age category ($p = 0.994$), perceptions of potential benefits of sensor networks ($p = 0.418$), and perceptions of potential drawbacks of sensor networks (p = 0.122) were not significantly different from zero. We thus removed these sets of indicators from the main model. As a robustness check, we report estimated coefficients and marginal effects of the variables included in our main model from models including them as additional controls (Table 7).

The coefficients of the variables included in the main model of demand for additional nodes all have signs consistent with our expectations (Table 7). They are also robust with respect to the inclusion of the additional control variables.

The coefficient of price is negative, consistent with downward sloping demand. It is significantly different from zero when additional controls are included but not otherwise. The effect of price on demand for additional nodes is quite small: a one percent increase in price decreases the unconditional expectation of the number of additional nodes demanded by 0.3 percent (Table 8). The effect of a change in price is split fairly evenly between reductions in the number of nodes demanded by those purchasing a positive amount (as indicated by an elasticity of 0.1) and reductions in the probability that a grower is willing to purchase any additional nodes (as indicated by a semi-elasticity of 0.09).

The coefficient of the percentage of revenue from ornamental production is positive and significantly different from zero, consistent with our hypothesis that growers who rely on nursery and greenhouse crops more heavily are likely to have a greater diversity of plant varieties and irrigation zones and thus need more nodes to obtain adequate coverage. Demand for additional nodes is quite inelastic with respect to the degree of specialization in greenhouse and nursery crops. A one percentage point increase in the share of income from ornamental production is associated with a 0.02 percent increase in the unconditional expectation of the number of additional nodes demanded. As with price, the effects of specialization in greenhouse and nursery crops are split fairly evenly between the extensive and intensive margins. A one percentage point increase in the share of income from ornamental crops is associated with a 0.6 percentage point increase in the probability that a grower is willing to purchase at least one additional node, compared to a 0.7 percent increase in the expected number of additional nodes demanded by growers willing to purchase at least one.

The estimated coefficients of size in terms of acres and in terms of revenue are both positive, as expected. The coefficient of income is significantly different from zero while the coefficient of size in acres is not, suggesting that financial capacity may constrain the size of system demanded.

Growers obtaining water from deep wells and surface waters and those using gray water are willing to buy a larger number of nodes at any given price. As noted earlier, water from deep wells is more expensive to pump, so that growers using this source stand to save more in expenditures on energy for irrigation. Surface water withdrawals are often limited either by permit level or, in the short run, by pump capacity; the positive coefficient of the surface water indicator is consistent with water having a higher implicit cost due to such constraints. Gray water is often more saline than other sources; more precise water application can reduce salt buildup.

Growers in the Appalachian region are willing to buy fewer nodes at any given price than growers in other regions. Possible explanations include less plant and irrigation zone diversity and less water scarcity among growers in this region.

Implications for Initial Adoption and Diffusion of Sensor Network Technology

The estimated coefficients of the probit model can be used to draw inferences about likely initial adoption and subsequent diffusion of sensor network technology in the greenhouse and nursery industry. As is standard, we assume that growers whose willingness to pay for a base system is at least as great as the current price of a system will adopt the technology while those with a willingness to pay less than the current price will not. We thus use estimates of willingness to pay to estimate the share of nursery and greenhouse operators likely to adopt this technology initially. Growers who did not adopt the technology initially may do so later on, if the cost of the technology falls, as often occurs as producers of the technology benefit from economies of scale or from learning from experience in producing the technology. Alternatively, growers who did not adopt the technology initially may do so later on as the benefits of the technology become better known and as uncertainty about the technology shrinks (Feder et al., 1985). We examine the effects of changes in price and perceptions about benefits and drawbacks of sensor networks by estimating their effects on the share of growers with a willingness to pay for a base system greater than or equal to the price of system.

Initial Adoption

Predicted willingness to pay for each respondent is equal to $\max\{0, \frac{Z'\beta}{\alpha}\}$. On average, respondents were willing to pay $1905 for a base system, substantially less than the projected initial price of $3500. There is substantial variability in willingness to pay for a base system, however, as indicated by a standard deviation slightly larger than the mean at $2015. Examination of the cumulative distribution of willingness to pay estimates (Figure 1) indicates that almost one fifth of our respondents were willing to pay at least the projected initial price of $3500. That estimate suggests that initial adoption of sensor networks could be high relative to many other new agricultural technologies generally and irrigation technologies in particular. For example, only 5.8% of irrigated farms used drip irrigation in 1978, the first year drip irrigation—

introduced in the US in the late 1960s—was reported by the Farm and Ranch Irrigation Survey (Census of Agriculture, 1979).

At the other end of the spectrum, roughly 30% of our respondents were not willing to pay anything for a base system. Respondents unwilling to pay anything for a base system differed from those with a positive willingness to pay in terms of size and reliance on nursery operations. The average income of those with an estimated willingness to pay of zero was lower than that of those with a positive willingness to pay ($p = 0.103$). The average share of income from greenhouse and nursery operations of those with an estimated willingness to pay of zero was similarly lower than that of those with a positive willingness to pay ($p = 0.009$). These differences are consistent with the notion that larger operations that specialize more in ornamental production are more likely to adopt sensor network technology.

