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SOIL TEST INFORMATION IN COTTON PRODUCTION: ADOPTION, USE, AND VALUE IN POTASSIUM MANAGEMENT

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SOIL TEST INFORMATION IN COTTON PRODUCTION: ADOPTION, USE, AND VALUE IN POTASSIUM MANAGEMENT

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Abstract

Soil sampling can help producers gain more accurate knowledge about soil nutrient properties and field-level characteristics. This information aids in the placement and timing of fertilizer application. Optimal input application may lower variable costs, increase economic returns, and moderate off-site environmental impacts of farming. Yet producer decisions to incorporate soil information into management practices and perceptions about the value of soil test information over time depends on a wide range of economic, social, and producer characteristics. Studies examining the value of soil information for optimal nutrient management may help inform producers considering adopting these technologies about the potential benefits of soil testing. This thesis provides two studies examining (1) the factors associated with the adoption of precision soil sampling and the length of time this information is perceived useful by cotton producers, and (2) the value of soil test information with regards to optimal potassium fertilizer management in cotton production over multiple growing seasons.

Perceptions about the usefulness of soil test information over time depend on a variety of factors directly or indirectly related to input management. In the first study, the adoption and frequency of soil testing is examined as a function of off-farm, farm business, information sources, and operator characteristics using a Poisson hurdle regression model. Analyzing data from a survey of cotton farmers in 12 Southern states, the length of time producers perceived soil test information to be useful were influenced by farmer experience, land tenure, and the use of other information gathering technologies such as Greenseeker® and electro conductivity.

In the second study, optimal potassium (K) management with information about fertilizer carryover was analyzed using a dynamic programming model. Monte Carlo simulation results suggest the information site-specific technologies provides with respect to residual fertilizer

carryover effects of K are greatest when a producer is able to identify the magnitude of soil carryover capacity and incorporate this information to manage K. The information obtained from this research may provide insight for cotton producers, agribusiness firms, and agricultural service providers about the perception and potential benefits of soil sampling information to manage inputs in cotton production.

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I: Introduction

Precision agriculture (PA) technologies provide producers more efficient methods to collect, manage, and interpret information. More accurate information about crop yield response, soil properties, and growing conditions can increase cost savings and improve profit margins (Swinton and Lowenberg–DeBoer, 1998). Precision agriculture technologies can also complement environmental conservation efforts by enhancing water quality and soil fertility by reducing nutrient runoff (Bongiovanni and Lowenberg-DeBoer, 2004); moderating the use or changing the mix of fertilizers and pesticides (Griffin et al., 2004); or improving tillage and chemical application efficiency using global positioning (GPS) guidance systems and variable rate applicators (Fawcett and Towery, 2002). For example, in 2006, the National Resource Conservation Service (NRCS) reported that if GPS guidance systems were used on 10% of the planted crop acres in the United States, herbicide use would decrease by 1.89 million liters per year and insecticide use would decrease by 2 million kilograms per year (NRCS, 2006). Precision agriculture technologies can also moderate direct and indirect energy costs by lowering the number of tractor trips across fields (Griffin, Lambert, and Lowenberg–DeBoer, 2004; Daberkow, Lambert, and Musser, 2007), with fuel savings estimated to be as much as 60.57 million liters per year (NRCS, 2006).

Yet despite the potential private and social benefits typically associated with precision agriculture, adoption rates of key components like variable rate management technologies (VRT) remain low. According to the USDA's Agricultural and Resource Management Survey (ARMS), 15% of the 30,946 ha corn acres planted in 2005 were managed using GPS-reference soil maps, and 12% of the total corn hectares planted were managed using some type of variable rate technology (ARMS, 2005). For cotton production, adoption rates appeared even lower according to national surveys. Of the 4,144 ha of cotton acres planted in 2003, GPS-based soil maps were

made on 6% of these hectares, and inputs were managed using VRT on 5% of the total cotton hectares planted (ARMS, 2003).

Some federal conservation programs provide cost-share incentives to encourage adoption of information gathering and variable rate management technologies. Under these voluntary nutrient management programs, producers collect information about soil and yield variability using precision soil sampling, conducting electroconductivity tests, or monitor yields with GPS before applying nutrients. Cost reimbursements for these programs typically range between $19.76 per ha (in Alabama, 2009) to $64.22 per ha (in Tennessee) (NRCS, 2010). Precision farming program eligibility requirements under federal and state programs such as the Environmental Quality Incentives Program (EQIP), the Conservation Stewardship Program (CSP), and the Agricultural Management Assistance (AMA) program familiarize producers with the potential benefits of precision input management while reducing the perceived risk producers may associate with technology adoption. Environmental and financial benefits typically associated with these programs may also be significant. According to the USDA's Final Benefit-Cost Analysis for EQIP, producers who adopted nutrient management conservation practices (e.g., NRCS conservation practice 590) applied significantly less nitrogen (27.97 kg/ha), potassium (5.59 kg/ha), and potash (14.54 kg/ha) compared to non adopters, leading to corn fertilizer input cost savings of $30.41 per ha for nitrogen and $5.93 per ha for potassium (USDA, 2010).

The value of soil information for managing nutrients has been studied in conjunction with federal cost-share support programs, along with a variety of crops, fertilizers, and field conditions (e.g., Perrin, 1976; Adams et al., 1983; Schnitkey et al., 1996; Watkins et. al., 1998; Bongiovanni and Lowenberg-Deboer, 2000; Bongiovanni and Lowenberg-Deboer, 2001; Hurley

et al., 2001; Lambert et al., 2003; Lambert et al., 2007). Previous studies examining the returns to management knowing yield response, soil dynamics, and input placement and timing are numerous. Yet the profitability of site-specific nutrient application of phosphorous (P), nitrogen (N), and potassium (K) based on soil test information varies according to research conditions, the crops studied, and in the case of on-farm trials, the managerial capability of producers and farm/field heterogeneity. The estimated returns to soil test information may affect producer perceptions of soil sampling as an effective management tool and hence the decision to adopt and continuing using soil testing, as potential profitability has been shown to influence the adoption decision (Batte and Arnholt, 2003; Daberkow and McBride, 2003; Roberts et al., 2004; Adrian et al., 2005; Walton et al., 2008; Walton et al., 2010). Yet in addition to prospects of increased returns, there are a number of factors explaining why producers may adopt and continue using precision soil testing. However, few studies have identified the factors influencing how long producers perceive soil test information to be useful after collecting grid or zone soil tests.

Anecdotal evidence suggests that precision soil sampling (PSS) information has a useful life of three to four years before information needs to be updated. The length of time a producer chooses between soil testing may be driven by a number of factors, including the extent to which the producer uses other PA technologies in conjunction with PSS, the information sources used to gather PSS information, and the economic value added in terms of increased profit margins from using soil information to manage inputs. Following optimal input policies, a producer will apply field information to manage nutrients so long as the marginal value of information is greater than the marginal costs of collecting, managing, and implementing that information.

Thus, in addition to its potential influence on adoption decisions, the perceived value of soil sampling information may affect how long a producer waits before updating soil information.

This two-part thesis identifies (1) the factors influencing the adoption and re-test decision of precision soil sampling information for cotton producers, and (2) the economic returns from using information about residual carryover capacity of soil to manage potassium. The first study uses a Poisson hurdle regression model to identify the off-farm, operator, business, and information sources influencing the decision to adopt precision soil sampling and subsequently the time period between updating soil test information. Understanding the factors contributing to the perceived usefulness of soil test information (as measured by the time between which producers conduct soil tests) may provide guidance to agricultural service providers with respect to product marketing, and may also augment Extension outreach efforts to provide information about the benefits and costs of soil sampling, nutrient management, and optimal time period between soil tests.

The second study analyzes a multi-year cotton yield response and K carryover experiment using dynamic programming to determine the benefits from optimal K fertilizer management in lieu of information about K soil carryover. The results suggest that proper identification of soil nutrient properties and fertilizer carryover may result in substantially higher expected profits over a multi-period planning horizon. Monitoring the cycle of potassium flow by soil testing over several years could provide valuable information about potassium carryover potential of soils, which in turn could lower input costs and increase profit over an intermediate planning horizon. Quantifying the value of soil sampling information as measured by increased economic returns may also provide information to cotton producers about the benefits of soil sampling with respect to potassium management when K carryover is significant.

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II. Adoption and Perceived Usefulness of Precision Soil Sampling Information: Evidence from a Regional Cotton Producer Survey

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Abstract

Precision soil sampling helps farmers identify nutrient variability within fields to optimize input management. Anecdotal evidence suggests that soil test information has a useful life of 3 to 4 years before information needs to be updated. However, perceptions about the perceived usefulness of soil test information over time may depend on a variety of factors, including field variability, farmer experience and education, farm size, Extension recommendations, and other factors indirectly related to input management. In 2009, a survey of cotton farmers in 12 Southern states collected information about the use of precision soil sampling technologies. A regression model including farm operator and business characteristics, use of precision agriculture technologies, and information sources analyzed (1) the adoption of soil testing technologies by cotton farmers and (2) the number of years adopters perceived soil test information to be useful. A number of farm operator and business characteristics were associated with the length of time producers perceived the information they obtained from soil tests to be useful, including farmer experience, land ownership, and the use of other information gathering technologies such as Greenseeker® and electroconductivity.

Introduction

Nutrient management decisions for cotton producers involve trade-offs among a number of crop, growing environment, and economic factors. These factors include plant genetics, weather, input and output prices, soil fertility heterogeneity, pest outbreaks, and other field characteristics. Determining optimal nutrient management policies is challenged by the inherent complexity and numerous interactions surrounding input management. Yet, identifying optimal nutrient management policies over a planning horizon is important for maintaining soil fertility, increasing profit margins, and reducing variable input costs. To gain a more comprehensive understanding of soil variability, crop nutrient requirements, and expected returns, producers often seek additional information. Precision soil sampling supplements a broader array of knowledge gathering technologies that can increase information about production and may be useful in making more informed nutrient management decisions.

Precision information gathering technologies that aid field data collection and site-specific referencing include personal digital assistants (PDAs) and global positioning (GPS) devices, yield monitors, aerial and satellite imagery, precision soil sampling technologies, and other-on-the-go sensors. Precision soil sampling technologies assist producers in identifying soil nutrient spatial variability for macro and micro-nutrients. Grid soil sampling, in which a field is systematically divided into equal-sized grids with a recommended 2.5 samples per ha (5 to 10 cores per sample) (Ferguson and Hergert, 2009) and zone sampling, in which historical knowledge of a field is used to partition the field into different management zones, are different from traditional methods of soil sampling by providing within-field nutrient levels as opposed to whole field nutrient levels. These methods may provide a more accurate representation of nutrient variability in fields and may help producers implement site-specific fertilizer

applications. Producers invest in precision agriculture (PA) technologies when the expected returns from information collection and implementation are greater than the fixed costs of adoption and variable managerial costs. Several studies have considered the factors related to the adoption of PA technologies and their continued use (e.g., Batte and Arnholt, 2003; Daberkow and McBride, 2003; Roberts et al., 2004; Walton et al., 2008; Walton et al., 2010). Ease-of-use, usefulness, and increased profits are common reasons why farmers adopt and continue to use PA technologies (Daberkow, 1997; Roberts et al., 1999; Adrian et al., 2005). Another reason for adoption may include the prospect of more reliable information newer technologies can provide compared to existing practices. While expectations about the profitability and usefulness of PA technologies may encourage producers to adopt soil testing, there is little empirical evidence explaining how long producers perceive soil information to be useful before they decide to re-test.

The length of time a producer chooses between taking soil samples is influenced by a number of factors, including familiarity with other PA technologies (e.g., yield monitoring, remote sensing, or variable rate technologies), the public or private information sources used by producers to gather knowledge about new technologies, and the inherent soil variability of fields. Direct experience with other PA technologies may offset unfamiliarity with processing and applying soil sampling information, which may correspond with improved synthesis of soil sampling data, its applicability, and an increased time period between testing. But over time, producer perceptions about the length of time soil test information is useful may change as experience with soil sampling technologies accumulates and information about within-field soil variability is updated.

This research identifies the farm business, operator, off-farm characteristics, and information sources used by producers that influence precision soil sampling adoption and the period of time soil test information is perceived to be useful by cotton farmers. As producers realize economic benefits from PA technologies, they may also demand more accurate, real-time, site specific information. Understanding the factors contributing to the perceived usefulness of soil test information as measured by the time producers wait between soil tests may provide guidance to agricultural service providers with respect to product marketing or farm visits. Findings may also help Extension tailor outreach efforts concerning the optimal timing between soil sampling. To the extent that soil tests are required by some conservation programs (e.g., the United States Department of Agriculture's (USDA) Environmental Quality Incentives Program and the Conservation Stewardship Program), information about the factors related to producer willingness to comply with prescribed nutrient management plans may also be helpful.

Data

The 2009 Cotton Incorporated Precision Agriculture survey was mailed to 13,783 producers in Alabama, Arkansas, Georgia, Florida, Louisiana, Mississippi, Missouri, North Carolina, South Carolina, Tennessee, Texas, and Virginia. Using Dillman's (1978) general mail survey procedure, the questionnaire was mailed February 20, 2009 with a reminder post card sent two weeks later and a follow-up mailing to producers who had not responded sent on March 27, 2009. The list frame comprised cotton producers in these states, and was provided by the Cotton Board (Memphis, Tennessee, November, 2009). The survey included questions about producer adoption of PA technologies, farm and operator characteristics, and the number of seasons producers waited between soil tests. The response rate was 12.5% (1,723). Mooney et al. (2010)

provide summary of the key details of the survey. Of the cotton farmers responding, 40% (652) had adopted precision soil testing, and the average time between soil tests was 2.5 years (Figure 1).

