Effects of Optical Sensing and Variable Rate Technology on Nitrogen Fertilizer Use, Lint Yields, and Profitability in Cotton Production

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ABSTRACT

Nitrogen (N) fertilizer is expensive and can be harmful to the environment. Precision agriculture (PA) has the capability to reduce the amount of excess N from crop production released into the environment, increase net returns to the grower, and reduce the risk of profit loss due to spatial and temporal variability. The objectives of this study were to evaluate the profitability, risk management potential, and N use efficiency of using real-time optical sensing with variable-rate technologies (VRT) to manage spatial variability in cotton production. Data collected from 29 field trials in Tennessee, Louisiana, Mississippi, and Missouri from 2011 to 2014 included lint yields harvested and N rates calculated from three N rate management strategies. The first N treatment was the existing farmer practice (FP), the second was a VRT treatment using optical sensing technology Greenseeker™, and the third was a VRT treatment using Greenseeker™ and yield monitor information. The two PA strategies were compared to the existing farmer practice. In addition, soil properties and weather were examined to determine their effects on lint yields, net returns, N rates, and N use efficiency.

Three methods used in this study each include an analysis of lint yields, N rates, net returns, and N use efficiency. The first model was an analysis of variance (ANOVA) to identify treatment mean differences. The second model was an ANOVA that measured soil and weather effects on mean differences between technology and FP. The third model was a logistic analysis to test for risk of a loss using VRT. Results indicated differences in technology net returns versus the FP and no differences between VRT and FP in yields, N rates, or N use efficiency. Warmer temperatures were negatively associated and a greater percentage of organic matter had positive associations with VRT net returns and N use efficiency relative to FP. Profit risk management benefits were identified using Greenseeker™ versus the FP. Results can be used by Extension

offices and cotton farmers in Tennessee, Mississippi, Louisiana, and Missouri to determine if adopting optical sensing and VRT would be beneficial to their operations.

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CHAPTER I: INTRODUCTION AND PROBLEM IDENTIFICATION

Fertilizer nitrogen (N) is an expensive and important input in the production of crops such as upland cotton (*Gossypium hirsutum* L.). The United States Department of Agriculture (USDA) estimated that farmers spent $7.2 billion on anhydrous ammonia and N solutions in 2011 (USDA 2013). Crop nutrient N consumption more than doubled, from 6.0 million to 13.7 million short tons, from 1967 to 2007 in the United States (USDA 2013). The increased use of N fertilizer has raised concerns about potential environmental damages due to the many ways N can be dispersed into the surrounding environment. N is unstable after it is applied (Raun and Johnson 1999) and can be lost into the environment through gaseous emissions, leaching, runoff, and soil denitrification (Peng et al. 2006). Waterways such as the Mississippi River and the Chesapeake Bay have experienced changes in water quality due to increased fertilizer use (Turner and Rabalais 1991; Roberts and Prince 2010).

Farmers have no easy way of containing the excess lost N but can apply the fertilizer more efficiently to limit N released to the environment. Conventional rates of fertilizer N used by growers were developed in small individual fields with little spatial variability (Isik and Khanna 2003). Uniform N rates were applied across entire fields that likely have variability in soils and other field factors that will result in sections of the field having more and less N fertilizer available to the crop than is necessary to maximize yields or profits (i.e., over- and under-application) (Scharf et al. 2005; Scharf et al. 2011; Vetsch et al. 1995; Isik and Khanna 2003). Over- and under-application can increase excess N released into the environment and decrease crop yield compared with economically optimal rates and, in turn, reduce profits (Lambert, Lowenberg-DeBoer, and Malzer 2006). With precision agriculture (PA) technology, defined by the National Research Council (1997) as “a management strategy that uses information

technologies to bring data from multiple sources to bear on decisions associated with crop production (p. 17)," growers can utilize several technologies to better manage N fertilizer application. For example, switching from N application using a uniform rate technology (URT) to a variable rate technology (VRT) in an attempt to reach the optimal application rate by varying the rate based on variable field factors (Sawyer 1994), and can reduce the amount of wasted N, costs, labor (Raun et al. 2002; Tubaña et al. 2008), excess N pollution that collects in the groundwater (Biermacher et al. 2009b; Raun and Johnson 1999; Roberts et al. 2002; Watkins, Lu, and Huang 1998), and runoff that contributes to water pollution (Larkin et al. 2005; Raun and Johnson 1999; Scharf et al. 2005; Isik and Khanna 2003).