Impact of Changes in Network Price

As noted above, one factor that often drives diffusion of new technologies is falling prices that render the technology affordable to larger and larger numbers of potential buyers. While we cannot predict the rate of change in the price of the sensor networks, we can use the experience of similar types of products to estimate the range of rates at which sensor network costs might change over time. For example, a comparison of the Producer Price Indexes for communications equipment during 2006-2013 and for wireless telecommunications services during 2009-2013 with the Consumer Price Index for the corresponding periods of time indicates that prices of these goods and services fell at respective annual average rates of 1.4% and 4.4% in real terms. The estimated coefficients of the probit model indicate that a 1% decrease in price results in an average 0.2 percentage point increase in the share of growers willing to purchase a base system (Table 10). If sensor network prices decrease at comparable rates, one would expect the share of growers willing to purchase a base system to increase at rates of 0.3-0.8 percentage points a year. This estimated rate of diffusion is slightly more rapid than that of drip irrigation: In 2008, 17.4% of irrigated farms used drip or trickle systems compared to 5.8% in 1978, corresponding to an average annual rate of increase of about 0.3%.

Impact of Changes in Grower Perceptions

Another factor known to drive diffusion of new technologies is the spread of information that increases expectations about profitability and reduces uncertainty about performance. To gauge the magnitude of the effect of information diffusion on rates of adoption of sensor networks, we conduct a set of simulations using the coefficients of current perceptions of the potential benefits of sensor networks. We focus on diffusion of beliefs that sensor networks increase irrigation efficiency and reduce irrigation management costs, since our analysis indicates that these two beliefs have a statistically significant effect on the probability that a grower would purchase a base system.

We model changes in adoption over time due to the spread of positive perceptions about sensor network performance as follows. Let P_{jt} be the number of growers who believe that sensor networks have benefits of type j in period t. Assume that each grower who does not believe that sensor networks have benefits of type j in period t changes that perception with probability $\boldsymbol{\Omega}$, so that the number of growers whose perception of sensor network benefits changes from negative to positive is $\Omega(1-P_{jt})$. We sample the population without replacement, so that growers change their beliefs about sensor network performance from negative to positive but not vice versa. In period T, we compare the adoption rate for every positive perception and several information dispersion rates $\boldsymbol{\Omega}$. We compare diffusion rates for $\boldsymbol{\Omega}$ =0.01, 0.1, and 0.2. We run 1000 trials for each value of Ω over a period of 200 years and report average adoption rates at the expected base system price of $3,500 for each period.

Our simulations indicate that diffusion of information about these benefits of sensor networks would have a very limited effect on rates of sensor network technology adoption (Table 9). Even after 50 years, of the 20% of non-adopters changing their beliefs about sensor network performance from negative to positive, the share of growers willing to purchase a base system increases by only 3-6 percentage points. The main reason is that a majority of growers already believe that sensor networks have these benefits: Over four-fifths believe that sensor networks can increase irrigation efficiency and almost three-fifths believe that sensor networks can reduce irrigation management costs (Table 4). These positive perceptions of sensor network performance result in relatively high likely initial adoption rates coupled with relatively small effects of information diffusion on subsequent adoption rates.

Sensor Network Profitability

The estimated coefficients of the probit and tobit models can also be used to draw inferences about current grower perceptions of the respective profitability of investing in a sensor network and additional nodes. Investing in a base system is profitable if the annual return on that investment is at least as great as the cost of system. Thus, the estimated willingness to pay for a base system is a conservative estimate of the expected annual profit from investing in a sensor network. The profit from additional nodes equals the consumer surplus under a grower's demand curve for additional nodes (Just et al., 1984). The estimated number of nodes that respondent i would purchase at price W is $\widehat{N}_i(W) = \max\{0, \gamma W + \boldsymbol{V}_i'\boldsymbol{\delta}\}$. We calculate consumer surplus assuming that demand is linear between the choke price for each respondent, $-\frac{\boldsymbol{V}_i'\boldsymbol{\delta}}{\gamma}$, and the expected market price of $800 per node (see Figure 2). Growers whose choke price is less than \$800 would not buy any additional nodes and thus have consumer surplus of zero, so that consumer surplus for each grower is $\max\left\{0, \frac{\left(\frac{v_i{}'\delta}{\gamma} - 800\right) * \widehat{N_i(800)}}{2}\right\}$, $\widehat{N_i}(800)$ is the expected number of nodes purchased by grower *i* at the price of \$800.

At the initial estimated price of \$800 per node, almost 2/3 of the respondents have positive consumer surplus from the purchase of additional nodes. The average consumer surplus for those growers is \$6,747. There is considerable variability in estimated consumer surplus from the purchase of additional nodes, as indicated by a standard deviation of \$20,708 and a range of \$0 to \$196,872.

Adding willingness to pay for a base system to consumer surplus from the purchase of additional nodes gives an estimate of each grower's anticipated profit from investment in a sensor network. These calculations indicate that the 165 growers with positive estimated profit from investing in a sensor network had an estimated annual profit of \$11,088. Slightly over half of these growers had estimated profit between \$1000 and \$5000 a year (Figure 3). Another fifth had estimated profit between \$5000 and \$10,000 a year and another tenth had expected profit between \$10,000 and \$20,000 a year. At the upper end of the scale, one grower had estimated annual profit at almost \$210,000 a year.

Increased profit averaged 5.9% of annual revenue. In almost every case, estimated profit from investing in a sensor network amounted to 5% or less of annual revenue, with a few growers having estimated shares much higher (Figure 4). Since profit usually also amounts to a small share of revenue, these calculations suggest that investing in this technology can increase profit substantially, consistent with findings from experimental studies (Belayneh et al., 2013; Lichtenberg et al., 2013; Saavoss et al., 2014).

Conclusion

Water scarcity is likely to grow in the coming years, making improvements in irrigation efficiency increasingly important. An emerging technology that promises to increase irrigation efficiency substantially is a network that uploads soil moisture and other sensor data into irrigation management software, creating an integrated system that allows real-time monitoring and control of moisture status. This technology, which is on the verge of commercial introduction, has been shown in experimental settings to reduce irrigation costs, lower plant loss rates, shorten production times, decrease pesticide application, and increase yield, quality, and profit (Lichtenberg et al., 2013; Saavoss et al., 2014).