Post-stratified survey weights were estimated to align the survey sample with the number of cotton farmers enumerated by the USDA's 2007 Agricultural Census (USDA, 2007). While the survey weights do not adjust for non-response, post-stratified weights are useful for calibrating the survey data such that the response pattern of respondents closely approximates the distribution of the population of cotton producers (see Lohr, 1999 for a review). The weights used in this study are 'raking' weights suggested by Brackstone and Rao (1976), which are estimated by iteratively normalizing cell weights by the Cartesian product of the marginal row (cotton hectares farmed size classes) and column (state cotton farm numbers) totals from the Agricultural Census cotton farm population. The weights are classified in a matrix along two dimensions: the number of cotton farms belonging to one of six size classes (i = .404 – 40.06, 40.47 – 100.77, 101.17 – 201.94, 202.34 – 404.28, 404.68 – 808.97, 809.37+ cotton ha) and the number of cotton farms in each state surveyed (h = Alabama, Arkansas, Missouri, Georgia, Virginia, South Carolina, North Carolina, Louisiana, Tennessee, Texas, Florida, and Mississippi), yielding 72 stratum. At the t-th iteration, the weight associated with the (i,h)th cell are the population of cotton farms (N) enumerated in the sampled states normalized by the number of farms (n) in the ih-th stratum (e.g., $w_{ih} = N_{ih}/n_{ih}$), where $N_{ih} = n_{ih}\, w_{ih}$. The raking algorithm minimizes the differences between the row-column sums of the cells with the target values of the farm size and state cotton farm numbers. The calculation rescaling the rows (e.g., cotton hectares farmed size classes) is:

(1) $$w_{ih}^{t+1} = \frac{w_{ih}^{t} b_i}{\sum_{h=1}^{n} w_{il}^{t}}.$$

The calculation rescaling the columns (number of cotton farms in each state) is,

(2) $$w_{ih}^{t+1} = \frac{w_{ih}^{t} c_i}{\sum_{h=1}^{n} w_{il}^{t}},$$

where *t* indexes the iterations, and *b* and *c* are the target row (the 2007 Agricultural Census total for each cotton farm size class in all states combined) and column totals (the 2007 Agricultural Census total number of cotton farms for all farm size classes in each state) respectively. The algorithm continues until convergence; e.g., the difference between the row and column sums of the matrix and the numerical values of *b* and *c* is small (for example, .00001). By construction, the sum-product of the weights with the survey counts in each size class-by-state category closely approximate the Agricultural Census 2007 farm numbers in the states and size classes surveyed. Thus, each respondent in a given farm size class and state receive the same weight. By incorporating information about the cotton farm population into the survey design, the leverage attributed to respondents belonging to different size classes and different states may be moderated or increased, depending on the characteristics of the entire population and the survey response pattern.

Conceptual Model

The decision to adopt soil testing and to retest following some period are examined using a hurdle count model (Cameron and Trivedi, 1998, p. 124). Hurdle models are typically applied

to attend to problems arising from sample selection bias and the discrete, non-negative nature of the outcome (i.e., the number of years soil test information is perceived to be useful). In the survey, a producer must have adopted grid or zone soil sampling to answer how long soil test information was perceived to be useful before retesting. Thus, the first stage of the model (the "hurdle") explains the decision to adopt precision soil testing using a logit regression that models the adoption decision (1 = yes, 0 = no) to use precision soil sampling. Given the decision to adopt precision soil testing (a binary outcome), the number of years between tests (a positive, discrete variable; $k = 1,2,\ldots,K$) is subsequently modeled using a Poisson regression.

A farmer is hypothesized to maximize expected (discounted) profits over a time horizon, subject to input and commodity prices and technology constraints. The producer must weigh the benefits and cost of incorporating precision agriculture technologies into their current operation. There are often additional variable and fixed costs to consider in the initial period such as the implementation of an input management plan based on soil test information and the collection and storage of data. These cost differences also affect profits.

Let the expected utility of profit (π) from adopting (not adopting) precision soil sampling (*PSS*) technology at the beginning of time period t_0 to be $\mathrm{E}[U(\pi_{t_0}^{PSS})]$ ($\mathrm{E}[U(\pi_{t_0}^{\mathrm{NONE}})]$). Define the latent utility producer *i* receives from adoption (*AD*) of precision soil sampling as $U_i^{AD*} = \mathrm{E}\left[U\left(\pi_{t_0}^{PSS}\right)\right] - \mathrm{E}[U(\pi_{t_0}^{\mathrm{NONE}})]$. Producers adopt soil sampling when $U_i^{AD*} > 0$ (Walton et al. 2008).

Given the decision to soil test, the producer subsequently chooses the amount of time until retesting. It is hypothesized that the time period between soil tests is also consistent with profit maximization. Let $\mathrm{E}[U\left(\pi_{t_0+k} \middle| U_i^{AD*} > 0\right)]$ represent the expected utility from profits *k*

seasons after the initial soil test and $U\left(\pi_{t_0+k-1}\middle|U_i^{AD*}>0\right)$ the utility of realized profits in k-1 seasons after the initial soil test in t_0. Defining

$$U_i^{RT*} = \mathrm{E}\left[U\left(\pi_{t_{0+k}}\middle|U_i^{AD*}>0\right)\right] - U\left(\pi_{t_0+k-1}\middle|U_i^{AD*}>0\right), \tag{3}$$

as the utility gained from retesting (*RT*) *k* periods after the previous soil test, a profit maximizing producer will retest soil when the realized utility from *k*-1 season is greater than the expected utility from waiting another period between soil tests; $\mathrm{U_i^{RT*}} < 0$.

The unobservable latent variables U_i^{AD*} and U_i^{RT*} are hypothesized to be functions of observable covariates, x_i, (including farm household and business attributes, operator characteristics, and possibly off-farm factors), and unknown parameters, β_{AD} and α_{RT}. The decision to adopt soil testing is modeled as a linear random utility function (McFadden, 1974):

$$U_i^{AD*} = \beta_{AD}^{'} x_i + \varepsilon_i^{AD}, \tag{4}$$

where ε_i^{AD} is a random disturbance term. Utility is unobservable, but the decision to adopt can be modeled with a dichotomous variable, such that I_i^{AD} = 1 if U_i^{AD*} > 0 and I_i^{AD}= 0 otherwise. The probability of adopting precision soil sampling is therefore:

$$\begin{aligned} \Pr[I_i^{AD} = 1] &= \Pr\,[U_i^{AD*} > 0] \\ &= \Pr\,[\varepsilon_i^{AD} > \beta_{AD}' x_i] \\ &= F_1(\beta_{AD}' x_i)\,. \end{aligned} \tag{5}$$

After adoption, the producer decides how long to wait between tests before updating soil test information. Because the choice set is observed as years (a discrete, countable decision), the decision is appropriately modeled using a count regression model such as the Poisson or negative binomial models (Cameron and Trivedi, 1998). Typically, the log link function is used to model expected counts, which implies $k_i^* = exp(\alpha'_{RT} x_i)$ (Madalla, 1983, p. 53; Greene, 1993, p. 676-677; Schabenberger and Pierce, 2002, p. 399; Cameron and Trivedi, 2005, p. 668). The decision how long to wait between soil tests is $k_i{}^* = k$ if $U_i^{RT*} < 0$. The conditional probability of waiting *k* years before re-testing after adopting precision soil sampling is therefore:

(6) $$\Pr[\, k_i = k_i^*] \;=\; F_2(\alpha'_{RT} x_i) = \frac{exp(\alpha'_{RT} x_i)^{k_i} \cdot exp\,(-\,exp(\alpha'_{RT} x_i))}{k_i!}$$

$$\Pr[\, k_i{}^* = k_i |\, I_i^{AD} = 1, k_i > 0] = \frac{F_1(I_i^{AD} = 1)}{1 - F_2(k_i = 0)} \cdot\; F_2(k_i > 0).$$

The model was estimated using full information maximum likelihood estimation (FIML). The statistical software program STATA® 11 was used to run the model with the command *hplogit*. A heteroskedastic robust covariance matrix was estimated using the survey weights (Wooldridge, 2004), which was subsequently used to make inferences about the covariates explaining adoption of soil sampling and the period between testing.

Empirical Model

The variables hypothesized to be associated with the precision soil test adoption decision and the length of time between soil tests are summarized as four categories: 1) farm operator characteristics, 2) information sources, 3) information gathering/processing technologies, and 4)

off-farm and regional attributes. Definitions of the covariates, their hypothesized signs, and the survey sample and weighted means are summarized in Table 1.

Farm Operator Characteristics

The natural logarithm of the average cotton hectares grown in 2007 and 2008 (ACRES) was hypothesized to be positively associated with the decision to adopt soil testing, but negatively related to the years between testing. The more acres a producer manages, the more likely soil fertility may vary, increasing the difficulty of efficient input management. Producers may therefore be more likely to invest in precision soil sampling technologies to better understand soil variability, but soil information may also need to be updated more frequently. The proportion of owned land to total farmland operated (LANDTEN) was expected to be positively correlated with PSS adoption and the period between sampling because operators who own relatively more land may be concerned about decisions affecting the future soil fertility and quality of their cropland. These operators may also consider management decisions over a longer time horizon and may take more time until updating soil information. Operators reporting higher shares of income from farming (INCFARM) were expected to be more likely to adopt precision soil sampling technologies and test more frequently. Producers with more farming experience (FARMCOMMIT), as measured by years farming divided by operator age, were hypothesized to be less likely to adopt precision soil sampling technologies but more likely to extend the time between soil tests. Previous studies identifying the factors affecting PA technology adoption decisions have included variables such as age, years farming, experience, and education (Daberkow and McBride, 2003; Sevier and Lee, 2004; Paxton et al., 2010). Including age and experience, for example, in the same regression may introduce redundant information and

possibly multicollinearity. The variable FARMCOMMIT constructed in this study is a proxy for the knowledge capital gained with increased years and commitment to farming. The variable provides a way to measure knowledge capital without having to include some combination of age or experience in the same model, thus reducing problems that could arise due to collinearity. Experienced farmers content with current management plans may perceive it too costly to change production practices and therefore may resist adoption of new technologies (Batte et al., 1990). And after adoption, producers may more easily understand how information relates to particular fields, which may correspond with longer lapses between soil testing. Operators with a bachelor's degree (BS) were expected to be more likely to adopt soil testing and to wait longer periods between soil tests because higher levels of education may facilitate the synthesis of complex information obtained from precision soil sampling (Batte et al., 1990). The percentage of non-cotton crop hectares to total hectares of crops farmed (OCROPS) and soil fertility variability (YVAR) of fields (as measured by the difference in fields' third most productive and third least productive areas) were hypothesized to be positively related with adoption of soil testing but negatively correlated with the time period between tests. Greater yield variability may encourage the adoption of information gathering technologies like soil sampling but also encourage more frequent testing.

Information Sources

Access to and use of information sources may influence the likelihood of adopting soil sampling and the time period between soil testing. Information from crop consultants (INFOCONS), trade shows (INFOSHOWS), and the use of consultants or dealers to apply inputs (APPCONS) were hypothesized to be positively correlated with the adoption of soil testing but

negatively associated with the time period between soil tests. Field operation consultants, or those working for private service providers, may have financial reasons for promoting or marketing soil tests and encouraging producers to test soils more frequently. The expected signs associated with information gathered from other farmers (INFOOTH) and university Extension services (INFOEXTEN) were ambiguous. Soil test adoption and soil testing frequency may be related to the field characteristics of a farm. Therefore, it is hard to definitively surmise the influence other farmers and Extension services would have on the adoption and frequency of soil testing, given that information derived from these sources will depend on differing field characteristics. Producers pursuing media outlets, such as the internet or other news sources (INFOMEDIA), for information about PA may be more likely to adopt soil testing and increase the time period between soil tests. In addition to the usual television and radio information outlets, the internet has become a fast-growing avenue through which communication and learning materials are acquired (Dimmick et al., 2004). Operators who frequently use the internet may already be familiar with computer technologies that might complement soil test interpretation and management. This complementary information used in conjunction with PSS may increase the time period between tests. The number of farm suppliers (FARMSUPPLY) located in a county may also be positively correlated with the soil test adoption decision, but negatively associated with the time period between soil testing. Access to technologies and technical support may increase the likelihood operators adopt soil test technologies but decrease the time period between tests.

Site-Specific Information Gathering Technologies

The use of aerial imagery (IMAGE), cotton yield monitors to generate yield maps (YMMAP), GPS/PDA handheld devices (HANDHELD), soil electroconductivity technologies (ELECTRIC), Greenseeker® technology (GREENSEEK), and the use of computers for farm management decisions (COM) were hypothesized to be positively associated with the likelihood of soil test adoption and the time period between testing. The use of handheld GPS/PDA devices may complement precision soil sampling, increasing the efficiency of field data information collection and storage (Walton et al., 2010) and thus increasing soil test adoption rates. Yet, the use of precision technologies with PSS may also provide complementary information about soil quality, which could moderate soil testing frequency.

The use of a variable rate technology plan (VRTPLAN) was excluded from the adoption equation but included in the time-between-testing equation. In the survey, cotton producers could only respond to the question concerning the use a variable rate fertilizer management plan if they had conducted soil sampling tests. Thus, the variable is not an accurate measure for explaining soil test adoption. VRTPLAN was hypothesized to be negatively correlated with the time period between soil tests.

Off Farm Regional Attributes

Six regional variables from the USDA's Economic Research Service (Table 1, USDA Farm Resource Regions, 2007) were included in the adoption and retesting period model. The Southern Seaboard was the reference region. Five other regions including Heartland (HEARTLAND), Prairie Gateway (PRAIRIE), Eastern Uplands (EASTUP), Fruitful Rim (FRUITFUL), and Mississippi Portal (MISSPORT) regions were included to control for

geographic differences in growing seasons, weather conditions, and input costs (Khanna, 2001). An orthogonal restriction was used to code these binary variables; therefore the coefficients associated with each region are interpreted as the difference between the regional average and the population average of the surveyed states (Lentner and Bishop, 1993).

Model Specification and Analysis

Specification tests were conducted to determine the appropriateness between several alternative models describing the PSS adoption decision and years between soil testing. Vuong's (1989) statistic was estimated to compare the zero-inflated Poisson (ZIP) model with a standard Poisson regression. A characteristic of the Poisson model is its tendency to display overdispersion due to the model's implicit assumption that the variance equals its mean (Greene, 2000, p. 884). Zero inflated count and hurdle models provide a way to model count data with many excess zeros while also allowing for overdispersion. The Vuong test is useful for comparing the two-non nested models. The null hypothesis of the Vuong test is that both models have similar measures of goodness-of-fit. The alternative hypothesis is that the ZIP's goodness-of-fit is statistically smaller than the standard Poisson. To test this hypothesis, likelihood ratio tests were estimated to determine the goodness-of-fit for the Poisson-hurdle model (PHM) and the ZIP models. The Poisson hurdle model differs from the zero-inflated Poisson model because the hurdle model parameters for the binary portion of the PHM can be estimated separately from the nonzero count portion of the model. The likelihood ratio statistic (LR) was calculated as LR = 2(log-likelihood unrestricted – log-likelihood restricted) with k - 1 degrees of freedom (Wooldridge, 2004). Lastly, the negative binomial logit hurdle model was compared to the Poisson hurdle model. The negative binomial logit hurdle model relaxes the assumption

maintained by the Poisson specification that the mean and variance are equal. When the overdispersion coefficient of the negative binomial regression is not different from zero, the negative binomial model reduces to the Poisson hurdle model (Freese and Long, 2006).

Variance inflation factors (VIFs) were used to detect multicollinearity. Multicollinearity arises when two or more regressors are highly, but not perfectly, correlated. Problems include coefficients with unexpected signs, high coefficients of determination, and low *t* statistics (Greene, 2000). In general, VIFs greater than ten suggest there may a problems arising from multicollinearity, and inference about covariates may be compromised (Chatterjee and Price, 1991).