Yields and net returns can also be affected by the anomalous factors such that rainfall and temperature cause yields to rise or fall below the same field's potential (Bullock and Bullock 1994; Isik and Khanna 2003; Elms, Green, and Johnson 2001; Carr et al. 1991; Vetsch et al. 1995; Wibawa et al. 1993). Zhang, Wang, and Wang (2002) categorized these types of spatial and temporal variability factors that influence the economic and environmental performance of PA into: 1) yield variability, such as historical and present distribution, 2) field variability, such as topography, 3) soil variability, such as nutrients in the soil, density, and moisture, 4) crop variability, such as plant density, height, and nutrient stress, 5) anomalous factors, such as weed, insect, and disease infestation and wind damage, and 6) management, such as tillage, crop rotation, and fertilizer application.

The risk of yield losses due to spatial or temporal variability in the aforementioned factors can theoretically be managed using PA. PA has the potential to create a more homogenous growing environment within the farm field, thus promoting increases in yields and net returns in problem areas in the field and reductions in production risk (Lowenberg-DeBoer

and Swinton 1997; Lowenberg-DeBoer 1999; Larson, English, and Roberts 2002). However, the adoption of PA is not without risk. The possibility of yield and net return losses due to human implementation or interpretation error and the risk of technology obsolescence have the potential to dissuade growers from adopting VRT (Lowenberg-DeBoer 1999).

Studies around the world have indicated risk management and environmental benefits and have shown mixed results in terms of profitability from the adoption of PA. There is, however, a lack of information in cotton production utilizing real-time optical sensing technologies and VRT N fertilization application in the Mississippi River Basin (MRB) states (Tennessee, Louisiana, Mississippi, and Missouri), and whether these technologies can reduce losses of N to the environment. The need for a cotton N utilization study using PA technologies in the MRB area was identified through surveys among producers in twelve southern states (Mooney et al. 2010). If growers had access to information/studies specific to the MRB region, they could make more informed decisions about adoption of real-time optical sensing and VRT in N fertilization with regard to soil types, reduced fertilizer costs, increased profitability, increased labor/application efficiency, and decreased excess N reaching groundwater (Biermacher et al. 2009b).

Policy makers, crop insurance companies, and technology manufacturers can also use economic information about PA technology to assist producers. Policy makers would have the resources to create incentive programs for farmers to adopt site-specific technologies like VRT. Externalities can be examined to determine a program that would either reduce N by charging a tax of sorts on excess fertilizer use or incentivize growers to adopt VRT with a subsidy for the technology (Larkin et al. 2005; Roberts et al. 2002; Zhang, Wang, and Wang 2002). This information is useful for crop insurance companies because they could potentially provide lower

rates to those who adopt a site-specific technology (Lowenberg-DeBoer 1999). Technology manufacturers could better pinpoint a target cost for the technology for the end consumer (Biermacher et al. 2009a).

Research Objectives

The objectives of this research are: 1) to evaluate the profitability and risk management potential of using real-time optical sensing and variable-rate application technologies to manage spatial variability in cotton fields in the MRB states (Tennessee, Louisiana, Mississippi, and Missouri), and 2) to assess how real-time optical sensing and VRT affect N use and N production use efficiency in cotton production.

CHAPTER II: LITERATURE REVIEW

Managing N using PA technologies has the potential to affect profits, N losses to the environment, and risk in cotton production. The pertinent literature has progressed over time along with the technology. Early literature begins with simulation analysis (Roberts et al. 2002; Watkins, Lu, and Huang 1998). Later studies analyze the impacts of VRT (N, phosphorus, and lime) compared to URT in crop production using experiments and farm field trial data (Bongiovanni and Lowenberg-DeBoer 2000; Hu et al. 2007; Lambert, Lowenberg-DeBoer, and Bongiovanni 2004; Lambert, Lowenberg-DeBoer, and Malzer 2006; Maine et al. 2010; Maine et al. 2007; Peng et al. 2006; Wang et al. 2003). The most recent literature involves optical sensing with VRT on wheat (*Triticum aestivum* L.) and corn (*Zea mays* L.) in experiments and farm field trials (Biermacher et al. 2006; Biermacher et al. 2009b; Butchee, May, and Arnall 2011; Ortiz-Monasterio and Raun 2007; Raun et al. 2002; Raun et al. 2005; Scharf et al. 2011). Literature examining the potential risk management benefits of VRT include Lowenberg-DeBoer (1999), Isik and Khanna (2003), and Larson, Roberts, and English (2002). A literature summary is in Appendix Table 1 (all Figures and Tables are in the Appendix section and will be referred to by Figure or Table number here on out).