This paper uses an original survey to investigate likely initial acceptance, ceiling adoption rates, and profitability of this new sensor network technology in the nursery and greenhouse industry. We find that adoption rates for a base system and demand for expansion components are decreasing in price, as expected. The price elasticity of the probability of adoption suggests that sensor networks are likely to diffuse at a rate somewhat greater than that of drip irrigation. Adoption rates for a base system and demand for expansion components are also increasing in specialization in ornamental production: Growers earning greater shares of revenue from greenhouse and nursery operations are willing to pay more for a base system and willing to purchase larger numbers of expansion components at any given price. Consistent with previous literature on adoption of new agricultural technologies, willingness to pay for a base system increases with education level and perceived benefits of sensor networks, notably increased irrigation efficiency, reduced irrigation management costs, and improved quality. We estimate that growers who are willing to purchase a sensor network expect investment in this technology to earn significant profit, consistent with findings from experimental studies.

Our estimates are based on responses to hypothetical choice questions for a technology that is not yet on the market. They suggest that a relatively large share of nursery and greenhouse operators could be early adopters and that diffusion of this technology could be more rapid than other precision irrigation technologies (or precision agricultural technologies more generally). Once this technology has been on the market for a few years, it would be interesting to compare actual adoption rates to the predictions made here.

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Table 1. Comparison of Sample with National Statistics on Nursery and Greenhouse Operations

Category	Percentage of Growers in Category	
	Nationwide	Survey Sample
Revenue		
$1,000,000 or more	6.56	35.26
$500,000 to $999,999	4.69	16.84
$250,000 to $499,999	6.29	14.21
$100,000 to $249,999	12.86	11.58
$50,000 to $99,999	10.16	5.79
$25,000 to $49,999	12.56	5.79
$10,000 to $24,999	17.91	7.89
$5,000 to $9,999	11.49	2.11
$2,500 to $4,999	8.78	0.00
$1,000 to $2,499	6.24	0.53
Less than $1,000	2.47	0.00
Acreage		
1 to 9	38.29	32.17
10 to 49	36.03	27.71
50 to 69	6.01	5.1
70 to 99	5.4	3.18
100 to 139	4.18	5.41
140 to 179	2.36	3.18
180 to 219	1.51	3.18
220 to 259	1.06	2.55
260 to 499	2.71	6.37
500 to 999	1.55	6.05
1000 to 1999	0.56	2.55
2000 or more	0.34	2.55
Region		
Pacific	18.81	21.31
North East	21.19	19.34
South East	14.41	20.98
Appalachia	12.26	19.34
Midwest	20.58	10.49
Great Plains	1.66	3.28
South Central	7.16	3.61
Mountain	3.72	1.64

Table 2. Potential Benefits and Drawbacks of Sensor Networks

Potential Benefits	Increase efficiency
	Reduce monitoring time/costs
	Reduce irrigation management costs
	Increase ability to manage growth rates
	Increase quality
	Reduce disease occurrence
Potential Drawbacks	The sensors would not control irrigation correctly
	The cost would be too high
	The sensors would not be reliable
	There would be too much maintenance involved
	The sensors would not be as efficient as our current system

Table 3. Distribution of Responses by Offered Price

Price Level for	**Number of Responses**	
Base System		***Number Who Would Buy a Base System***
$1000	59	32
$2000	50	19
$3000	52	26
$4000	58	15
$5000	49	14
Additional Node		***Average Number of Additional Nodes Purchased***
$ 500	62	4.5
$1000	52	3.9
$1500	57	2.0
$2000	56	3.8

Table 4. Descriptive Statistics of Variables Used in the Probit and Tobit Models

Variable	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Farm Operation				
Operation Size (Acres)	222.8773	610.8162	0	6000
Annual Income ($1000)	2252.068	11279.64	0	150000
Percent of Income from Greenhouse and Nursery Crops	83.97398	33.51402	0	100
Located in Appalachian Region	0.197026	0.398494	0	1
Located in Midwest	0.096654	0.296037	0	1
Located in Northeast	0.193309	0.395629	0	1
Located in Pacific Region	0.230483	0.421927	0	1
Located in Southeast	0.189591	0.392708	0	1
Located in South Central Region	0.037175	0.189542	0	1
Use Water from Shallow Well	0.29368	0.456296	0	1
Use Water from Deep Well	0.460967	0.499403	0	1
Use Surface Water	0.301115	0.459598	0	1
Use Recycled Water	0.215613	0.412014	0	1
Use Rain Water	0.182156	0.386693	0	1
Use Municipal Water	0.193309	0.395629	0	1
Use Gray Water	0.048327	0.214856	0	1
Use Water from Other Sources	0.04461	0.20683	0	1
Farm Operator				
High School Graduate	0.063197	0.243771	0	1
Some College	0.107807	0.310714	0	1
Associate Degree	0.078067	0.268777	0	1
Bachelor’s Degree	0.360595	0.481068	0	1
Post-Graduate Degree	0.122677	0.328677	0	1
Age 20-29	0.033457	0.180163	0	1
Age 30-39	0.118959	0.324344	0	1
Age 40-49	0.197026	0.398494	0	1
Age 50-59	0.260223	0.439574	0	1
Age 60+	0.122677	0.328677	0	1
Perceptions of Wireless Sensor Networks				
Sensor Networks Can Reduce Product Loss	0.609665	0.488735	0	1
Sensor Networks Can Improve Increase Quality	0.70632	0.456296	0	1
Sensor Networks Can Improve Irrigation Efficiency	0.825279	0.380436	0	1
Sensor Networks Can Reduce Disease	0.572491	0.495639	0	1