Coefficient Interpretation

The log odds ratio (LOGODDS) was used to determine the effect covariates had on the odds of a cotton producer adopting precision soil sampling. The log odds ratio for the logit regression model is,

$$LOGODDS = \frac{\Pr(I_i^{AD}=1)}{1-\Pr(I_i^{AD}=1)} = \exp(\beta_j^{AD}) \ , \tag{7}$$

where $\Pr(I_i^{AD} = 1)$ is the probability a cotton producer adopted precision soil sampling, and β is the estimated parameter of covariate j.

For the Poisson regression model, the coefficients measure the effect a covariate had on the number of years between soil retesting. To interpret the Poisson coefficients, the average response was calculated for all individuals following Cameron and Trivedi (1998, p. 80). The Poisson model coefficients are reported (Table 2), and the marginal effects are discussed with

respect to the variables influencing the perceived years of usefulness. The marginal effects of the Poisson count model for continuous explanatory variables were estimated as,

(8)

$$\frac{1}{n}\sum_{i=1}^{n}\frac{\partial \mathrm{E}[y_i|x_i]}{\partial x_{ij}} = \widehat{\alpha_j}\,\bar{y}$$

where $\bar{y}$ is the average years precision soil sampling information is considered useful by producers who adopted precision soil sampling, and α is the estimated parameter associated with covariate *j* (Cameron and Trivedi,1998). For discrete explanatory variables, the marginal effects were estimated as,

(9)

$$\frac{\mathrm{E}[y_i|d = 1, x_2]}{\mathrm{E}[y_i|d = 0, x_2]} = exp(\widehat{\alpha_j})$$

in which *d* is a covariate that takes on values of 0 or 1. Thus, a producer with characteristic *j* would, on average, wait $exp(\widehat{\alpha_j})$ more years before retesting.

Results

Results from the 2009 survey showed that of the cotton farmers responding, 40% (652) had adopted precision soil testing. Of those producers indicating they currently used or who had previously adopted grid or zone soil sampling, 14% (258) responded that they had adopted GPS technology to collect soil sampling information.

The first-stage logit and second stage Poisson models appear to explain adoption and the period between soil tests as a function of farm operator, business, and regional attributes. In regards to the adoption decision, the logit model correctly predicted 94.1% of actual producer responses. The null hypothesis that all coefficients (β_{AD}, α_{RT}) were zero was rejected at the 1% level (Wald = 197, d.f. = 26). The pseudo R^2 measure was 0.52. The VIFs suggested collinearity was not serious for the logit model (average 2.2; maximum 8.2) or the Poisson model (average 1.9; maximum 7.1).

The Vuong test statistic, comparing the zero-inflated Poisson (ZIP) model to the standard Poisson model was 8.24, indicated the ZIP model was favored over the standard Poisson model. This suggests some gains in efficiency with respect to censoring zero counts. The likelihood ratio comparing the ZIP to the Poisson hurdle specification was 18,180 (13 degrees of freedom), which suggests that the Poisson hurdle model is preferred to the ZIP specification. Lastly, the negative binomial hurdle model's overdispersion parameter was not different from zero, suggesting overdispersion was not an issue. Therefore, the Poisson-hurdle model was used to explain the adopt retesting decision of cotton producers.

Precision Soil Sampling Adoption

Characteristics associated with the likelihood of adopting soil sampling and the time period between soil tests are summarized in Table 2. Operators obtaining information from trade shows, the use of a consultant to apply inputs, the generation of a yield map using a yield monitor, and the use of electroconductivity devices were positively associated with soil sampling adoption. Farmers using information from trade shows were about two (= $e^{0.541}$) times more likely to adopt PSS than producers who did not pursue information about PA technologies from

this source. The use of private consultants to apply inputs also increased the odds of a producer adopting PSS by a factor of 20 (= $e^{2.964}$). These positive results could be because private consultants and companies attending trade shows may generate financial benefits from producers' adoption of PSS technologies. Promoting soil test information may be a key component of their marketing plans. The use of a yield monitor to generate a yield map and the use of electroconductivity devices were positively associated with the adoption decision, increasing the odds a cotton producer would adopt PSS by about six for the former (= $e^{1.772}$) and 11 (= $e^{2.393}$) for the latter. These results suggest that producers making a yield map using a yield monitor may recognize the managerial benefits of soil sampling. Additionally, producers already using technologies that may supplement PSS information in nutrient management may be more accustomed with information gathering technologies and comfortable adopting PSS technology.

Alternatively, the use of Greenseeker® technology was negatively correlated with soil test adoption, and was associated with a decrease in the odds a cotton producer adopted PSS by 0.10 (= $e^{-2.290}$). This result suggests cotton farmers who used precision agriculture technologies that provide information that complemented precision soil sampling data were less likely to use soil sampling technologies.

Years Between Soil Testing

The number of years between soil testing increased with land tenure (hectares owned/hectares operated), farmer experience, the use of electro conductivity devices, and Greenseeker® technology. Producers with more farming experience may be more familiar with field soil conditions and nutrient variability; a one year increase in experience for a producer would increase the years between testing by 2, while a one percent increase in land tenure would

increase years between testing by 0.82 years (Table 2). The positive correlation with the time between re-testing and these factors suggest that operators with more experience and a greater percentage of owned to operated land may understand soil and field variability to an extent that requires less soil testing with respect to fertility management. Interest in newer technologies was also positively correlated with longer periods between grid or zone soil testing. The use of electro conductivity and Greenseeker® technologies increased the time between soil testing by 1.3 (= $e^{0.295}$) and 2 (= $e^{0.692}$) years respectively. Thus, there appears to be some degree of substitution between the information acquired from precision soil testing that is often considered an "entrance" technology (Walton et al., 2008), and the information generated from newer sensor-based technologies like Greenseeker® or electroconductivity.

Farm size and adoption of a variable rate fertilizer management plan based on GPS-referenced soil sample information were associated with more frequent soil testing. A 1 hectare increase in farm size decreased the time between soil tests by 0.35 years and the use of a variable rate plan by a producer decreased the length by 0.66 years (= $e^{-0.407}$). This result suggests that farmers using a VRT plan for production management decisions may be inclined to test more frequently to update soil information for increased input application effectiveness.

Conclusions

The adoption of precision soil testing by cotton farmers in the Southern United States and the perceived usefulness of soil test information over time were analyzed using a Poisson-hurdle regression model. Under this model, a profit maximizing producer must have adopted soil testing to subsequently decide on the years between soil testing. In order to moderate or increase the leverage attributed to respondents in different size classes depending on the characteristics of the

entire population, survey post-stratification weights were estimated to align the survey sample with the number of cotton farmers enumerated by the USDA's 2007 Agricultural Census. The results suggest that operators obtaining information from trade shows, the use of a consultant to apply inputs, the generation of a yield map using a yield monitor, and the use of electroconductivity devices were positively associated with soil sampling adoption. Subsequently, of those farmers who did adopt soil testing, land tenure, farmer experience, the use of electrical-conductivity devices, and Greenseeker® technology increased the number of years between soil testing. These results suggest that producers already using technologies that supplement PSS information may be more likely to adopt PSS technology. Additionally, there appears to be some degree of substitution between the information acquired from precision soil testing and the information generated from newer sensor-based technologies, resulting in longer periods between soil testing.

This research builds upon previous precision agriculture technology studies in regards to the factors affecting the adoption of precision grid or zone soil sampling, but it also provides insight on the perceptions of cotton producers about the length of time soil sampling is useful. The lack of literature regarding the length of time PSS is perceived useful in cotton production makes this a practical study for agriculture service providers, Extension services, and cotton producers. In regards to product and service marketing, understanding the factors contributing to the perceived usefulness of precision soil test information may provide guidance to industry and agribusiness firms. Based on the results from this study, agribusiness firms and trade-shows sponsors may be inclined to target farmers already using precision technologies that complement PSS. Furthermore, this information may help conservation program managers better understand

producer willingness to comply with prescribed nutrient management plans and may help Extension programs tailor outreach efforts about optimal timing between soil sampling.

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Appendix

Table 1. Variable Definitions, Hypothesized Signs, and Means in the Precision Soil Sample Adoption and Perceived Years Useful Equations

Variable	Definition	Hypothesized Sign		Mean	
		adopt	years useful	un-weighted	Weighted
Farmer Characteristics:					
ACRES	Average cotton acreage grown in 2007 and 2008	+	–	561.157 (0.032)[1]	379.934 (0.044)
LANDTEN	Percentage of owned land to total land farmed	+	+	0.343 (0.011)	0.368 (0.014)
INCFARM	Percentage of 2007 taxable household income from farming	+	–	0.743 (0.009)	0.694 (0.012)
FARMCOMMIT	Years farming divided by farmer age	–	+	0.548 (0.005)	0.543 (0.006)
BS	1 if farmer had a B.S. degree[2]	+	+	0.909 (0.009)	0.898 (0.011)
OCROPS	Percentage of non-cotton acres to total farmed acres	+	–	0.208 (0.009)	0.216 (0.012)
YVAR	Difference in average yields between the most productive 1/3 and the least productive 1/3 of a typical field	+	–	5.455 (0.089)	5.390 (0.103)
Information Sources:					
INFOCONS	1 if used information from a crop consultant	+	–	0.319 (0.015)	0.308 (0.016)
INFOEXTEN	1 if used information from Extension	+/–	+/–	0.399 (0.015)	0.390 (0.017)
INFOOTH	1 if used information from other farmers	+/–	+/–	0.606 (0.015)	0.602 (0.017)
INFOSHOWS	1 if used information from trade shows	+	–	0.343 (0.015)	0.336 (0.017)
INFOMEDIA	1 if used information from the media	+	+	0.479 (0.016)	0.484 (0.018)
FARMSUPPLY	Number of farm input suppliers in the region	+	–	7.657 (0.290)	7.937 (0.317)

APPCONS	1 if farmer used a consultant or dealer to apply inputs	+	–	0.151 (0.011)	0.138 (0.012)
Information Technologies:					
IMAGE	1 if used aerial imagery	+	+	0.065 (0.008)	0.056 (0.007)
YMMAP	1 if used a yield monitor and generated a yield map	+	+	0.050 (0.007)	0.038 (0.006)
COM	1 if computer used for farm management	+	+	0.600 (0.015)	0.552 (0.018)
VRTPLAN	1 if made a Variable Rate Fertilizer Management plan using the GPS-referenced soil sample information	+	+	0.213 (0.013)	0.192 (0.013)
HANDHELD	1 if used a handheld GPS/PDA	+	+	0.034 (0.006)	0.034 (0.006)
ELECTRIC	1 if used electro conductivity	+/–	+/–	0.033 (0.006)	0.032 (0.006)
GREENSEEK	1 if used Greenseeker®	+/–	+/–	0.006 (0.002)	0.005 (0.002)
Regional Characteristics:					
FARMDENS	Number of farms in county divided by the total county land in farms (2007)	+/–	+/–	-5.915 (0.033)	-5.932 (0.033)
HEARTLAND	1 if farm located in the Heartland	+/–	+/–	-0.266 (0.015)	-0.264 (0.019)
PRAIRIE	1 if farm located in the Prairie Gateway	+/–	+/–	0.110 (0.026)	0.086 (0.029)
EASTUP	1 if farm located in the Eastern Uplands	+/–	+/–	-0.253 (0.016)	-0.260 (0.018)
FRUITFUL	1 if farm located in the Fruitful Rim	+/–	+/–	-0.212 (0.018)	-0.212 (0.021)
MISSPORT	1 if farm located in the Mississippi Portal	+/–	+/–	-0.101 (0.021)	-0.108 (0.025)

[1]Numbers in Parentheses are standard errors.
[2] Variables defined as having a value of "1" have a value of zero if the condition does not hold.
[3] USDA Farm Resource Region

Table 2. Logit and Hurdle Poisson Estimates for the Factors Influencing Adoption and Perceived Years of Usefulness of Precision Soil Sampling Technology

	Logit[1]			Poisson[2]		
Independent Variable	Coeff	P-value		Coeff	P-value	
		Wtd[3]	Unwtd		Wtd	Unwtd
ACRES	0.154	.307	.142	-0.144	.022	.075
LANDTEN	0.801	.828	.375	0.305	.094	.173
INCFARM	0.511	.357	.147	-0.255	.255	.860
FARMCOMMIT	-0.381	.739	.301	0.748	.063	.530
BS	-0.031	.950	.909	0.115	.628	.935
OCROPS	0.434	.348	.249	-0.139	.400	.380
YVAR	0.072	.104	.052	-0.001	.958	.985
Information Sources:						
INFOCONS	0.036	.914	.614	-0.006	.961	.761
INFOEXTEN	0.328	.277	.186	0.189	.121	.163
INFOOTH	0.119	.686	.605	0.066	.521	.391
INFOSHOWS	0.541	.068	.015	-0.112	.358	.113
INFOMEDIA	0.193	.489	.903	0.126	.344	.176
FARMSUPPLY	0.024	.212	.259	-0.005	.717	.363
APPCONS	2.964	.000	.000	-0.143	.250	.957
Information Technologies:						
IMAGE	0.622	.214	.088	-0.153	.334	.590
YMMAP	1.772	.001	.001	-0.039	.794	.929
COM	0.528	.105	.244	-0.171	.221	.225
VRTPLAN				-0.407	.052	.131
HANDHELD	0.330	.512	.469	0.032	.818	.798
ELECTRIC	2.393	.001	.000	0.295	.095	.089
GREENSEEK	-2.290	.009	.011	0.692	.030	.194
Regional Characteristics:						
FARMDENS	-0.098	.471	.353	-0.020	.713	.612
HEARTLAND	0.910	.177	.025	0.180	.369	.570
PRAIRIE	-1.955	.000	.000	0.413	.166	.223
EASTUP	0.477	.307	.453	-0.031	.911	.581
FRUITFUL	-0.977	.084	.075	-0.305	.052	.626
MISSPORT	1.053	.001	.000	0.290	.009	.057

$R^2 = 0.52$

AIC (Akaike Information Criterion) = 9.367

Sample Size = 1,008

Expanded cotton farm population = 9,951

[1]Logit regression models the probability that a producer adopts grid or zone soil test technology.

[2]The Poisson regression models the years between soil tests.

[3]Post-stratification sampling weights.