Early literature used simulation to estimate the economic and environmental benefits from VRT. These studies are useful but simulation models may not be as accurate as assessing data from field experiments because they may underestimate the variability within a field (Swinton and Lowenberg-DeBoer 1998). Watkins, Lu, and Huang (1998) and Roberts et al. (2002) used the Environmental Policy Integrated Climate (EPIC) model, a daily time step crop and soil simulation model, to simulate crop yields and soil processes including soil water

balances, nutrient runoff, and so forth. Both studies realized the positive environmental impact of adopting VRT N application but neither found economic benefits.

Watkins, Lu, and Huang (1998) evaluated the profitability and environmental externalities of VRT N application versus URT. Results of the EPIC model indicated URT application was more profitable than VRT application and N losses were roughly the same for both application technologies. The most economic and environmentally beneficial method of N application was to split the applications between pre-plant N and post-plant N during the growing season. This split application approach generated larger profits and reduced N loss for both VRT and URT applications. URT application, however, realized profits slightly higher than VRT (increases of \$2 ha^{-1} and \$1 ha^{-1}, respectively).

Similar to Watkins, Lu, and Huang (1998), Roberts et al. (2002) simulated the profitability and environmental effects of VRT N application versus URT in corn production using the EPIC model. Incorporating three weather scenarios and three West Tennessee soil types (Collins, Memphis, and Loring), VRT N application resulted in a reduction in N loss in comparison with URT application. The difference in spatial variability between fields changed how profitable VRT was in corn production. Smaller amounts of spatial variability within a field reduced the profitability of VRT.

Later studies were based on experimental data conducted on rice (*Oryza sativa* L.) (Hu et al. 2007; Peng et al. 2006), corn (Lambert, Lowenberg-DeBoer, and Bongiovanni 2004; Maine et al. 2010; Wang et al. 2003), and wheat (Biermacher et al. 2006; Biermacher et al. 2009b; Raun et al. 2002; Raun et al. 2005). Hu et al. (2007) and Peng et al. (2006) evaluated the potential for improving N efficiency through site specific management technologies. Peng et al. (2006) and Hu et al. (2007) used experimental data on irrigated rice in four Chinese provinces to compare

current farming practices with alternative N management systems. Peng et al. (2006) compared current practices with two site specific management systems; real-time N management and fixed-time adjustable-dose N management. Nitrogen use efficiency (NUE) was found in this case by using an N-omission plot. Results indicated site specific N management systems reduced N applied, increased NUE (in some cases doubled NUE), and produced similar or higher yields than current farming practices. Hu et al. (2007) had similar findings using three N application management techniques: current N practices, site specific management, and a modified site specific management plan. The average N use for site specific management was 48 kilograms per hectare (kg ha^{-1}) less N than current management practices and 23 kg ha^{-1} less with modified management when compared to current practices. Further examination indicated increased profits of \$82 ha^{-1} to site specific management and \$63 ha^{-1} for modified management without reducing yields. Peng et al. (2006) and Hu et al. (2007) found that NUE increased by reducing the N rate applied without reducing yields.