Variable	Mean	Standard Deviation	Minimum	Maximum
Sensor Networks Can Reduce Irrigation Management Cost	0.587361	0.493227	0	1
Sensor Networks Can Increase Ability to Manage Growth Rates	0.550186	0.498402	0	1
Sensor Networks Can Reduce Monitoring Cost	0.505576	0.500901	0	1
Sensor Cost Would Be Too High	0.825279	0.380436	0	1
Sensors Would Not Control Irrigation Correctly	0.431227	0.496171	0	1
Sensors Would Not Be Reliable	0.516729	0.500652	0	1
Sensors Would Require Too Much Maintenance	0.330855	0.471398	0	1
Sensors Would Not Be as Efficient as Current System	0.148699	0.356455	0	1

Table 5. Estimated Coefficients of the Probit Willingness to Purchase Base System Model

Variable	**Base Model**	**Model with Additional Controls**
Base System Price	-0.000204*** (0.001)	-0.000211*** (0.002)
Operation Size (Acres)	0.000206 (0.198)	0.000165 (0.386)
Operation Size Missing (0/1)	0.548 (0.579)	0.772 (0.538)
Annual Income ($1000)	0.0000155 (0.167)	0.0000145 (0.178)
Annual Income Missing (0/1)	-0.490 (0.101)	-0.637** (0.047)
Percent of Income from Greenhouse and Nursery Crops (0-100)	0.0160** (0.035)	0.0150* (0.080)
Percent of Income from Greenhouse and Nursery Crops Missing (0/1)	1.427* (0.079)	1.341 (0.144)
High School Diploma/Some College (0/1)	-0.714*** (0.005)	-0.781*** (0.006)
Education Level Missing (0/1)	0.290 (0.332)	0.435 (0.366)
Sensor Networks Can Reduce Product Loss (0/1)	0.152 (0.477)	0.171 (0.447)
Sensor Networks Can Improve Increase Quality (0/1)	0.405* (0.069)	0.398* (0.093)
Sensor Networks Can Improve Irrigation Efficiency (0/1)	0.448* (0.098)	0.493 (0.114)
Sensor Networks Can Reduce Disease (0/1)	-0.435** (0.033)	-0.381* (0.089)
Sensor Networks Can Reduce Irrigation Management Cost (0/1)	0.385** (0.049)	0.408* (0.059)
Sensor Networks Can Increase Ability to Manage Growth Rates (0/1)	-0.142 (0.488)	-0.187 (0.406)
Sensor Networks Can Reduce Monitoring Cost (0/1)	0.119 (0.552)	0.172 (0.428)
Constant	-1.847** (0.018)	-1.951** (0.048)
Number of Observations	268	268
p-values in parentheses. ***, **, * denote significantly different from zero at 1%, 5%, and 10% levels, respectively. Additional controls include region indicators, indicators of beliefs about drawbacks of sensor networks, water source indicators, and age.		

Table 6. Average Partial Effects of Independent Variables on the Probability of Purchasing a Base System

Independent Variable	Change in Probability of Purchasing a Base System due to	
	One unit change in independent variable	One percent change in independent variable
Base System Price	-0.0000665*** (0.000)	-0.190*** (0.000)
High School Diploma/Some College (0/1)	-0.232*** (0.004)	
Operation Size (Acres)	0.0000671 (0.195)	0.0147 (0.205)
Annual Income ($1000)	0.00000503 (0.163)	0.00842*** (0.003)
Percent of Income from Greenhouse and Nursery Crops (0-100)	0.00521** (0.031)	
Sensor Networks Can Reduce Product Loss (0/1)	0.0494 (0.475)	
Sensor Networks Can Improve Increase Quality (0/1)	0.132* (0.064)	
Sensor Networks Can Improve Irrigation Efficiency (0/1)	0.146* (0.094)	
Sensor Networks Can Reduce Disease (0/1)	-0.142** (0.029)	
Sensor Networks Can Reduce Irrigation Management Cost (0/1)	0.125** (0.044)	
Sensor Networks Can Increase Ability to Manage Growth Rates (0/1)	-0.0463 (0.487)	
Sensor Networks Can Reduce Monitoring Cost (0/1)	0.0387 (0.551)	
Observations	268	268
p-values in parentheses. ***, **, * denote significantly different from zero at 1%, 5%, and 10% levels, respectively.		

Table 7. Estimated Coefficients of the Two-Limit Tobit Additional Node Demand Model

Variable	Base Model	Model with Additional Controls
Additional Node Price	-0.00159 (0.113)	-0.00174* (0.083)
Operation Size (Acres)	0.00109 (0.294)	0.00111 (0.302)
Operation Size Missing (0/1)	-6.212 (0.308)	-8.589 (0.164)
Annual Income ($1000)	0.000138*** (0.003)	0.000152*** (0.002)
Annual Income Missing (0/1)	-2.791** (0.046)	-2.468 (0.181)
Percent of Income from Greenhouse and Nursery Crops (0-100)	0.122** (0.013)	0.120** (0.014)
Percent of Income from Greenhouse and Nursery Crops Missing (0/1)	12.20** (0.024)	11.56** (0.034)
Located in Appalachian Region (0/1)	-4.900** (0.030)	-5.284** (0.023)
Located in Midwest (0/1)	0.872 (0.716)	0.568 (0.815)
Located in Northeast (0/1)	-3.498 (0.117)	-3.273 (0.160)
Located in Pacific Region (0/1)	-0.208 (0.921)	-0.716 (0.740)
Located in Southeast (0/1)	-2.372 (0.274)	-2.746 (0.209)
Use Water from Shallow Well (0/1)	0.561 (0.701)	0.400 (0.791)
Use Water from Deep Well (0/1)	3.262** (0.025)	2.741* (0.065)
Use Surface Water (0/1)	2.509* (0.071)	2.773** (0.046)
Use Recycled Water (0/1)	0.771 (0.568)	0.183 (0.891)
Use Rain Water (0/1)	0.888 (0.554)	-0.212 (0.890)
Use Municipal Water (0/1)	1.170 (0.492)	0.986 (0.559)
Use Gray Water (0/1)	9.105*** (0.001)	8.117*** (0.002)