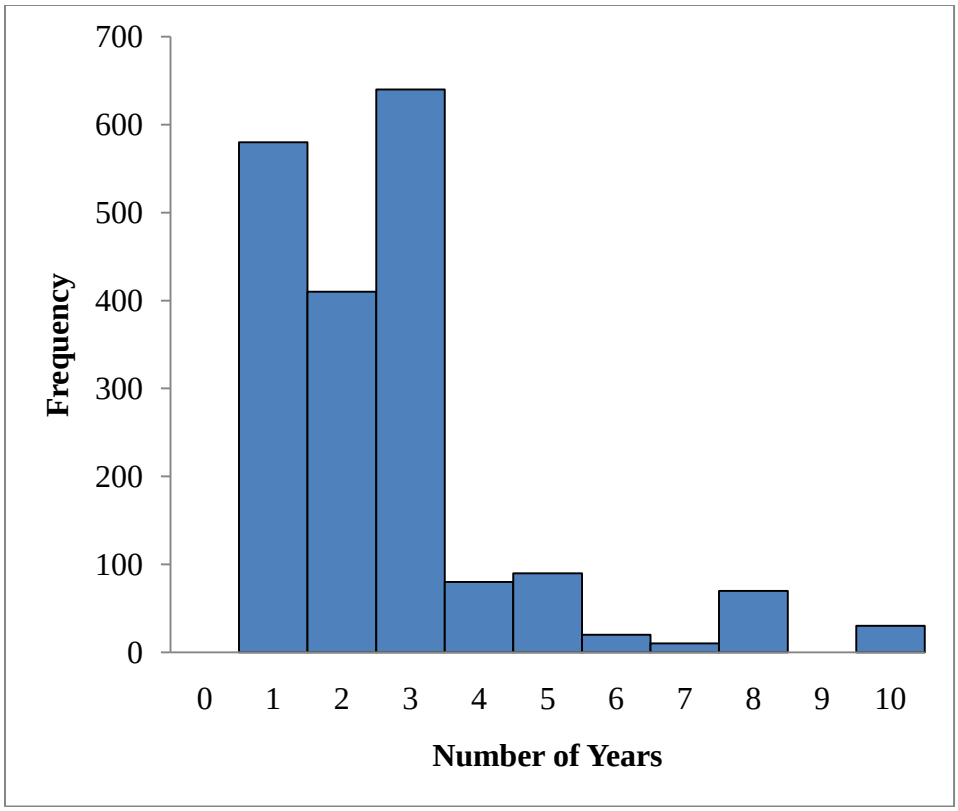

Figure 1. Weighted Frequency Distribution of Years Soil Test Information was Useful

II. Optimal Potassium Application Policies and Potassium Carryover Dynamics in Cotton Production: A Simulated Dynamic Programming Approach

Abstract

Spatial and temporal information about soil dynamics can assist cotton producers with optimal management of potassium (K) fertilizer. Optimal K management promotes cotton plant health, may lead to lower input costs, and increases cotton lint yields. A dynamic programming model was developed to determine optimal K application rates and economic returns under different soil information scenarios based on cotton yield response estimates to K fertilizer from a multi-year field trial. A Monte Carlo analysis was conducted to simulate the impact of stochastic input and lint prices and cotton yield on K management over a five-year time horizon. Soil test data could provide important information about K carryover, which may lead to more efficient fertilizer use and higher profit margins.

Introduction

Understanding soil nutrient dynamics is important for the optimal management of potassium (K) for cotton production. Knowing how and when to apply K to maximize plant uptake efficiency is important for maintaining cotton plant health and increasing profits. In cotton production, inadequate application of K disrupts the pH balance in plant cells (Hake et al., 1991), stresses cotton plants, delays fiber maturity, and reduces nutrient uptake (Pettigrew et al., 1996). Potassium deficiency in cotton plants may even occur in soils thought to have adequate amounts of K (Cassmen et al., 1981). Thus, under or over-applying K may lead to lower profit margins (Pettigrew and Meredith, 1997). The capacity of different soils to retain and release K in subsequent growing seasons as influenced by weather and erosion makes understanding the soil K dynamics important for implementing the site-specific management of K.

Ascertaining when and where to apply K is not always evident. Producers face a diverse set of field conditions, market uncertainty, and weather conditions; all of which make managing inputs over multiple growing seasons difficult. Soil K carryover dynamics between growing seasons may also increase the challenge of optimal K management. But over a planning horizon, soil testing can provide information about spatial and temporal K nutrient availability. The value that soil testing adds to a K nutrient management plan is also reflected in increased returns when this information is used to determine fertilizer rates. Previous studies examining the returns from examining yield response variability, soil dynamics, and input placement and timing are numerous (e.g., Perrin, 1976; Adams et al., 1983; Schnitkey et al., 1996; Watkins et. al., 1998; Bongiovanni and Lowenberg-DeBoer, 2000; Bongiovanni and Lowenberg-DeBoer, 2001; Hurley et al., 2001; Lambert et al., 2003; Lambert et al., 2007; Maine et al., 2007; Park et al., 2007). Yet findings about the profitability of site-specific management of phosphorous (P),

nitrogen (N), and K based on soil test information varies according to research conditions, the crops studied, and in the case of on-farm trials, the managerial capability of producers and farm/field heterogeneity. This is not surprising because of the site-specific nature of information generated by precision agriculture technologies. Perrin (1976) used corn yield response functions to estimate the value of soil test information in corn production in Brazil, determining a range of $6.16 to $30.92 per hectare increase in net returns when soil test information was used to determine fertilizer rates. Adams et al. (1983) also found increased returns from managing fertilizer using soil test information, concluding a $696 increase in returns per ha when soil test information was used to determine fertilizer rates for sugar beets. Hurley et al. (2001) found that basing N fertilization rates on soil nitrate tests increased producer profits by $6.42 per ha. In another study examining corn response to N application in Argentina, Anselin et al. (2004) found $7.65 per ha increased returns under variable rate N management as compared to uniform N application strategies. Lambert et al. (2003) estimated corn and soybean response to manure to examine the potential of site-specific manure management, finding higher returns under variable-rate manure management with information about P, K, and lime. Furthermore, they found that the value of soil test information increased with site-specific manure application. Bongiovanni and Lowenberg-Deboer (2000) examined the profitability of variable rate application (VRA) of lime based on agronomic, economic, and site-specific information rules for corn and soybeans, finding an increase in profit of $7.24 to $19.55 per hectare compared to a whole field lime management strategy. Velandia et al. (2006) estimated cotton response to N and found increased net returns ranging from $4.29 to $5.45 per ha for variable rate N application compared to uniform rate application. Yang et al. (2001) found increases in profit from site-specific management of N and P over uniform management of these inputs for grain sorghum. But Liu et

al. (2006) estimated corn response to N and found that variable rate N application based on site-specific information did not cover the costs associated with variable rate application. Swinton et al. (2002) also found that the site-specific management of P, K, and lime based on soil tests of P, K, and pH was not profitable compared to uniform whole field application for corn and soybean production.

Much of this previous research examined ex post changes in profitability after managing fertilizer inputs based on soil test information, but few studies have taken into account the temporal carryover effects of soil nutrients. Most of these studies have also used static, partial budgets to estimate the value added from soil test information. A dynamic programming (DP) approach is used in this research to estimate the value added from managing potassium carryover for continuous cotton production. Dynamic programming models allow optimal input levels to be determined in each growing period over a specified time horizon for a more accurate characterization of returns. That is, the decisions producers make about current input use have repercussions on input management in subsequent seasons depending on residual fertilizer carryover capacity of soils. The two key elements needed to optimally manage K over a time horizon are: (1) knowledge about how plants respond to K, and (2) the extent to which K is carried over as "residual" between seasons. The first often requires controlled field experiments, but well-planned on-farm trials may provide similar information (Bongiovanni and Lowenberg-DeBoer, 2001; Griffin et al., 2006; Lambert et al., 2007). Combined with yield goals, producers may be able to ascertain how plants respond to different input levels. The second element may be discerned by soil testing over several production cycles. For example, the rate of change in soil nutrients over time that can be derived from soil test data may provide important information about nutrient carryover capacity of soils.

Dynamic programming models have been developed to analyze the effects of residual fertilizer carryover on crop yield (Kennedy et al., 1973; Gooden and Heylar, 1980; Stauber, Burt, and Linse, 1975). However, experimental or on-farm trials that collect yield response information and nutrient fertilizer dynamics are rare and expensive. Lambert et al. (2007) used 5 years of data from an experiment evaluating variable rate application of N and P for a corn and soybean rotation to determine the economic returns to site-specific management of N and P in soils where P-carryover was significant. They found that the net present value from variable rate P and N management based on soil information was higher than managing those inputs in the absence of P carryover under a uniform management strategy. Schnitkey et al. (1996) derived similar conclusions for P and K on corn and soybean fields, taking into account nutrient carryover between growing seasons. Their results indicated that managing P and K soil dynamics based on soil test information was profitable over a 20-year horizon. In another study, Lowenberg-DeBoer and Reetz (2002) compared P and K management scenarios for a continuous corn and soybean rotation with soil nutrient residual dynamics similar to those in Schnitkey et al. (1996). They found a rapid build-up strategy of P and K to reach critical soil test levels increased producer profits more than a gradual application plan by $8.25 per ha. Jomini et al. (1991) found similar results with increases in profit for millet grown on fields when optimal levels of P and N fertilizer are applied based on soil testing. In a study of plantain response functions to K and organic soil matter and economic returns over a 30-year horizon, Tré and Lowenberg-DeBoer (2005) found increased returns ranging from 72% to 154% for mulch-based application technologies as compared to traditional fallow systems with K and organic matter carryover present. Yet, in a potato and barley study, Watkins et al. (1998) found that variable-rate N application costs resulted in decreased returns when compared to conventional application

methods because of the increased costs associated with variable rate application even when N carryover was significant.

This study uses a DP method that modifies Kennedy's (1986) and Lambert et al.'s (2007) analytical model to determine optimal K management strategies using data from a three-year cotton yield response trial in West Tennessee. By incorporating K carryover dynamics into nutrient management decisions, the economic benefits observed under alternative information scenarios can be compared to estimate the value soil test information adds in managing dynamic soil nutrient dynamics.

This paper is organized into six sections. The first section outlines the conceptual models used to determine the optimal amount of potassium to apply using a dynamic programming approach; the cotton lint yield and soil K carryover response models which regulate total available K; and the models used to introduce uncertainty into input and output prices. The second section summarizes the econometric procedures used to estimate cotton lint yield response and residual K fertilizer. The regression methods used to estimate the input and output price expectation models are also summarized. The simulation model and the distributions used to make price and soil K carryover stochastic are discussed in the third section. The fourth section outlines the data used to parameterize the DP model. Results from the econometric estimation procedures and the net present value estimated under deterministic and stochastic frameworks are discussed in the fifth section. The final section concludes, providing insight into the value of site-specific information gathering technologies (e.g., soil testing) for input management.

Conceptual Models

The following section discusses the conceptual models used to determine optimal K application, residual K fertilizer effects on yield, and input and output prices. First, the decision rules for deriving the optimal amount of total available K fertilizer subject to soil K carryover are presented. Deriving optimal K fertilizer under alternative states of soil carryover nature provides a framework for estimating net present value when prices and yields are deterministic or stochastic. Second, the estimated yield response function used to characterize cotton plant response to K is described. Third, residual carryover can affect K availability in subsequent years, and the functional form used to model residual K available to plants in future periods is discussed. Fourth, a closed-form solution for determining the optimal amount of total K available to cotton plants under alternative K carryover scenarios is presented. Lastly, input and output price expectations and the functional forms used to model the lagged input and output price effects are described.

Optimal Fertilizer Management with Residual K Carryover

Soil K tests can provide producers information about how potassium may carry over as "residual fertilizer" in subsequent growing seasons. The value added from soil testing is determined by comparing economic returns under alternative K application strategies when two soil states of nature exist: (1) K fertilizer carries over as a residual nutrient between seasons, and (2) fertilizer K carryover is absent. Potassium fertilizer may be applied every season, less frequently, or at lower rates depending on the residual soil K carryover as well as how efficiently K is absorbed by cotton plants. When soil test information suggests that K levels are above biologically optimal thresholds, K can be "mined" out from the soil for some period. Once

optimal levels are achieved, remedial applications ("amendments") of K may be required every season to maintain optimal production thresholds.

Profit-maximizing producers will apply fertilizer such that the discounted marginal product value (MPV) of the fertilizer equals its marginal cost (MFC). Economic models for determining optimal fertilizer application when residual fertilizer carryover is present have been developed extensively (Kennedy et al., 1973; Kennedy, 1981; Kennedy, 1986; Jomini et al., 1990; Schnitkey et al., 1996; Lowenberg-DeBoer and Reetz, 2002; Tré and Lowenberg-DeBoer, 2005; Park et al., 2007; Lambert et al., 2007). The dynamic programming approach assumes the fertilizer management problem can be divided into discrete stages, where the optimal strategy at each stage can be calculated separately (Fisher and Lee, 1981). In the original model by Kennedy et al. (1973), K application in each growing season is determined separately even though each successive fertilizer application decision may be influenced by residual K from the previous season. Thus the decision making sequence can be reduced to a Markov process in which the distribution of K application in future periods, K_{i+1}^{APP}, is only dependent on the levels in the present period, K_i^{APP}. In period i + 1, the problem is "memoryless" to past fertilizer application outcomes other than in time period i. To optimally manage K, all the needed management information is embedded in the current production period.

The fertilizer carryover model developed below assumes (1) there is only a single fertilizer input (K), (2) the input is applied at the beginning of each season, and (3) the producer controls the level of total available K fertilizer (residual + applied) by choosing how much fertilizer to apply each season, (4) soil tests provide accurate information about residual carryover of K, and (5) the producer maximizes the net present value (NPV) of cotton production (Kennedy, 1986). Profit in period i is:

(1) $$\prod_i = \alpha p_i^{CY} y_i\{K_i^{CAR} + K_i^{APP}\} - p_i^K K_i^{APP} - FIXED\ COSTS,$$

where K_i^{CAR} is potassium carryover ("residual") fertilizer (kg/ha); K_i^{APP} is applied K fertilizer (kg/ha); p_i^{CY} and p_i^K are cotton lint ($/kg) and K fertilizer ($/kg) prices, respectively, in period *i*; $y_i\{K_i^{CAR} + K_i^{APP}\}$ is the cotton lint response to total available K in period *i*; and (α) is a discount factor of time preference 1/(1+ *r*), where *r* is a discount rate reflecting the producers' time preference. Fixed costs may include soil sampling costs (*s*).

The producer maximizes net present value over $i = 1,\ldots,N$ periods subject to a potassium carryover function,

(2) $$\max_{K_i^{APP}\ldots K_n^{APP}} \sum_{i=1}^{N} \alpha^{i-1} (\Pi_i)$$

$$\text{s.t. } K_i^{APP} \geq 0$$

$$K_{i+1}^{CAR} = \theta + h\left(K_i^{CAR} + K_i^{APP}\right)$$

$$K_0^{CAR} \text{ given}$$

$$i = 1,2,3\ldots.N,$$

where $h\ \epsilon(0,1)$ is a constant determining the proportion of residual fertilizer available to plants in the following season, and θ is K in the soil not available to the plant. The initial K carryover amount (K_0^{CAR}) is given (i.e., the farmer knows the amount of K in the soil from soil testing). In terms of the dynamic programming problem, information derived from soil testing is embedded in the K carryover parameter. The value added from soil K testing can be estimated by determining how much input prices are discounted between periods through the accumulation of potassium carryover "credits".