Literature regarding VRT application to corn is more readily available due to the large amount of corn grown in the United States and more extensive N use when compared to other crops (U.S. Department of Agriculture 2013). Before 2000, 64% of studies on PA profitability found that PA provided economic benefits though there was a wide range of results (Lambert and Lowenerg-DeBoer 2000). The recent studies on corn have suggested some profitability compared to a whole-field management system. Lambert, Lowenberg-DeBoer, and Bongiovanni (2004), Wang et al. (2003), and Maine et al. (2010) examined the economic benefits of adopting VRT in corn production. Lambert, Lowenberg-DeBoer, and Bongiovanni (2004) did an economic analysis of VRT in corn response to N by comparing four spatial regression methods on data from an experiment conducted in 1999 in Córdoba Province, Argentina. While the

assumptions for the four methods were different, the results were similar and indicated that including a spatial component allowed site-specific patterns to be identified. Net returns to N use were found to be \$1 to \$2 ha^{-1} more profitable compared to URT when spatial components were included in the analysis. Lambert, Lowenberg-DeBoer, and Malzer (2006) did a spatial analysis on yield response to VRT using N and/or phosphorus on a 5 year corn-soybean rotation in Windom, Minnesota. In terms of temporal stability, results specified that corn and soybean response to P were not stable in some areas but were in others and crop response to N indicated no stability. In terms of profitability, an ex post analysis resulted in average returns to VRT (including both N and phosphorus) were \$28 ha^{-1} more profitable than the URT management system.

Wang et al. (2003) found profitability and environmental benefits through VRT N application versus two different URT N applications. Data from four claypan soil fields in Missouri were analyzed through a combination of field measurements and simulation. VRT was more profitable in all fields with respect to the URT application based on soil depth and two of the four fields with respect to a second URT application based on prior N rate knowledge. VRT was overall more beneficial in terms of water quality (less potentially leachable N) than in either URT.

Bongiovanni and Lowenberg-DeBoer (2000) estimated the profitability of VRT lime application to corn and soybean production in 18 sites spanning the Eastern and Midwestern United States and one in Canada. Two site-specific management strategies and one intermediate strategy were used to apply lime to compare the profitability of these strategies. The first strategy used the recommended rate rule after soil sampling and increased average annual returns by \$7.24 ha^{-1}, 1.78 percent (%). The second strategy used a decision-rule, the rate that

maximized net present value, and increased average annual returns by \$19.55 ha^{-1} (4.82%). The information technology strategy used site-specific information to determine the most optimal URT application rate of lime and resulted in increased average annual returns by \$14.38 ha^{-1} (3.54%). All three strategies employed at least some PA technologies, two of which use VRT, and realized increased profits.

VRT phosphorus and N fertilizer applications on corn production in South Africa indicated profitability over conventional methods (Maine et al. 2007; Maine et al. 2010). Maine et al. (2007) analyzed the profitability of VRT phosphorous application. Response functions estimated using spatial analysis indicated varying yield responses between management areas. When applying phosphorus at the profit-maximizing VRT rates, yields were the highest at 8.06 metric tons ha^{-1} and profits were \$633.08 ha^{-1}, \$45.30 higher than URT. URT applications generated higher average yields than VRT, but VRT resulted in higher unweighted profits relative to URT treatments. Maine et al. (2010) utilized ordinary least squares regression and spatial autoregressive methods to analyze VRT N fertilizer application in comparison with URT N application. Overall, VRT was found to be more profitable than URT. A year-by-year comparison was not always the same as some years actually showed more profitability for URT.

The most recent literature includes optical plant sensing of the crop canopy in the examination of economic and environmental benefits to PA. Sensor based technology, including GreenSeeker™, was utilized to analyze the profitability and measure NUE of precision N application to wheat and corn (Biermacher et al. 2006; Biermacher et al. 2009b; Butchee, May, and Arnall 2011; Ortiz-Monasterio and Raun 2007; Raun et al. 2002; Raun et al. 2005; Scharf et al. 2011). Scarf et al. (2011) assessed sensor based, VRT N application versus current farmer uniform N rates in corn production in Missouri. Over four years, 55 replications were conducted

to determine the profitability of PA. VRT N fertilizer applications increased yields by 110 kg ha^{-1} and reduced N by 15 kg ha^{-1}, increasing partial profits (value of corn grain minus cost of N applied) by \$42 ha^{-1} over producer chosen uniform N rates.