Variable	Base Model	Model with Additional Controls
Use Water from Other Sources (0/1)	-0.238 (0.932)	-1.339 (0.647)
Constant	-9.575* (0.063)	-7.977 (0.167)
Sigma	7.432*** (0.000)	6.991*** (0.000)
Number of Observations	233	233
p-values in parentheses. ***, **, * denote significantly different from zero at 1%, 5%, and 10% levels, respectively. Additional controls include indicators of education level, indicators of beliefs about benefits of sensor networks, indicators of beliefs about drawbacks of sensor networks, and age.		

Table 8. Average Partial Effects of Independent Variables on the Demand for Additional Nodes

Independent variable	Expected number of additional nodes demanded			Expected number of additional nodes demanded conditional on positive demand			Probability of positive demand	
	Average absolute change due to a one unit change	Average percent change due to a one percent change	Average percent change due to a one unit change	Average absolute change due to a one unit change	Average percent change due to a one percent change	Average percent change due to a one unit change	Average absolute change due to a one unit change	Average absolute change due to a one percent change
Additional Node Price	-0.000855 (0.110)	-0.320 (0.121)		-0.000572 (0.110)	-0.109 (0.111)		-0.0000748 (0.107)	-0.0919 (0.109)
Operation Size (Acres)	0.000586 (0.292)	0.0354 (0.260)		0.000392 (0.292)	0.0131 (0.283)		0.0000513 (0.291)	0.00968 (0.280)
Annual Income ($1000)	0.0000742*** (0.002)	0.0265*** (0.000)		0.0000496*** (0.002)	0.0135*** (0.000)		0.00000650*** (0.003)	0.00693*** (0.000)
Percent of Income from Greenhouse and Nursery Crops (0-100)	0.0655** (0.012)		0.0194** (0.014)	0.0438** (0.012)		0.00685** (0.012)	0.00574*** (0.010)	
Located in Appalachian Region (0/1)	-2.630** (0.029)		-0.777** (0.031)	-1.759** (0.029)		-0.275** (0.030)	-0.230** (0.026)	
Located in Midwest (0/1)	0.468 (0.715)		0.138 (0.715)	0.313 (0.715)		0.0490 (0.715)	0.0410 (0.715)	
Located in Northeast (0/1)	-1.877 (0.115)		-0.555 (0.117)	-1.256 (0.115)		-0.196 (0.116)	-0.164 (0.112)	
Located in Pacific Region (0/1)	-0.112 (0.921)		-0.0330 (0.921)	-0.0747 (0.921)		-0.0117 (0.921)	-0.00978 (0.921)	
Located in Southeast (0/1)	-1.273 (0.273)		-0.376 (0.274)	-0.852 (0.274)		-0.133 (0.274)	-0.112 (0.271)	

Independent variable	Expected number of additional nodes demanded			Expected number of additional nodes demanded conditional on positive demand			Probability of positive demand	
	Average absolute change due to a one unit change	Average percent change due to a one percent change	Average percent change due to a one unit change	Average absolute change due to a one unit change	Average percent change due to a one percent change	Average percent change due to a one unit change	Average absolute change due to a one unit change	Average absolute change due to a one percent change
Use Water from Shallow Well (0/1)	0.301 (0.700)		0.0890 (0.700)	0.201 (0.700)		0.0315 (0.700)	0.0264 (0.700)	
Use Water from Deep Well (0/1)	1.751** (0.023)		0.517** (0.025)	1.171** (0.023)		0.183** (0.024)	0.153** (0.022)	
Use Surface Water (0/1)	1.347* (0.068)		0.398* (0.071)	0.901* (0.069)		0.141* (0.070)	0.118* (0.067)	
Use Recycled Water (0/1)	0.414 (0.568)		0.122 (0.568)	0.277 (0.568)		0.0433 (0.568)	0.0363 (0.568)	
Use Rain Water (0/1)	0.477 (0.553)		0.141 (0.553)	0.319 (0.553)		0.0499 (0.553)	0.0417 (0.553)	
Use Municipal Water (0/1)	0.628 (0.491)		0.186 (0.492)	0.420 (0.491)		0.0657 (0.492)	0.0550 (0.491)	
Use Gray Water (0/1)	4.886*** (0.000)		1.444*** (0.001)	3.268*** (0.001)		0.511*** (0.001)	0.428*** (0.000)	
Use Water from Other Sources (0/1)	-0.128 (0.932)		-0.0377 (0.932)	-0.0854 (0.932)		-0.0134 (0.932)	-0.0112 (0.932)	
N	233	233	233	233	233	233	233	233
p-values in parentheses. ***, **, * denote significantly different from zero at 1%, 5%, and 10% levels, respectively.								