The problem of determining the optimal amount of K to apply in each period can be solved using the following Bellman's recursive equation (Bellman, 1957),

(3)
$$V_i\{K_i^{CAR}\} = \max_{K_i^{APP}} \ [\Pi_i + \ \alpha^{i+1} V_{i+1}\{h(K_i^{TOT})\}]$$

$$\text{s.t. } K_i^{APP} \geq 0$$

$$\text{with } K_0^{CAR} \text{ given}$$

$$V_N\{K_N^{CAR}\} = 0$$

$$K_i^{TOT} = \ K_i^{CAR} + K_i^{APP},$$

where $V_i\{K_i^{CAR}\}$ is the present value of net returns ($/ha) from using an optimal K fertilizer application strategy in each of the *i* periods, given soil K carryover (K_i^{CAR}) in the beginning of each period *i*; K_i^{TOT} is the total amount of available K fertilizer (kg/ha), which is the sum of residual and applied fertilizer. The state variable is residual fertilizer remaining in the soil before cultivation. The decision variable is the amount of potassium to apply each growing period. Any K fertilizer remaining after the last period (*N*) has no value to the produce; $V_N\{K_N^{CAR}\} = 0$ (a "terminal" condition).

Differentiating the expression in equation (3) with respect to the control variable, K_i^{APP}, the first order condition for an interior maximum is,

(4)
$$\frac{\partial y_i}{\partial K_i^{APP}} \alpha^i p_i^{CY} - p_i^K + \ \alpha^i \frac{dV_{i+1}}{dK_{i+1}^{CAR}} \frac{dK_{i+1}^{CAR}}{dK_i^{CAR}} = 0,$$

$$\text{with } \frac{dK_{i+1}^{CAR}}{dK_i^{CAR}} = h.$$

Differentiating the expression in equation (3) with respect to K fertilizer carryover, K_i^{CAR}, the first order condition for profit maximization (assuming diminishing marginal and that second order conditions hold) is,

(5) $$\frac{dV_i}{dK_i^{CAR}} = \frac{\partial y_i}{\partial K_i^{APP}} \alpha^i p_i^{CY} + \alpha^i \frac{dV_{i+1}}{dK_{i+1}^{CAR}} \frac{dK_{i+1}^{CAR}}{dK_i^{CAR}}.$$

Inserting equation 4 into equation 5, it can be shown that,

(6) $$\frac{dV_i}{dK_i^{CAR}} = p_i^K,$$

which states that potassium carryover should be valued as the price of potassium fertilizer in the current period. After substitution of equation (6) into equation (4), the condition defining optimal K application rates is,

(7) $$\alpha^i p_i^{CY} \frac{\partial y_i}{\partial K_i^{APP}} = p_i^K - \alpha^i \frac{dK_{i+1}^{CAR}}{dK_i^{CAR}} p_{i+1}^K.$$

The first order condition (FOC) is solved to determine the optimal total available potassium to the cotton plant from residual *and* applied fertilizer K. The FOC states that the discounted value of the marginal product of K fertilizer must equal the marginal unit cost of K fertilizer to maximize net revenue. The marginal factor cost of K fertilizer is the price in period *i* less any savings from fertilizer K carryover accrued in the previous period. A producer maximizes net present value when the marginal product value of fertilizer (in terms of yield

price) is greater than the marginal costs of fertilizer discounted by the nutrient carryover rate. The optimal amount of K fertilizer is achieved when $K_i^{APP} = K_i^{APP*}$ no matter the value of K_i^{CAR}.

The economically optimal K application rate generating the greatest economic return can be determined under alternative soil information scenarios over some time horizon and under stochastic prices. Using a simulation approach, the hypothesis that information about residual K carryover increases profit margins can be tested.

Cotton Yield Response Modeling

Choosing an appropriate yield response function is important for partial budget comparisons of different technologies or the adoption of management decision aids. There are numerous functional forms that have been used to estimate crop yield response to fertilizer and other inputs. Common functional forms include the Mitscherlich, quadratic, or Cobb-Douglas specifications (Hall, 1983; Ackello-Ogutu, Paris, and Williams, 1985; Frank, Beattie, and Embleton, 1990; Bullock and Bullock, 1994; Bongiovanni and Lowenberg-Deboer, 2000; Tumusiime et al., 2010). Yield response functions may also be based on the biological and physical constraints of plants, soils, statistical measures of fit, or ease of estimation (Heady and Dillon, 1961).

A quadratic response plateau function was used to model cotton lint yield response to potassium. In general, the quadratic function is a (1) second-order approximation of any function (Hurley et al., 2001; Hurley et al., 2005), (2) allows for diminishing marginal returns, and (3) facilitates closed-form solution for determining economically optimal input levels. The third point is especially relevant with respect to solving Bellman's equation. As suggested by inspection of the raw yield data (Figure 3), total available K increases cotton lint yield to a

maximum, and then plateaus. The plateau model therefore appears to be appropriate, especially when total available K is considered. The quadratic response plateau function is,

$$y_i = \begin{cases} \beta_0 + \beta_1 K_i^{TOT} + \beta_2 K_i^{TOT^2} + u_i^{LY} & \text{if } K_i^{TOT} \leq K_i^{TOT*} \\ K_i^{TOT*} = -\frac{\beta_1}{2\beta_2} & \text{if } K_i^{TOT} > K_i^{TOT*} \end{cases} \tag{8}$$

where y is the cotton lint yield (kg/ha), K_i^{TOT} is the total amount of potassium fertilizer available to the cotton plant, K_i^{TOT*} is the biologically optimal amount of K available to the plant and the level of K at which cotton response begins to plateau, u_i^{LY} is a random disturbance term, β_0 is the amount of cotton expected in the absence of K fertilizer, β_1 is the plant response to a kilogram of total K fertilizer available ($E[\beta_1] > 0$), and β_2 is a parameter reflecting diminishing marginal biological growth to K ($E[\beta_2] < 0$). The estimated response function is used in the producers' dynamic optimization problem (Eq. 3) to derive the NPV received under different information scenarios.

Residual Carryover Modeling

Potassium residual carryover was approximated using a linear function. The decision to use a linear carryover equation was based on (1) the examination of the raw K carryover data (Figure 4), and (2) the relatively sparse literature regarding nutrient carryover functions. The estimated linear carryover function is similar to carryover models used by Kennedy (1981), Segarra (1989), Tré and Lowenberg-Deboer (2005), and Park et al. (2007) where residual soil nutrient levels in the next period is linearly proportional to the total available soil nutrients available to the plant in the current production period. The K carryover model is;

(9) $$K_{i+1}^{CAR} = \theta_0 + hK_i^{TOT} + u_{i+1}^{CAR},$$

where K_{i+1}^{CAR} is the amount (kg) of carryover in year i + 1, and u_{i+1}^{CAR} is a random disturbance representing fluctuations in carryover due to weather and other unforeseen events.

Closed Form Solution for Economically Optimal K Rate

The lint yield a producer can expect in any period is determined by the optimal level of total available K. When equations of motion are linear and the return function is concave and twice-differentiable, a closed form solution to Bellman's equation describing the optimal control of fertilizer over successive periods is tractable. Optimal total available K is calculated by inserting the response function from equation 8 into equation 7. When fertilizer K carryover is significant, the optimal total available amount of K is expressed as:

(10) $$K_i^{TOT*} = \left[\left(\frac{p_i^K - \alpha h p_{i+1}^K}{\alpha p_i^{CY}}\right) - \beta_1\right] / 2\beta_2,$$

where $\beta_1$and β_2 are the parameters from the cotton lint yield response function. The closed form solution is therefore based on the marginal effect of the first unit of K on plant growth, the diminishing effects over-application of K might have on growth, current period K and lint prices, a discount factor, and the expected price of K in the next period. In the absence of K carryover (i.e., when h = 0), the optimal K level corresponds with what one would expect the discounted profit maximizing level to be in the absence of any dynamics:

(11) $$K_i^{TOT*} = \left[\left(\frac{p_i^K}{\alpha p_i^{CY}}\right) - \beta_1\right] / 2\beta_2.$$

Given these terms, the profit a producer can expect in any period is determined by substituting these expressions into the objective function given the presence or absence of residual fertilizer carryover.

Stochastic Price Expectations

The optimal control of K fertilizer is a function of the next period K price. To reflect this expectation, prices were modeled as a random variable based on historical price records. The expected price of K in future periods is subsequently used to simulate expected profits based on Bellman's equation. Examination of potassium prices and cotton lint prices over time revealed an upward trend over a 21-year period, noting that lagged prices appeared to strongly explain future prices. Thus, the input and output prices in the current period were used to predict next period prices. To reflect how next period prices were related to prices in the previous period, parameters determining the evolution of input and output prices were estimated using a least squares regression. For example, cotton lint yield prices were regressed on the previous year's cotton lint price (Figure 5A).

The plots of input and output prices suggest candidate function forms for cotton and K prices. Cotton lint yield price parameters were estimated using a linear regression equation. The linear regression model explaining cotton lint yield prices is:

(12) $$P_{i+1}^C = W_0 + W_1 P_i^C + u_{i+1}^C,$$

where P_i^C is the cotton lint price in year *i*, P_{i+1}^C is the price of cotton lint in year *i* + 1, W_0 is the intercept term, $W_1$is a lagged price parameter, and u_{i+1}^C is a random disturbance with $E(u_{i+1}^C) = 0$.

The lagged potassium price model was fitted using a log-linear function, as plots of the data suggested that K input price evolution was non-linear (Figure 5B). The functional form used to describe the relationship between current and next period prices is:

$$\ln(P_{i+1}^K) = Z_0 + Z_1 P_i^K + u_{i+1}^K, \tag{13}$$

where P_i^K is the price for elemental potassium in year *i*, $P_{i+1}^K$is the price of elemental potassium in period *i* + 1, Z_0 is an intercept term, Z_1 is the lagged price parameter estimate, and u_{i+1}^K is a random disturbance term with $E(u_{i+1}^K) = 0$.

ECONOMETRIC PROCEDURES

Cotton Lint Yield and K Carryover Response

Yield response and carryover were jointly estimated as a system of equations using non-linear general methods of moments (GMM) (Hansen, 1982). The GMM estimator is robust to unspecified forms of heteroskedasticity and relaxes distributional assumptions about the error terms (Cameron and Trivedi, 2005). The system of equations is,

(14)
$$\begin{bmatrix} y_{01i} \\ y_{02i} \\ K_{01i}^{CAR} \\ K_{02i}^{CAR} \end{bmatrix} = \begin{bmatrix} 1 & K_{01i}^{TOT} & K_{01i}^{TOT^2} & 0 & 0 \\ 1 & K_{02i}^{TOT} & K_{02i}^{TOT^2} & 0 & 0 \\ 0 & 0 & 0 & 1 & K_{01i}^{TOT} \\ 0 & 0 & 0 & 1 & K_{02i}^{TOT} \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \theta \\ h \end{bmatrix} + \begin{bmatrix} u_{01i}^{LY} \\ u_{02i}^{LY} \\ u_{01i}^{CAR} \\ u_{02i}^{CAR} \end{bmatrix},$$

where i = 2001, 2002, with 32 observations recorded in each period i.

The GMM objective function is:

(15)
$$Q_N(\Gamma) = \frac{1}{N} u' Z (Z' \Omega Z)^{-1} Z' u,$$

where $\Omega = diag(u_0)$.

The notation for systems of equations can be simplified as $Y = X\Gamma + U$, with the first round residuals defined as $U_0 = Y - X\Gamma_0$ and Z a set of exogenous instruments that includes fertilizer K applications and the initial fertilizer K carryover in year 2000 (Cameron and Trivedi, 2005). The function is iteratively minimized to increase efficiency. The weights ($(Z'\Omega Z)^{-1}$) allow for different moments to carry different weights, and thus the moments with larger variance are given smaller weights, while those with smaller variance are given larger weights. The iterated GMM estimation procedure was estimated using the PROC model procedure of SAS® 9.0.

The year 2000 is the base year for the yield model. Cotton lint yield for the year 2000 is a function of total available K in 2000, which is the sum of residual fertilizer K based on total available K in 1999 and K fertilizer applied in 2000. Because there is no data for the total amount of available K fertilizer in 1999 to determine residual K carryover in 2000, cotton lint yield in the year 2000 was not used to estimate the system of equations.

Price Expectation Regressions

Ordinary least squares was used to estimate the cotton lint and potassium price models. The variances of the residuals associated with each model were used to simulate residual draws for the cotton lint yield and K prices and inserted into the price equations for years 2-5 (Figure 2).

Data Sources

Cotton Crop Response Data

Cotton yield response to K and K carryover data was from a three year (2000-2002) research trial in Tennessee at the Ames Plantation Research and Education Center in Fayette and Hardeman counties in West Tennessee, 60 miles east of Memphis and 10 miles north of the Tennessee-Mississippi line near Grand Junction, Tennessee. The first year of the trial began in Spring 2000 with the planting of cotton variety PM1218BG/RR on May 8th, the first harvest on September 14th, and the second harvest on October 10th. In 2001, cotton was planted on May 14th with the first harvest on October 3rd and the second harvest on October 18th. In 2002, cotton was planted on May 16th, with the first harvest on September 19th, and the second harvest on October 8th. Seed cotton was harvested using a 2-row John Deere spindler picker. The plot size for each treatment was 37.16 square meters with 40 rows. The soil in each plot was classified as Loring-Henry silt loam and the topography was upland. K fertilizer rates were 0, 67.23, 134.44, and 268.88 kg K_2O/ha. The K_2O fertilizer was applied before planting in each year of the experiment on March 3rd in 2000, April 11th in 2001, and May 8th in 2002. Fertilizer treatments were replicated four times in a randomized complete block experimental design. Soil tests measured the residual fertilizer after each season (kg K/ha), the lint yield (kg/ha), and the total amount of K

fertilizer (kg K/ha) available before the next planting season after the second harvest of each year. Nitrogen fertilizer was applied at a constant rate of 89.61 kg/ha each season. Soil tests were not collected for nitrogen.