Four Oklahoma based studies found profitability and/or NUE benefits of sensor based technology in wheat production (Biermacher et al. 2006; Biermacher et al. 2009b; Raun et al. 2002; Raun et al. 2005). Raun et al. (2002) analyzed optical sensing and VRT in Oklahoma winter wheat production. The study examined four winter wheat experiments that compared these technologies with URT. The NUE, defined here as yield times total N divided by the N application rate, on average increased by more than 15% when comparing VRT to URT. They found extra income due to efficiency to cover the expected costs of the technology (\$4.00 to \$5.00 ha^{-1}) and that optical sensing would be most beneficial in areas of high spatial variability. Raun et al. (2005) found N reductions as well, measuring an increase of 15% in NUE via the adoption of optical sensing.

Biermacher et al. (2006) assessed over 30 years of data from two sites in Oklahoma that estimated net returns of adopting sensor based precision agriculture in wheat production. Overall, the two sites showed average profitability of \$21.80 to \$24.30 ha^{-1} over conventional practices and reduced pre-plant N by 59% to 82%. In another study, Biermacher et al. (2009b) evaluated data from an experiment that took place in seven Oklahoma locations across nine years. Results from the yield response to N showed that the perfect information system (a variable-rate system of N fertilization based on real-time sensing and an optimization algorithm) generated \$16 ha^{-1} more and the uniform topdress-sensed system returned \$9 more ha^{-1}, respectively, in comparison with conventional practices. Increasing prices for N and wheat caused the potential advantage of

precision farming to nearly double. The Oklahoma experiments demonstrated increased economic and environmental benefits from optical sensing and VRT.

Ortiz-Monasterio and Raun (2007) and Butchee, May, and Arnall (2011) assessed N application efficiency in wheat utilizing N-rich strips with GreenSeeker™ sensing technology. In Yaqui Valley, Mexico, validation experiments were conducted that led to eight field trial experiments comparing VRT to conventional practices (Ortiz-Monasterio and Raun 2007). The validation trials indicated an average savings of 69 kg ha^{-1} of N without a reduction in wheat yields. Across all field trials, optical sensing technologies increased average profitability by $56 ha^{-1}. Butchee, May, and Arnall (2011) utilized the same technologies to assess the NUE compared to farmer practice (FP) in Oklahoma. On average, using the sensor based calculator to apply N produced similar wheat yields but reduced N by 22 kg ha^{-1} compared to current FPs. Optical sensing technologies increased NUE and provided environmental benefits in both of the aforementioned studies.

PA has the potential to apply N more efficiently and to reduce production risk by creating a more homogenous growing environment within the farm field (Lowenberg-DeBoer and Swinton 1997; Lowenberg-DeBoer 1999; Larson, English, and Roberts 2002). Several articles have assessed the risk management benefits to farmers of PA. Lowenberg-DeBoer (1999) examined data from on-farm trials in Indiana, Ohio, and Michigan from 1993 to 1995 on either corn-soybean or corn-soybean-wheat crop rotations. He found that there are risk management benefits of using VRT application of phosphorus and potassium through a reduction in the probability of low net returns. A comparison of the distributions of net returns indicated that VRT application of phosphorus and potassium based upon soil type was not preferred to uniform application of fertilizer across the field using first degree stochastic dominance criterion.

However, VRT application of fertilizer would be preferred by risk-averse farmers according to the mean-variance decision rule.

Isik and Khanna (2003) examined the uncertainties of weather and soil types in relation to production and the adoption of PA. Uncertainty may prevent a risk-averse farmer from adopting PA and thereby reducing excess N lost to the environment. Subsidy programs, however, may incentivize growers to adopt the technology. Results from the survey conducted in the Otter-Lake watershed of Illinois indicated that increased N and phosphorus decreased the yield variability, making them risk-decreasing production inputs.

A simulation modeling study of VRT N application using soil management zones for three Tennessee soil types was conducted by Larson, English, and Roberts (2002). They found that VRT could provide risk management benefits on corn fields with large spatial variability. From an environmental standpoint, however, URT would be preferred by farmers who are risk averse. The whole field fertilizer application reduced N rates more than with VRT and, thus, reduced N lost to the environment more than VRT.

Based on the existing literature, VRT profitability results and risk management benefits compared to URT or FP are mixed and involve N, phosphorus, and/or lime fertilizer on corn, wheat, or rice production. There is a lack of information in optical sensing and VRT N management strategy comparisons in cotton production. This study will add information to the discipline regarding the profitability and risk management benefits of using VRT and optical sensing compared to FP in cotton production in the MRB states.