Table 9. Effects of Information Diffusion on the Share of Growers Willing to Purchase a Sensor Network at the Current Price

Year	Sensors Can Increase Irrigation Efficiency			Sensors Can Reduce Irrigation Management Cost		
	Annual Rate of Information Diffusion (Ω)			Annual Rate of Information Diffusion (Ω)		
	1%	10%	20%	1%	10%	20%
0	0.19403	0.19403	0.19403	0.194030	0.194030	0.194030
1	0.194328	0.196716	0.199702	0.194664	0.195299	0.205597
2	0.194590	0.198843	0.204216	0.195037	0.196493	0.214291
3	0.194739	0.200896	0.207313	0.195634	0.197500	0.222761
4	0.195000	0.202313	0.209851	0.196269	0.198619	0.228843
5	0.195299	0.203806	0.212351	0.196866	0.199179	0.233993
6	0.195560	0.205411	0.213881	0.197500	0.199776	0.238172
7	0.195597	0.207127	0.215037	0.197948	0.200299	0.241530
8	0.195858	0.208209	0.216231	0.198619	0.200709	0.243769
9	0.196045	0.209179	0.217127	0.199366	0.201045	0.246306
10	0.196269	0.210336	0.217575	0.200187	0.201493	0.247873
20	0.198396	0.216978	0.219888	0.205597	0.203806	0.252836
30	0.200634	0.218843	0.220075	0.209925	0.251194	0.253694
40	0.202724	0.219627	0.220149	0.214515	0.252649	0.253731
50	0.204403	0.219963	0.220149	0.218619	0.253284	0.253731