Input and Output Prices and Soil Test Costs

Average market prices (1989-2009) for prices paid to farmers for cotton lint yield were obtained from the National Agricultural Statistics Service (NASS, 2010). The annual K_2O fertilizer cost ($/ha) for elemental K fertilizer was obtained from extracting the price of elemental K from KCl (0-0-60) fertilizer prices containing 27.21 kg K_2O per 45.36 kg fertilizer (UT Extension Budgets, 1989-2009). The cost of elemental potassium was estimated using the formula:

(16) $$\frac{\$}{acre} = \frac{\left({}^{kg\ K}/_{ha}\right)\text{x}\left({}^{\$}/_{ton\ KCl}\right)\text{x}\left({}^{1.2046\ kg\ K_2O}/_{kg\ K}\right)}{\left({}^{0.6\ kg\ K_2O}/_{kg\ KCl}\right)\text{x}\left({}^{907.18\ kg\ KCl}/_{ton\ KCl}\right)}.$$

Nominal prices were converted to constant, real prices using the United States Bureau of Economic Analysis' (BEA) producers' price index (BEA, 2010). Information costs for soil tests were based on the 2007 Precision Farm Dealership Survey conducted by Akridge and Whipker (2007) in which soil sampling with GPS was $15.68/ha.

Simulation Exercise

A Monte Carlo experiment using expected cotton lint yields, soil K carryover, cotton lint prices, and K fertilizer prices was conducted to gain an understanding of how the optimization model performed when prices or yields were uncertain. The net returns a producer could expect

under different soil information scenarios depended on whether or not the producer identifies K carryover using soil tests and subsequently uses that information to apply K fertilizer.

A flow-chart depicting the simulation steps, corresponding variables, and stochastic parameters describes the dynamic programming model used to determine NPV over four information scenarios (Figure 2). Input and output prices affect the optimal amount of potassium to apply each planting season and are also modeled recursively using equation 3 to estimate discounted net returns for each period. Input and output prices in period i affect prices in period $i+1$, and fertilizer K not used in period i is returned as a residual and is available to plants in period $i+1$. The magnitude of soil K carryover therefore influences the optimal amount of K fertilizer a producer needs to apply in each period. Stochastic parameters represented by boxes A, 2A, B, 2B, C, and D, and the random draws for each respective box are based on the distributions described in Table 4. From this procedure, the order and degree of stochastic dominance from the four management scenarios was determined by examining the empirical distributions of the simulated NPVs (Clemen and Reilly, 2004).

Distributions Used in the Simulation

Simulating Stochastic Cotton Lint and K Fertilizer Prices

Over a planning horizon, the real price of cotton lint, the real price of K fertilizer, the amount of cotton lint yield harvested, and the amount of soil K carryover are stochastic. To reflect this uncertainty, distributions based on known expected means and variances were used to render these variables stochastic. Explanations of the stochastic parameters and their corresponding distributions used are summarized in Table 4.

Potassium and cotton lint prices were simulated using a random walk procedure based on the price regression parameters ($\widehat{W}$). For the initial cotton lint price in simulated year 1, each lint price was chosen from a historical distribution (1989-2009) with uniform probability. Thus, each of the 21 cotton lint prices from the 21-year data period had an equal probability of selection as the initial price in year one of the simulated 5-year planning horizon. Cotton lint prices in years two though five were generated using the parameters estimated in the price regression of equation 12. Residuals from the cotton lint regression were randomly generated from a normal distribution according to its expected variance, which made the cotton lint price stochastic. The residual, (u_{t+1}^{C}) was inserted into the lint price model in years 2-5 to incorporate uncertainty about output prices over the planning horizon. An example of how the random walk was simulated using cotton lint prices follows:

Historical lint price sequence: $\underbrace{P_{1989}^{C} \ldots P_{i+1}^{C} \ldots . P_{2009}^{C}}$

Initial Price: P_0^C = initial uniform random draw of one price from the historical sequence

Simulated Price, Period 1: $P_1^C = \widehat{W}_0 + \widehat{W}_1 P_0^C + u_1^C, u_1^C \sim N(0, \sigma_C^2)$

Simulated Price, Period 2: $P_2^C = \widehat{W}_0 + \widehat{W}_1 P_1^C + u_2^C, u_2^C \sim N(0, \sigma_C^2)$

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Simulated Price, Period 4: $P_4^C = \widehat{W}_0 + \widehat{W}_1 P_3^C + u_4^C, u_4^C \sim N(0, \sigma_C^2)$,

where $u_i^C \sim N(0, \sigma_C^2)$ represents a draw from the normal distribution and σ_C^2 is the residual variance from the linear cotton lint price model (eq. 12).

A similar approach was used to simulate potassium prices. A potassium price for the initial year was selected from the historical price distribution with uniform probability. Residuals from the potassium price regression were randomly generated from a normal distribution according to its expected variance, which made the potassium price stochastic. A lognormal distribution was used to randomly generate residuals to be used in the K price equations for years 2-5 because of the functional form used to estimate the price trend. The residual, (u_{t+1}^{K}), was inserted into the potassium price model in years 2-5 to incorporate uncertainty about input prices over the planning horizon. The random walk for K price was simulated as:

Historical K price sequence: $\underbrace{P_{1989}^{K} \ldots . P_{i+1}^{K} \ldots . P_{2009}^{K}}$

Initial Price: P_0^K = initial uniform random draw of one price from historical sequence

Simulated Price, Period 1: $\ln(P_1^K) = \hat{Z}_0 + \hat{Z}_1 P_0^K + u_1^K, u_1^K \sim log\ normal\ (0, \sigma_K^2)$

Simulated Price, Period 2: $\ln\ (P_2^K) = \hat{Z}_0 + \hat{Z}_1 P_1^K + u_2^K, u_2^K \sim\ log\ normal\ (0, \sigma_K^2)$

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Simulated Price, Period 4: $\ln\ (P_4^K) = \hat{Z}_0 + \hat{Z}_1 P_3^K + u_4^K, u_4^K \sim\ log\ normal\ (0, \sigma_K^2)$,

where $u_i^K \sim\ log\ normal\ (0, \sigma_K^2)$ represents the draw of the residual from a lognormal distribution and σ_K^2 is the residual variance from the log-linear potassium price regression model (eq. 13).

Input and output prices also exhibited upward trends in price over the 21 year period model and appeared to be correlated. To reflect this dependence, a Pearson's correlation

coefficient was used to correlate the initial draws of the input (P_0^K) and output (P_0^C) prices, thereby reflecting the historical correspondence between lint and K price trends.

Simulating Stochastic Cotton Yield Response and Soil K Carryover

Lint yield and soil K carryover residuals were incorporated into the yield response model to account for fluctuations in cotton lint yield and residual fertilizer carryover due to weather or other random shocks. Residuals from the respective regressions were bootstrapped, assuming a uniform, equal probability of selection. Explanations of the procedures and distributions used to model the stochastic parameters are summarized in Table 5.

Hypotheses Tested and Experimental Design

Four scenarios were compared to evaluate the optimal application of K fertilizer in the presence or absence of knowledge about soil K carryover (Table 6). The cases examined are designed to reproduce the fertilizer carryover scenarios presented in Kennedy (1986). The four information scenarios are:

(SCENARIO 1) K fertilizer is applied knowing K carryover absent – K carryover is truly absent: In scenario one (S1), the producer has complete information about cotton lint yield response to potassium. The producer purchases soil test information and applies potassium at economically optimal rates. The producer is charged *s* for the soil tests, but soil K carryover is not detected. The producer applies K fertilizer at an economically optimal rate (EORK).

(SCENARIO 2) K applied believing K carryover present – K carryover truly absent: In the second scenario (S2), the producer has complete information about cotton lint yield response to potassium. The producer *does not* purchase soil test information but the producer applies potassium to adjust fertilizer K *as if* residual soil K was significant. In fact the producer should apply potassium at an economically optimal rate as if there were no K carryover.

(SCENARIO 3) K applied believing *NO* K carryover present – K carryover actually present: In the third scenario (S3), the producer has complete information about cotton lint yield response to potassium. The producer *does not* purchase soil test information but applies potassium at the economically optimal rate *as if* fertilizer K carryover does not exist when in fact there is significant carryover potential. The producer applies potassium at an economically optimal rate, but should in fact adjust K rates to reflect residual K available after each growing season.

(SCENARIO 4) K applied knowing K carryover present – K carryover actually present: In the fourth scenario (S4), the producer has complete information about cotton lint yield response to potassium. The producer purchases soil test information and applies potassium at the economically optimal rate. Carryover is significant, the producer knows this with certainty, and adjusts potassium to reflect residual K availability at the beginning of each planting season. The producer pays *s* for the soil carryover information.

Each scenario was examined over a 5-year time horizon under deterministic and stochastic conditions. In the deterministic scenario, there is no uncertainty regarding lint yield, K

carryover, or input and output prices. Prices are constant and yield and carryover residuals are certain. The 2000 prices for cotton lint and potassium were used for input and output prices. Profitability in this case is ex post; the producer knows exactly the yield response of cotton to potassium inputs and can determine the optimal amount of potassium to apply. In non-experimental situations, a producer may not have access to such information, but after the fact determinations may provide insight about applying inputs under varying soil conditions given certainty about crop response.

In the stochastic version of the model, the analysis is ex ante. The NPV outcomes are determined alongside the realizations of the stochastic parameters. Ex ante determinations allow "beforehand" value approximations under differing soil conditions and in efforts to real-world situations.

For both the deterministic and stochastic cases, the value of information about K carryover was calculated as the difference in economic returns generated in each respective state of nature. Thus, the NPV generated under Scenario 4 is compared to Scenario 3 because both application strategies are implemented when K carryover is significant. When K carryover is absent, the loss in realized profits from using soil information to implement the correct K application management strategy can be calculated as the difference in NPVs generated under Scenarios 1 and 2. The difference in economic benefits generated in these scenarios under provides an ex ante estimate of the value of soil test information. It is hypothesized that Scenario 4 will generate higher economic returns than Scenario 3, and Scenario 1 will generate higher returns than Scenario 2. The cumulative distributions of the net present values under the four information scenarios were determined based on the 500 simulations.

Results

Cotton Lint and Potassium Price Regressions

The estimated cotton lint price lag parameter was significant at the 1% level. The cotton lint price model explained 96% of the variation in historical price variation (Figure 5A). The residual variance of the cotton lint price model was $\sigma_C^2 = .003$. The parameter describing how the previous period lint price influenced the next period price was 0.979. This implies that 98% percent of the variation in lint price in the next period can be attributed to the current cotton lint price. The next period lint price is greatly influenced by the current period lint price.

The log linear potassium price model (equation 14) explained 86% of the variation in historical potassium prices. The residual variance of the potassium model was σ_K^2 .919 (Figure 5B). The parameter describing how the previous period potassium influences the next period price was 4.121. The high measures of fit values associated with the price models suggest a strong correlation between lagged and current prices for lint and potassium. The Pearson's correlation coefficient was r = 0.65.

Potassium Carryover Model

The K carryover equation explained about 79% of the variation in residual K carryover. The carryover parameter *h* measures the marginal contribution of total available K in period *i* to the next period K levels. The carryover coefficient was *h* = 0.72 (t-test = 27.97, p-value < .05); 72% of total available K in period *i* carried over to the next period as residual and is available to the plant the following season. This value is between Ackello-Ogutu et al.'s (1985) estimated K carryover parameter of 77% and Tré and Lowenberg-DeBoer's (2005) estimated carryover parameter of 52%.

Cotton Yield Response

The cotton lint yield response models (equation 8) explained 88% of the variation in cotton lint yield in 2001 and 84% of the variation in 2002. The coefficients had the appropriate expected signs, with β_1 being positive (estimate = 5.014, t-test = 5.87, p-value < .05). This positive value indicates a positive linear response of cotton lint yield to potassium fertilizer and that a one kilogram increase in total available K fertilizer will increase lint yields by nearly 5.01 kilograms. The quadratic term, β_2, representing diminishing marginal returns, was negative (estimate = -0.005, t-test = -3.18, p-value < .05) (Table 4). The plateau point for the yield response model was 1530.44 kg/ha. At this point, the marginal value of another pound of K fertilizer is zero; any increase in K would not increase cotton lint yield.

Simulation Results: Expected NPVs

Deterministic Results

Table 7 reports the expected net present value (NPV) for K management under different information scenarios. Scenario 4 resulted in the greatest returns to a producer with returns of $10,556 per ha. This was almost $475 per ha more than under Scenario 3, which resulted in a NPV of $10,080 per ha. When carryover was not present, Scenario 1 resulted in higher returns than for Scenario 2. The NPV under S1 was $10,064 per ha while only $7,208 for S2.

In determining the gain in revenue from using soil K carryover information when residual K carryover was substantial but ignored or unknown, net revenue increased by nearly 4.5% when a producer uses soil information to apply K (Table 7). When fertilizer K carryover was absent, the loss in realized profits from applying K as if residual K carryover was significant (S2)

compared to identifying the absence of residual K fertilizer and applying K appropriately (S1) was over $2,800 per ha (or 28%).

Stochastic Results

NPVs for the stochastic case presented in Table 7 are similar to the deterministic case. The NPV was highest when residual K carryover was significant and fertilizer was adjusted accordingly (S4) at $10,578 per ha, followed by Scenario 3 at $8970 per ha. In S3, K was optimally applied but residual K was unacknowledged when in fact it was present. The expected NPV under Scenario 3 was higher than Scenario 1, in which K was applied optimally but there was no K carryover ($8811 per ha). The difference between S3 and S1 may be attributable to the boost in cotton lint yield from residual K and the corresponding cost savings in applied K. Scenario 2 resulted in the lowest expected NPV for a producer at $7316 per ha. Under Scenarios 1, 3, and 4, a sufficient amount of K was applied to attain the economically optimal lint yield, but Scenario 2 suggests K was under-applied K and cotton lint yields were not optimal. This caused returns to be lower in S2 than the other scenarios.

The value of K carryover information was estimated by the differences in the expected NPVs between management practices under similar states of nature (i.e., when fertilizer K carryover was present or nonexistent). When residual K carryover was substantial but ignored or unknown, net revenue decreased over $1,600 per ha (or 15%) (Table 7). When fertilizer K carryover was absent, the loss in realized profits from applying K as if residual K carryover was significant (S2) compared to a identifying the absence of residual K fertilizer and apply K appropriately (S1) was nearly $1,500 per ha (or 17%).

The empirical distributions of the NPVs for each of the 500 simulations under each scenario are summarized in Figure 6. For S4, nearly all of the Monte Carlo iterations generated net present values above $3,000, while 45% of the iterations in S2 generated a NPV above $3,000. The simulated net present value distributions of Scenarios 1 and 3 were nearly identical. In terms of first-order stochastic dominance for scenarios 1-4, $F_{S3}(NPV) \geq F_{S1}(NPV) \geq F_{S2}(NPV) \geq F_{S4}(NPV)$. The conclusion is clear because the tails of the distributions were not overlapping.