CHAPTER III: CONCEPTUAL FRAMEWORK

Treatment Effect

Net Returns

A risk-neutral, profit-maximizing producer will adopt VRT N application if the profitability of VRT is greater than the profitability of the current FP N application. The typical FP is to apply the same rate of N across the farm field. The profitability of VRT involves tradeoffs among: 1) cost of information, 2) cost of VRT application, 3) changes in yield, and 4) changes in N use (Biermacher et al. 2009a; Lowenberg-DeBoer 1999). In addition, site-specific factors, such as soil variability within fields and weather can influence the producer's decisions of how much N to apply and whether to use a new technology (Bullock and Bullock 1994; Isik and Khanna 2003; Lowenberg-DeBoer 1999; Whelan and McBratney 2000; Zhang, Wang, and Wang 2002).

The profit equations for FP N application and VRT N application include the tradeoff between the factors listed above. The profit equation for FP N application decision for cotton is:

$$NR_{FP} = P \times Y_{FP} - r^{B}N_{FP}^{B} - r^{T}N_{FP}^{T} - IAC_{FP} - OCP, \quad (1)$$

where *NR* is cotton net returns (\$ ha^{-1}), *P* is cotton lint price (\$ kg^{-1}), *Y* is cotton lint yield (kg ha^{-1}), r^{B} is the pre-plant N price (\$ kg^{-1}), N^{B} is the pre-plant N fertilization rate (kg ha^{-1}), r^{T} is the top (or side) dress N price (\$ kg^{-1}), N^{T} is the top (or side) dress N fertilization rate (kg ha^{-1}), *IAC* is the information and application cost used in the FP N fertilization process (\$ ha^{-1}) including labor and equipment, and *OCP* represents the other costs of cotton production (\$ ha^{-1}) that do not change across N application technologies.

The producer's profit equation for the VRT N application decision for cotton is:

$$NR_{VRT} = P \times Y_{VRT} + IP_{VRT} - r^B N_{VRT}^B - r^T N_{VRT}^T - IAC_{VRT} - OCP,$$

(2)

where *IP* is an incentive payment received from a government agency, such as the USDA Natural Resource Conservation Service (NRCS) Environmental Quality Incentives Program (EQIP)[1], to adopt VRT, and information costs (*IC*) include the ownership and labor costs of VRT. USDA (NRCS) and the Environmental Protection Agency are interested in reducing the amount of N applied by incentivizing the adoption of conservation practices such as VRT N application (USDA 2014b). Considering the incentive payments in net returns allows the effectiveness of these incentives in adoption of VRT N application to be determined.

Using the profit equations for FP (1) and VRT (2), NR_{FP} can be set equal to NR_{VRT} and the terms rearranged to analyze the sensitivity of changes in prices to profitability in VRT N application. The left-hand side of the equation is the change in the cost of the technology (cost of machinery ownership, fertilizer application, and labor):

$$IAC_{VRT} - IAC_{FP} =$$

$$P \times (Y_{VRT} - Y_{FP}) + IP_{VRT} + r^B \times (N_{FP}^B - N_{VRT}^B) + r^T \times (N_{FP}^T - N_{VRT}^T). \quad (3)$$

Equation 3 yields a partial budgeting net returns relationship, a common way to analyze the economic benefits of a technology (Boehlje and Eidman 1984; Thrikawala et al. 1999; Koch et al. 2004; Biermacher et al. 2009a; Boyer et al. 2011).

Equation 3 assumes that the VRT costs are more expensive than FP. The costs of VRT (C_{VRT}) on the left-hand side of Equation 3 can be denoted as

[1] NRCS precision nutrient management practice code number 590 used for incentive payment in Equation 2.

$$C_{VRT} = IAC_{VRT} - IAC_{FP}$$

(4)

and Equation 3 can be rewritten as an inequality:

$$C_{VRT} <$$

$$P \times (Y_{VRT} - Y_{FP}) + r^B \times (N_{FP}^B - N_{VRT}^B) + r^T \times (N_{FP}^T - N_{VRT}^T) + IP_{VRT}, \quad (5)$$

where the cost of using VRT ($ ha^{-1}) is on the left-hand side and three sources of potential cash inflows to offset the cost are on the right-hand side, i.e., higher yields, N savings, and incentive payments. If C_{VRT} is less than the cash flows on the right-hand side, VRT is profitable; otherwise, not.