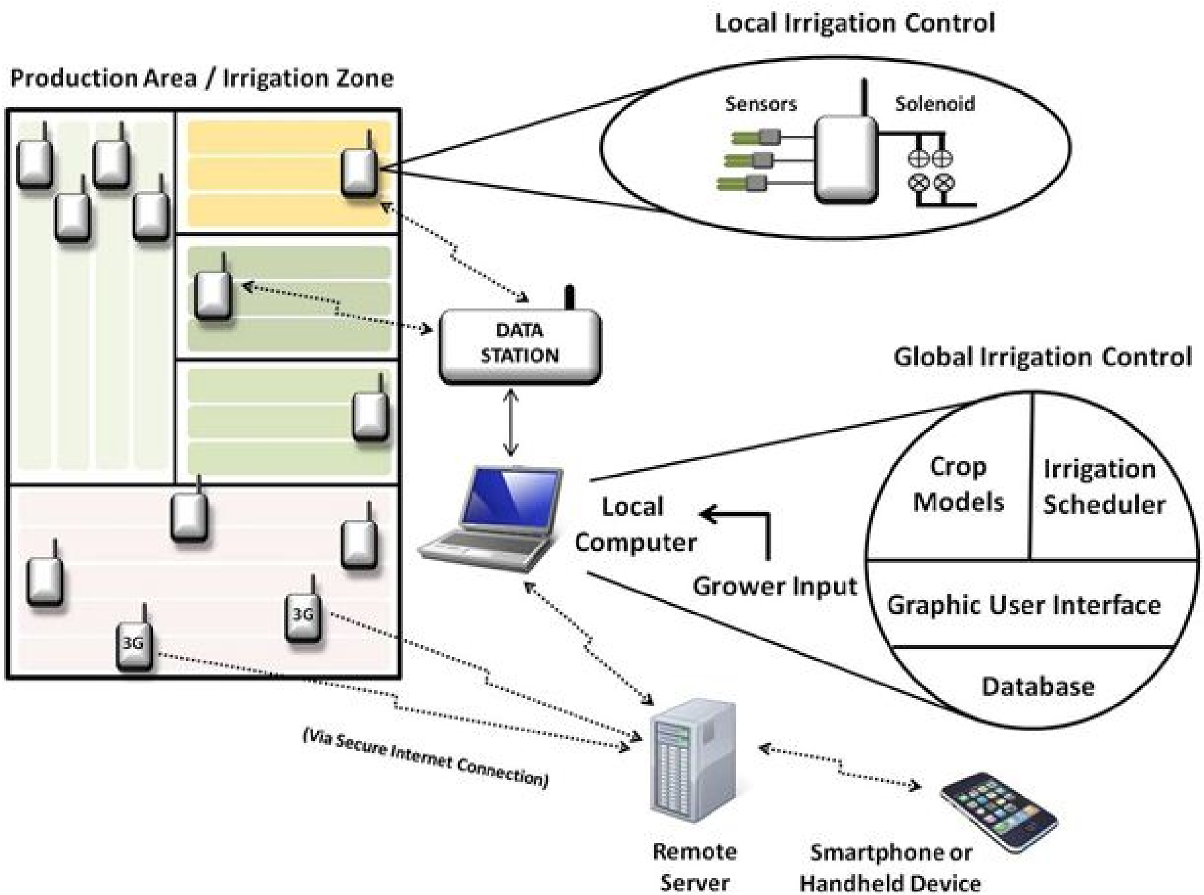

Figure 1. Schematic of Sensor Network Base System

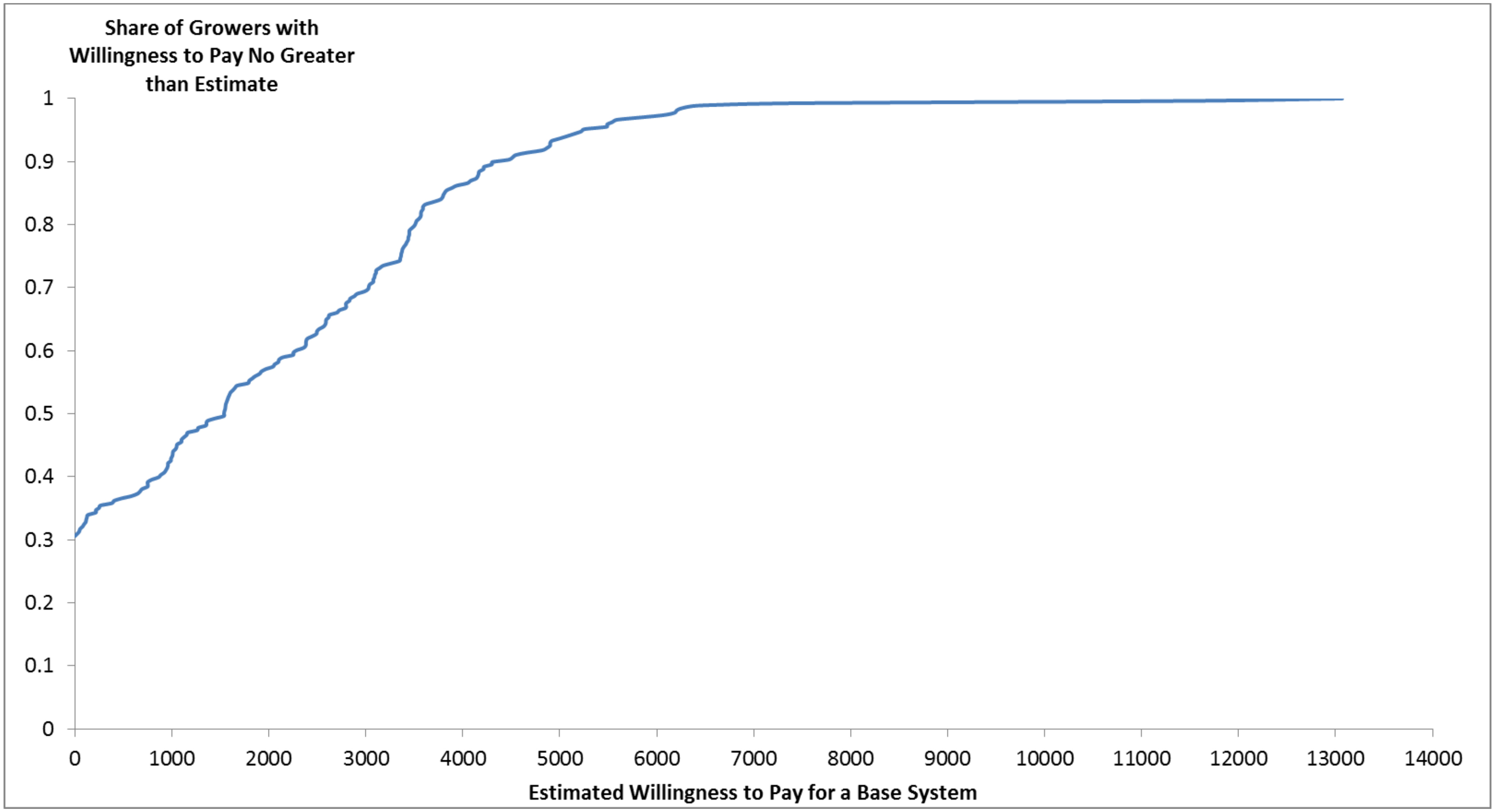

Figure 2. Cumulative Distribution of Estimated Willingness to Pay for a Base System