Conclusions

Potassium carryover and cotton lint yield data was collected from experimental research plots over 3 years. A quadratic response plateau function was used to estimate cotton lint yield response to total available K, including residual K from previous seasons. Using a dynamic programming framework, the hypothesis that using soil test information about residual K would increase profits was compared to other cases where K soil test data was nonexistent or ignored. When the producer had full information about yield and K and residual K fertilizer was significant, the NPV over a 5-year planning horizon was highest when application rates were adjusted to reflect soil carryover potential. Hence, a producer using soil test information when residual K fertilizer is significant results in higher economic returns than when soil information was ignored. When carryover was absent, returns were $1,495 per ha (or 15 %) higher when the producer had complete soil test information compared to when carryover was incorrectly accounted for in application decisions. When carryover was significant, returns were $1,609 per ha (or 17%) higher when the producer had complete soil test information compared to when carryover was not correctly accounted for in application decisions

These results suggest in general that proper identification of soil nutrient properties and fertilizer carryover may result in substantially higher expected profits over a multi-period planning horizon. Monitoring the cycle of potassium flow by soil testing over several years could also provide valuable information about potassium carryover potential, which in turn could lower input costs and increase profit over an intermediate planning horizon in cotton production.

While these results suggest that cotton producers should identify nutrient variability to determine optimal K fertilizer policies, the applicability of these results may be limited. Soil conditions are unique to each field, and different soil conditions may preclude soil testing. Furthermore, the managerial capacity of each producer and the way in which soil information is applied to nutrient management may also influence profit. Finally, only 3 years of yield response and soil carryover data were available. While these types of longitudinal trials are expensive, longer trials would provide more information about yield response stability over time. This information could provide a means to testing the statistical robustness of these results.

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Appendix

Table 3. Yield Response, K Carryover, and K Input and Lint Yield Price Equations

Equation	Variable		Description
Potassium Price	P_i^K	Dep. Variable:	K price, current period
	P_{i+1}^K	Ind. Variable:	K price, next period
	Z_0		Intercept coefficient
	Z_1		Slope coefficient
	u_{i+1}^K		Residual
Cotton Price	P_i^C	Dep. Variable:	Cotton price, current period
	P_{i+1}^C	Ind. Variable:	Cotton price, next period
	W_0		Intercept coefficient
	W_1		Slope coefficient
	u_{i+1}^C		Residual
Cotton Lint Yield	$K_i^{TOT} = K_i^{CAR} + K_i^{APP}$		Total K available, *i* = 2001,2002
	$K_i^{TOT^2}$		Total K available squared
	β_0		Intercept
	β_1		Linear response coefficient
	β_2		Quadratic response coefficient
	u_i^{LY}		Residual
K Carryover	$K_i^{TOT} = K_i^{CAR} + K_i^{APP}$		Total K available, *i* = 2000, 2001, 2002
	θ_0		Intercept
	h		Carryover coefficient
	u_{i+1}^{CAR}		Residual

Note: K_i^{CAR} = Fertilizer K Carried Over in period *i*
K_i^{APP} = K Fertilizer Applied in period *i*
Dep. = Dependent
Ind. = Independent

Table 4. Quadratic Yield Response Plateau Parameter Estimates, Carryover Equation Estimates, and Model Fit Statistics

$$\text{Lint Yield: } y_i = \begin{cases} \beta_0 + \beta_1 K_i^{TOT} + \beta_2 K_i^{TOT^2} + u_i^{LY} & \text{if } K_i^{TOT} \leq K_i^{TOT*} \\ K_i^{TOT*} = -\frac{\beta_1}{2\beta_2} & \text{if } K_i^{TOT} > K_i^{TOT*} \end{cases}$$

Year	Adjusted R^2	
2001	0.88	
2002	0.84	
Parameter	**Estimate**	
β_0	133.504	
β_1	5.014	***
β_2	-0.005	***
Maximum yield response (kg/ha)	1530.44	

$$\text{Potassium Carryover: } K_{i+1}^{CAR} = \theta_0 + hK_i^{TOT} + u_{i+1}^{CAR}$$

Year	Adjusted R^2	
2001	0.79	
2002	0.78	
Parameter	**Estimate**	
θ	8.810	
h (carryover coefficient)	0.724	***

$$\text{Cotton Lint Price: } P_{i+1}^{C} = W_0 + W_1 P_i^{C} + u_{i+1}^{C}$$

Parameter	Estimate	
W_0	0.102	
W_1	0.979	***
Adjusted R^2	0.96	
σ_C^2	0.003	

$$\text{Potassium Price: } \ln(P_{i+1}^{K}) = Z_0 + Z_1 P_i^{K} + u_{i+1}^{K}$$

Parameter	Estimate	
Z_0	-2.467	*
Z_1	4.121	***
Adjusted R^2	0.86	
σ_K^2	0.919	

***,**,* represent significance at the 1%, 5%, and 10% level.

Table 5. Identification and Explanations of Stochastic Parameters used in the Dynamic Programming Simulation

Variable	Description	Distribution	Comment
	Random Draw A		
P_0^K	Potassium Price in First Period of Simulation	Discrete Uniform corr (P_0^K, P_0^C)	Year 1 K price drawn from empirical distribution of K prices, 1989-2009, correlated with lint yield price
P_{i+1}^K(given P_i^K)	K Price in Periods 2-5		K prices in years 2-5 based on linear regression model
	Random Generator 2A		and
u_{i+1}^K	Residual of K Price	Log normal(0,σ_K^2)	Residual generated from the log normal distribution
	Random Draw B		
P_0^C	Cotton Lint Yield Price in First Period of Simulation	Discrete Uniform corr (P_0^K, P_0^C)	Year 1 cotton lint price drawn from empirical distribution of cotton prices, 1989 – 2009, correlated with K price
P_{i+1}^C(given P_i^C)	Cotton Lint Yield Price in Periods 2-5		Cotton lint prices in years 2-5 based on exponential price model
	Random Generator 2B		and
u_{i+1}^C	Residual of Cotton Lint Yield Price	N(0,σ_C^2)	Residual generated from the normal distribution
	Random Draw C		
u_i^{CY}	Lint Yield Residual	Discrete uniform bootstrap	Yield residual drawn from a discrete uniform distribution and added to lint yield equation in each simulated year
	Random Draw D		
u_{i+1}^{CAR}	K Carryover Residual	Discrete uniform bootstrap	Carryover residual drawn from discrete uniform distribution and added to carryover equation in each simulated year

Note: See Figure 2 for supplemental information

Table 6. Information Management Scenarios, Descriptions of Soil States of Nature, and Producer Behavior

	Producer Knows Lint Yield Response	Producer Purchases Soil Test Information	K Carryover Present	Producer Believes K Carryover Present	Producer Applies K in Conjunction with Soil Test Results
Scenario 1	√	√			√
Scenario 2	√			√	
Scenario 3	√		√		
Scenario 4	√	√	√	√	√

Table 7. Comparison of NPV for Economically Optimal Input K Management Strategies with Single-Period Carryover and No Carryover States of Nature

Deterministic

	S1: EORK with no soil K carryover				S3: EORK, K carryover exists, but ignored			
Period	K^{TOT*} (kg/ha)	K^{APP} (kg/ha)	C.O. (kg/ha)	Profit ($/ha)	K^{TOT*} (kg/ha)	K^{APP} (kg/ha)	C.O. (kg/ha)	Profit ($/ha)
1	562.15	562.15	0	2213.86	578.14	562.15	211.07	2217.52
2	562.15	562.15	0	2108.44	578.14	562.15	507.91	2111.92
3	562.15	562.15	0	2008.04	578.14	562.15	699.50	2011.35
4	562.15	562.15	0	1912.42	578.14	562.15	823.16	1915.58
5	562.15	562.15	0	1821.35	578.14	562.15	902.98	1824.36
			NPV	10064.13			NPV	10080.75
	S2: EORK adjusted as if K soil carryover exists, but K carryover does in fact not exist				S4: EORK adjusted for K carryover when K carryover is significant			
1	578.14	578.14	0	2212.24	562.14	351.07	211.07	2283.52
2	578.14	215.30	0	1382.01	578.14	206.47	371.67	2223.71
3	578.14	215.30	0	1316.20	578.14	196.14	381.99	2120.90
4	578.14	215.30	0	1253.52	578.14	196.14	381.99	2019.91
5	578.14	180.15	0	1060.18	578.14	196.14	381.99	1923.72
			NPV	7208.49			NPV	10556.10

Stochastic

NPV for S1			NPV for S3		
NPV	8811.68	$\pm$ 1479.2	NPV	8970.64	$\pm$ 1461.42

NPV for S2			NPV for S4		
NPV	7316.48	$\pm$ 1189.68	NPV	10579.88	$\pm$ 1522.26

Note: C.O stands for carryover
Tables 2 and 3 refer to this simulation
EORK = Economically Optimal Potassium Rate

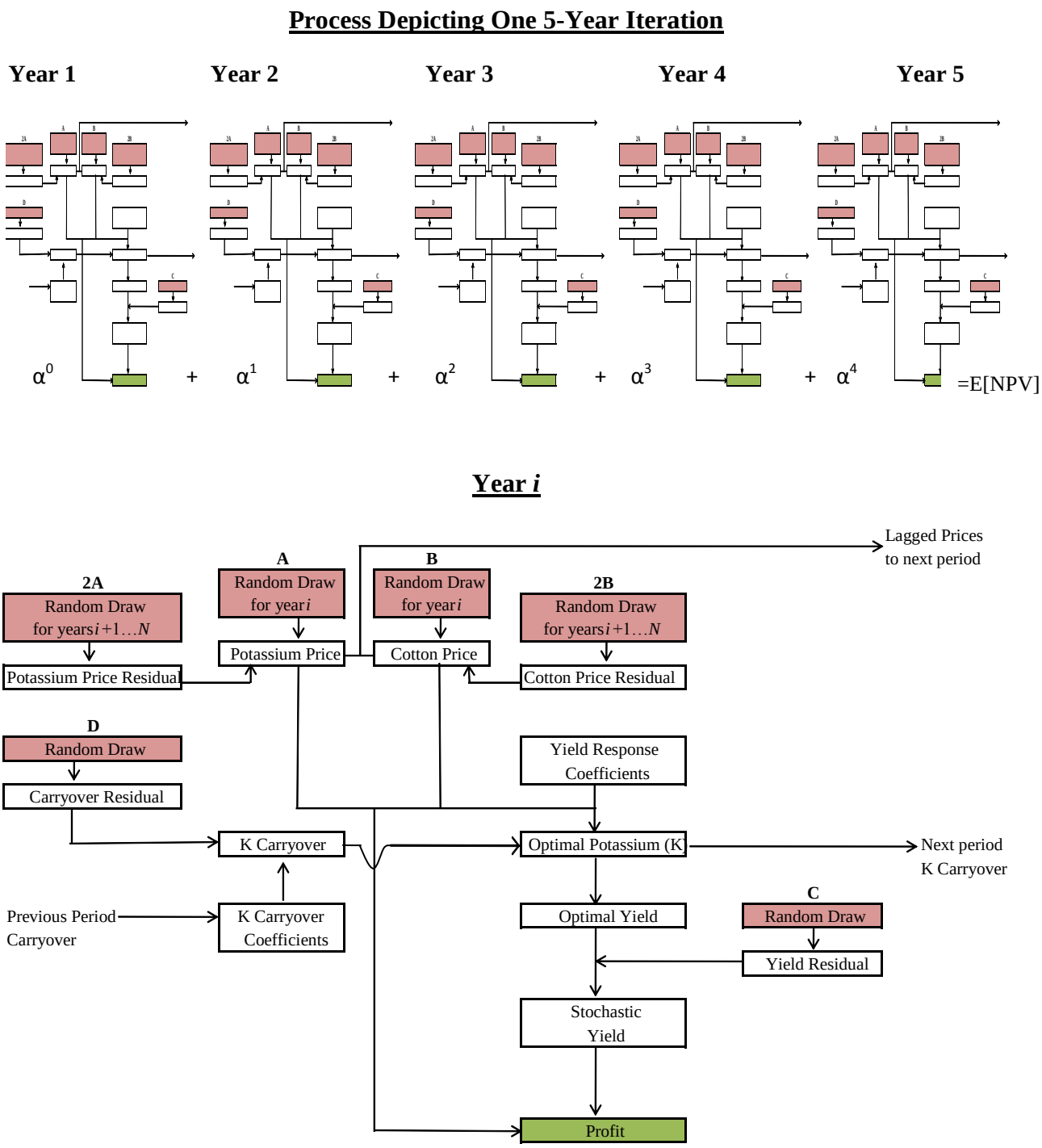
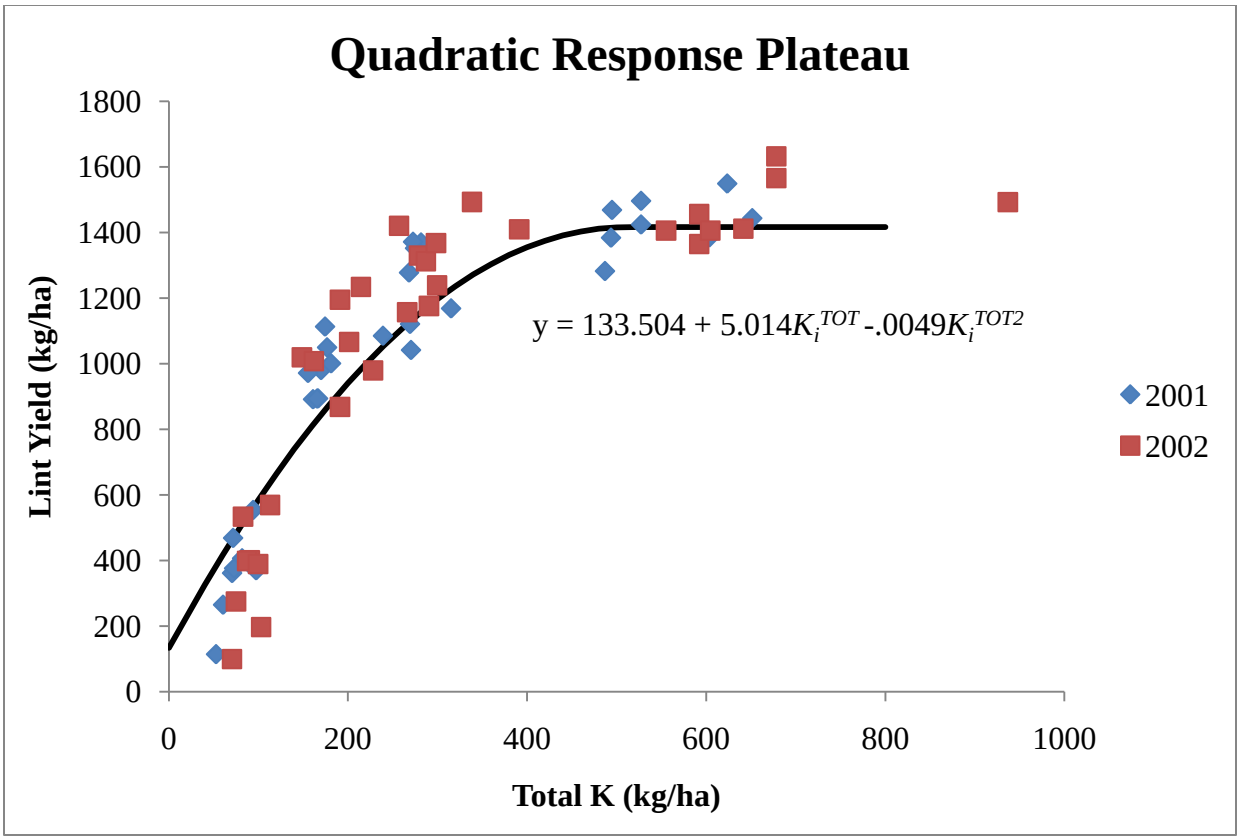