Based on the implications drawn from Equation 5, changes in yields and N rates are the driving factors influencing technology profitability holding lint cotton and N prices constant. Changes in net returns and N use efficiency due to changes in yields and N rates with the adoption of VRT are of interest to the farmer. Given that crop production is affected by managerial and growing environment factors such soils and weather (Bullock and Bullock 1994; Isik and Khanna 2003; Lowenberg-DeBoer 1999; Whelan and McBratney 2000; Zhang, Wang, and Wang 2002), yield for the N fertilizer management decision can be written as a function of crop management and exogenous environment factors:

$$Y_{a,d} = f(N_d, Z_d, W_d, S_d, O_d), \quad (6)$$

where *Y* is yield (kg ha^{-1}) , *a* is the N fertilizer management strategy (FP or VRT), *d* is a sub-field area (e.g., management zone) within a field used to apply N at the rate (kg ha^{-1}) determined by management strategy *a*, *Z* is a vector of other crop inputs applied by the farmer, *W* is a vector of weather parameters such as precipitation and temperature, *S* is a vector of farm field soil properties and landscape characteristics, and *O* is a vector of other random factors affecting

production such as pests. The N management decision can be written as a function of the previously mentioned exogenous environmental factors:

$$N_{a,d} = g(Z_d, W_d, S_d, O_d). \quad (7)$$

Average yields and N rates at the field level for the FP and VRT N management strategies are:

$$Y_{FP} = \sum_{d=1}^{D} Y_{d,FP}/D, \text{ and } N_{FP} = \sum_{d=1}^{D} N_{d,FP}/D, \text{ and} \quad (8)$$

$$Y_{VRT} = \sum_{d=1}^{D} Y_{d,VRT}/D, \text{ and } N_{VRT} = \sum_{d=1}^{D} N_{d,VRT}/D, \quad (9)$$

where *D* is the total number of management zones in the field as indicated by the N management studies.

In this thesis, the effects of optical sensing and VRT on average yields, N rates, and net returns relative to the FP are evaluated at the field level. In addition, the effects of exogenous weather, soil properties, and landscape characteristics on differences in yields, N rates, and net returns for VRT versus the FP are evaluated at the sub-field level.

N Production Use Efficiency

VRT NUE has been measured in several ways, most of which comprise a zero-N applied plot (omission plot) or N-rich plot for comparison purposes. Butchee et al. (2011) found the N rate using the NUE factor: $N\ rate = \{(YPO \times RI) - YPO\} \times \%grain\ N \times NUE\ factor$, where *YPO* represents the yield potential for zero N, *RI* represents response index measured by a sensor based N-rate calculator, and the grain is winter wheat. Cassman et al. (1998) and Cassman et al. (1996) employed partial factor productivity (PFP) as a measure of nutrient-use efficiency: $PFP = \frac{(Y_0 + \Delta Y)}{N_t}$ where Y_0 is the yield from a N omission plot, ΔY represents the change in yields from zero-N applied, and N_t is the N rate applied per treatment (*t*). Raun et al. (2002) measured

NUE by subtracting N removed (grain yield times total N) in the grain in zero-N plots from that found in plots receiving added N, divided by the rate of N applied.

A nitrogen production use (NPU) efficiency is used here to measure N use by normalizing the yield for a given technology (*Y*) by dividing by the corresponding N rate applied (*N)* such that:

$$NPU_a = \frac{Y_a}{N_a}, \tag{10}$$

where *a* is N management strategy used (VRT or FP). This variable is a proxy for the environmental benefits from using VRT. The effects of VRT on average NPU relative to the FP are evaluated at the field level. In addition, the effects of exogenous weather, soil properties, and landscape characteristics on differences in NPU for VRT versus the FP is evaluated at the sub-field level.