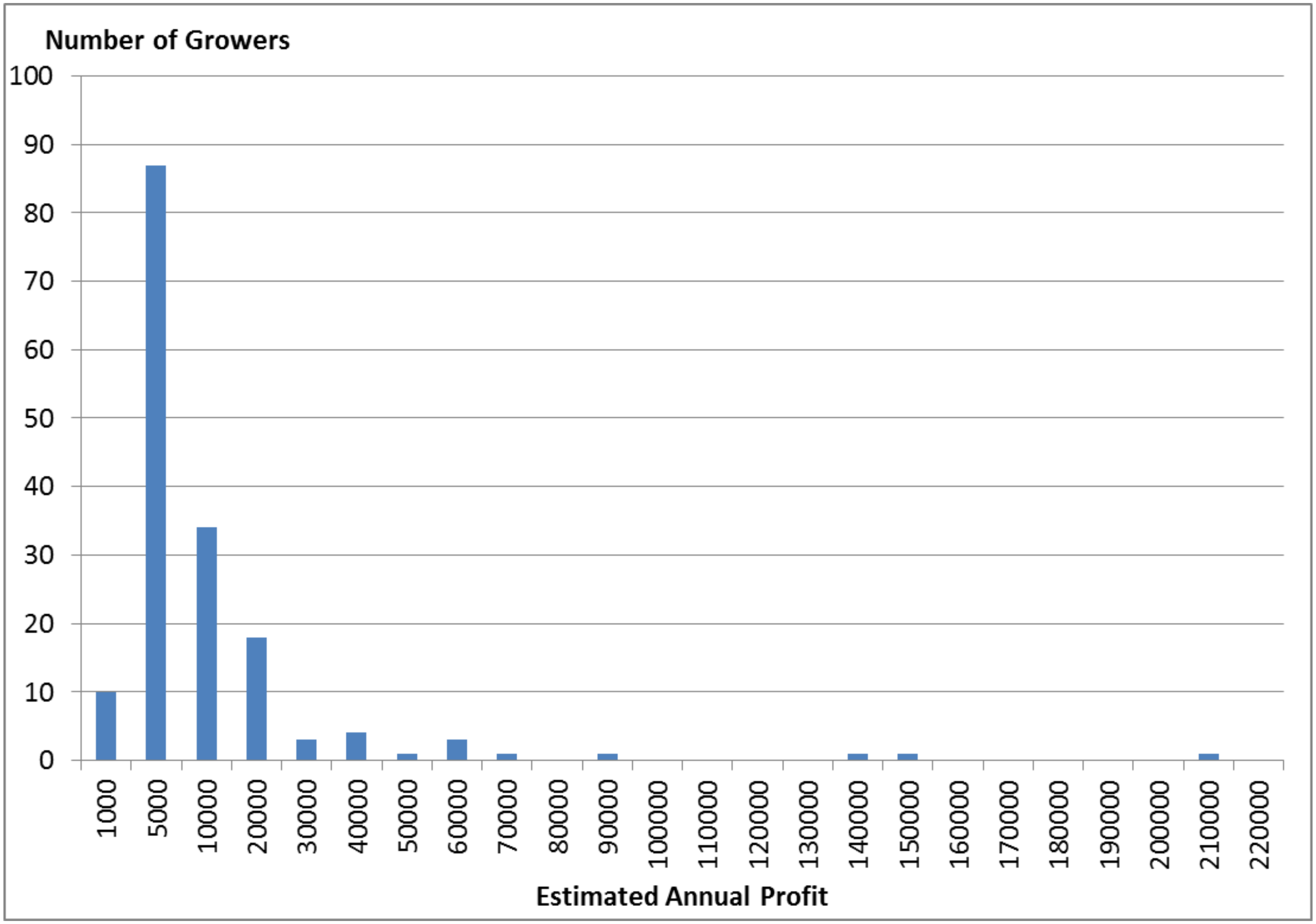

Figure 3. Distribution of Estimated Annual Profit from Investing in a Sensor Network

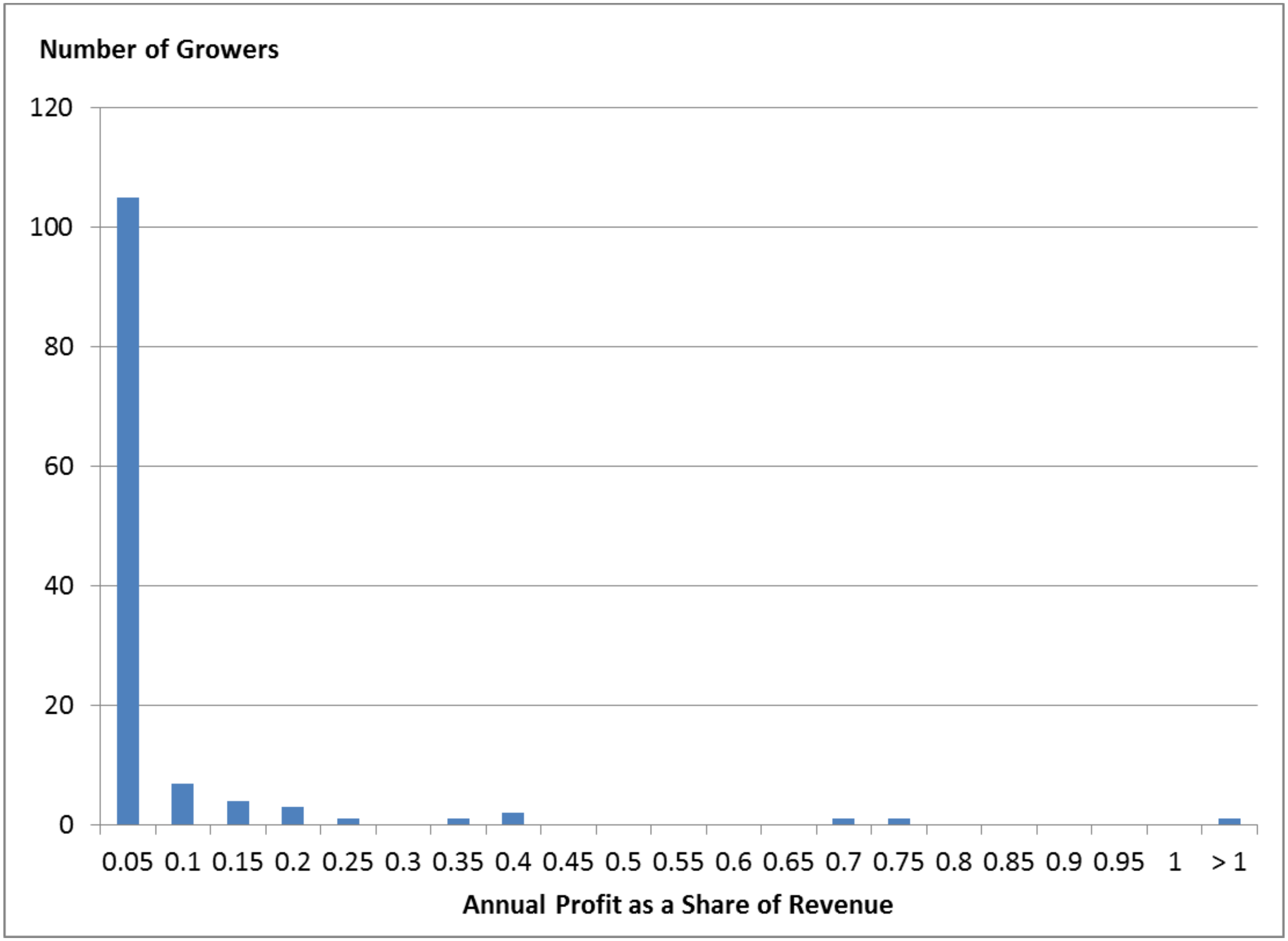

Figure 4. Distribution of Estimated Annual Profit from Investing in a Sensor Network as a Share of Revenue