Figure 2. Flow Chart of Dynamic Programming Model with Stochastic Parameters



K^{TOT*}= 511.63 kg/ha
y^*= 1416.16 kg/ha

Figure 3. Total Potassium Available and Cotton Quadratic Plateau Yield Response Curves for Ames Plantation TN, 2000-2002

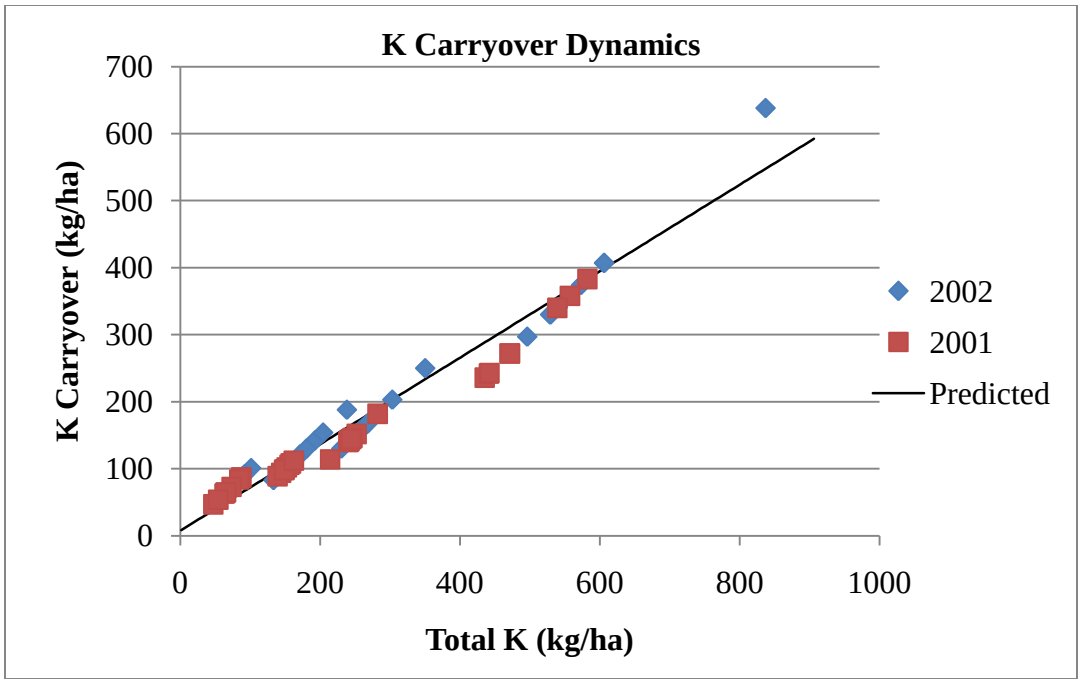


Figure 4. Carryover Dynamics (kg/ha) to Total K (kg/ha) (2001, 2002)

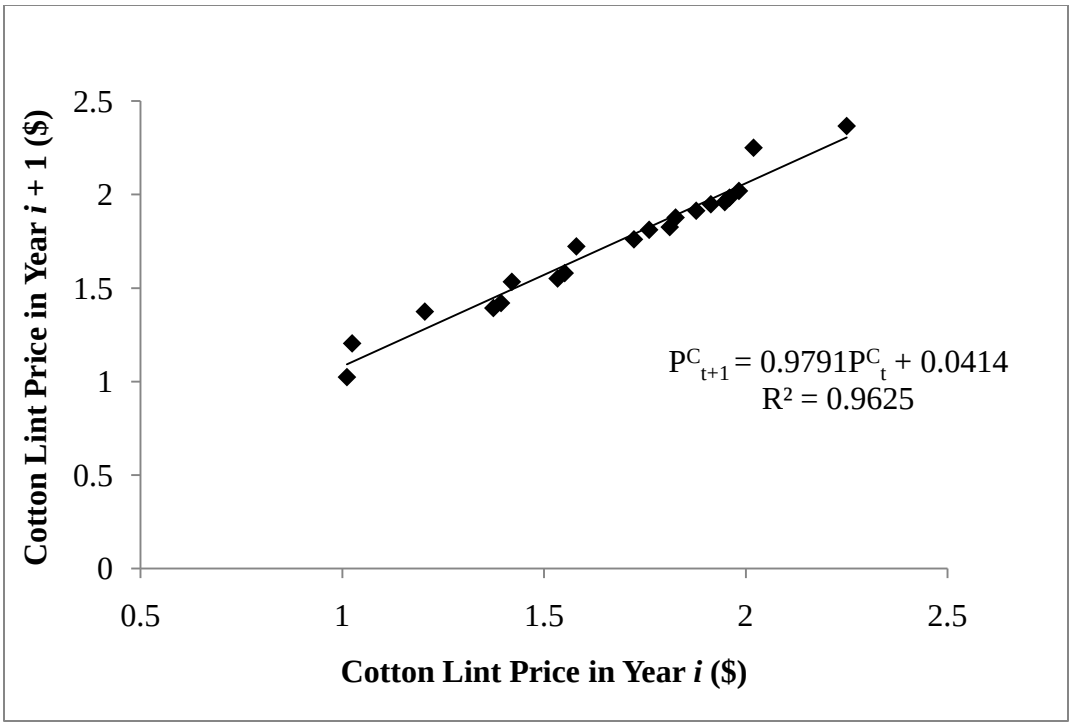


Figure 5A. Cotton Lint Yield Lagged Price Model

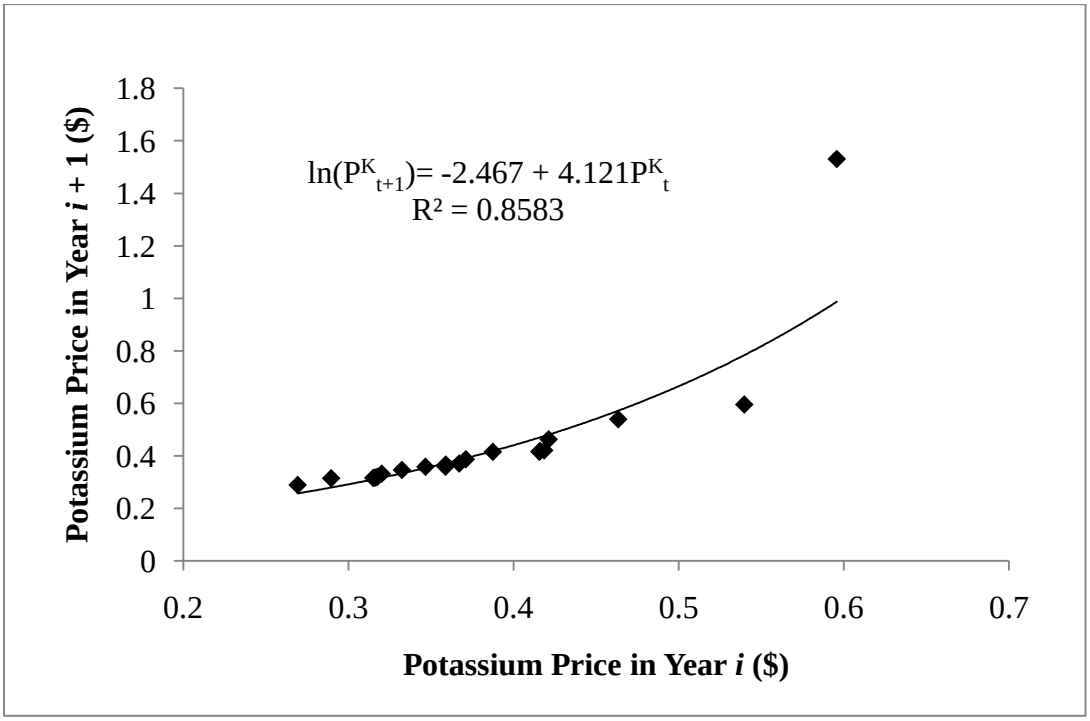
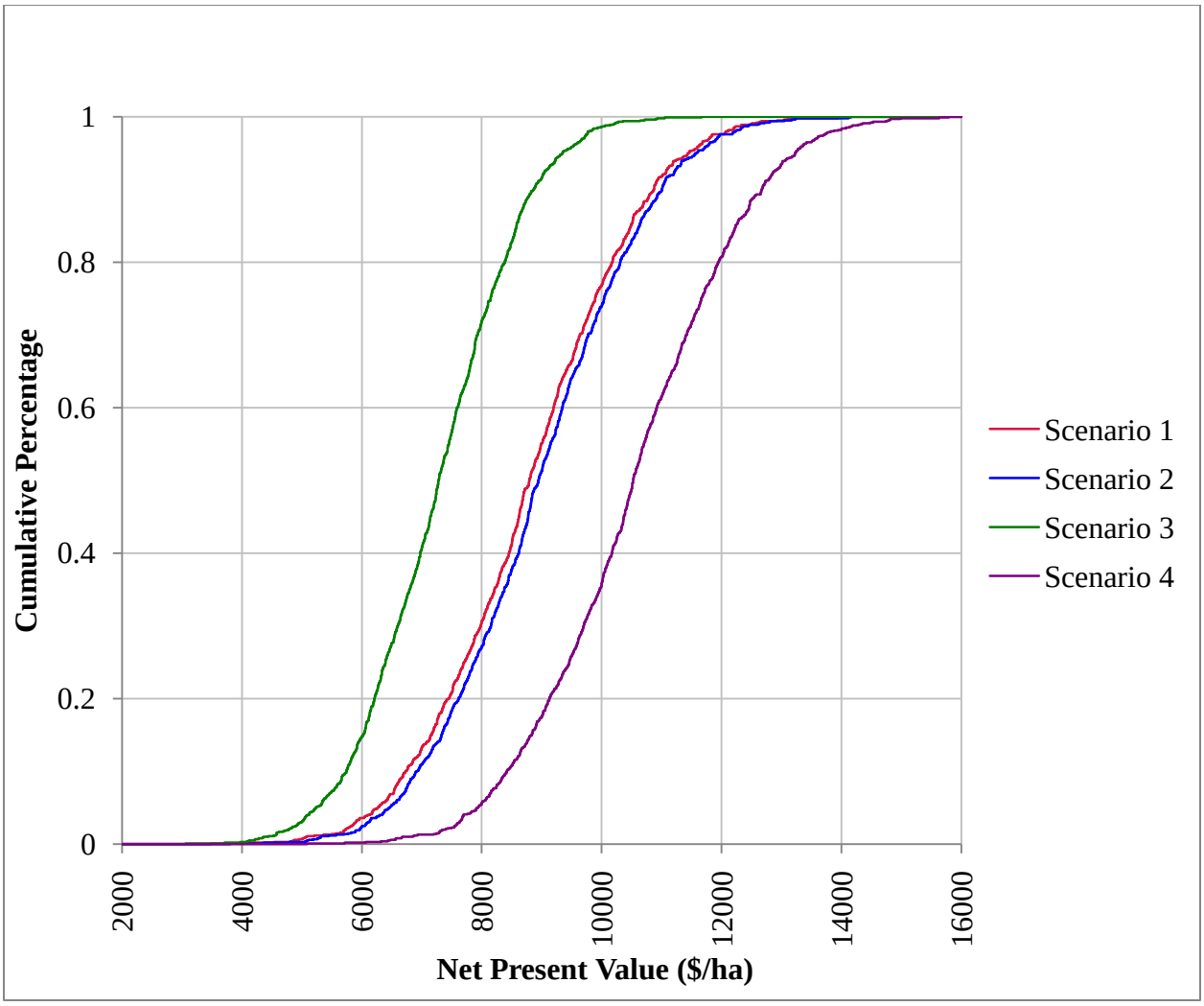


Figure 5B. Potassium Lagged Price Model



Notes: S1 = E(NPV) ($ /ha) = 8811.67 ± 1479.23 (std. deviation)
S2 = E(NPV) = 7316.49 ± 1189.68
S3 = E(NPV) = 8970.64 ± 1461.42
S4 = E(NPV) = 10583.82 ± 1522.26

Figure 6. Cumulative Distributions of Net Present Value Totals under Alternative Management Scenarios and Soil Conditions, Average

IV. Summary and Conclusions

This these focused on the adoption and usefulness of precision soil sampling in cotton production and the value soil sampling information provides in determining optimal potassium application under alternative information scenarios. In examining the adoption and re-testing decision of cotton producers in regards to precision soil sampling information, the use of a consultant to apply inputs, the generation of a yield map using a yield monitor, the use of electroconductivity devices, and operators obtaining information from trade shows were positively associated with soil sampling adoption. Subsequently, of those farmers who did adopt soil testing, land tenure, farmer experience, the use of electricalconductivity devices, and Greenseeker® technology increased the number of years between soil testing. These results suggest that producers already using technologies which complement PSS may be more apt and likely to adopt PSS technology. Additionally, there appears to be some degree of substitution between the information acquired from precision soil testing and the information generated from other sensor-based technologies, resulting in longer periods between soil testing.

In the second study, the hypothesis that using soil test information about residual K would increase profits was compared to other cases where K soil test data was nonexistent or ignored. When the producer had full information about cotton yield response to K and K carryover was significant, the NPV over a 5-year planning horizon was highest when application rates were adjusted to reflect carryover potential. Hence, a producer using soil test information when residual K fertilizer is significant would enjoy higher economic returns than when this information was ignored. When K carryover was absent, returns were 15 % higher when the producer had complete soil test information compared to when carryover was incorrectly accounted for in application decisions.

These results suggest in general that proper identification of soil nutrient properties and soil K carryover may result in substantially higher expected profits over a multi-period planning horizon. Monitoring the cycle of potassium flow by soil testing over several years could provide valuable information about potassium carryover potential, which in turn could lower input costs and increase profit over an intermediate planning horizon in cotton production.

Vita

David Harper was born in Nashville, Tennessee to Marion and Nancy Harper. He currently holds a B.S. in Environmental Economics and Management from the University of Georgia, in Athens, GA. He obtained an M.S. degree in Agricultural Economics from the University of Tennessee in Knoxville, Tennessee in May 2011. He would like to thank his family, friends, and professors for their continued help and support in completing his degree.