Risk Management Benefits

Besides expected profit, farmers may be interested in the potential risk management benefits of VRT fertilizer management. Assuming farmers are risk-averse, the potential for yields and net returns to fall below a target value is a main concern; i.e., farmers are particularly concerned about reducing the probability of yields and NR in the lower tail of the probability distribution (Binswanger 1981; Selley 1984; Antle 1987; Lowenberg-DeBoer 1999; Chavas 2004). Physical soil properties (e.g., soil organic matter content and depth) and topography (e.g., slope and elevation) of farm fields that can limit yields remain relatively fixed over time (Larson, Roberts, and English 2002). One potential risk management benefit of VRT is reducing the variability of growing environment factors across a field, making the field more homogenous (Lowenberg-DeBoer and Swinton 1997). Another potential risk management benefit may come from reducing

the field average temporal yield variability across soil types under VRT compared to applying the same rate of inputs across the farm field (Larson, Roberts, and English 2002).

Stochastic dominance and lower partial moment criteria can be useful for evaluating the risk management benefits of optimal sensing and VRT fertilizer management. The risk-neutral farmer will choose the treatment that produces the highest mean net return. The decision cannot solely be made on mean net returns when there is a level of risk involved. Stochastic dominance is a helpful tool in evaluating the decision between random variables (Post and Kopa 2013; Dhompongsa, Nguyen, and Sriboonchita 2010). When making a decision between VRT and FP, for instance, first degree stochastic dominance states that VRT would dominate FP if $F_{VRT}(NR) \leq F_{FP}(NR)$ for all observations (π) where $F_{VRT}(NR)$ is some function of VRT and $F_{FP}(NR)$ represents a function of FP (Dhompongsa, Nguyen, and Sriboonchita 2010), here cumulative distribution functions.

Lower partial moment measures the downside risk, i.e., yields, N rates, net returns, and NPU that fall below a target level (Fishburn 1977):

$$LPM_n = \frac{1}{m}\sum_{i=1}^{m} Max[0, Y_{FP,i} - Y_{VRT,i})]^n, \quad (11)$$

$$LPM_n = \frac{1}{m}\sum_{i=1}^{m} Max[0, N_{VRT,i} - N_{FP,i})]^n, \quad (12)$$

$$LPM_n = \frac{1}{m}\sum_{i=1}^{m} Max[0, NR_{FP,i} - NR_{VRT,i})]^n, \quad (13)$$

$$LPM_n = \frac{1}{m}\sum_{i=1}^{m} Max[0, NPU_{FP,i} - NPU_{VRT,i})]^n \quad (14)$$

where *LPM* is the lower partial moment, *m* is the number of observations (*i*), *FP*, *VRT*, *Y*, *N*, *NR*, and *NPU* were defined previously, and *n* is the degree of the moment. The classifications of the degree of the moment (*n*) are *n* = 0 is the probability of a loss, *n* = 1 is the target shortfall, *n* = 2 is the target semi-variance, and *n* = 3 is the target skewness. The probability of a loss, where *n* =

0, provides the probability of VRT yields, net returns, and N use efficiency being lower than the current FP.

Hypothesis Testing

Given the potential effects of optical sensing and VRT on crop yields, N rates, net returns, NPUs, and crop risk management, the three hypotheses that are tested in this study are:

1. **Optical sensing and VRT treatments versus the FP:** The null hypothesis is that using optical sensing and VRT for N management do not generate yields, N rates, NPU, and net returns that are different from FP yields, N rates, net returns, and NPUs. The alternate hypothesis is that the aforementioned factors differ with N management using optical sensing and VRT when compared with the FP.

2. **Weather, soil, and landscape characteristic effects on optical sensing and VRT versus FP:** The null hypothesis is that yields, N rates, net returns, and NPUs from N management using optical sensing and VRT relative to the FP are not influenced by weather and farm field soil and landscape characteristics. The alternative hypothesis is that weather and farm field soil properties and landscape characteristics influence differences in the aforementioned factors when using optical sensing and VRT as compared with the FP.

3. **Risk management benefits of optical sensing and VRT:** The null hypothesis is that optical sensing and VRT do not provide a higher (lower for N rates) probability of yields, N rates, net returns and NPU being in the lower tail compared to the respective FP yields and net returns as influenced by weather and farm field soil properties and landscape characteristics. The alternative hypothesis is that optical sensing and VRT do provide a higher (lower for N

rates) probability of yields, N rates, net returns and NPU above FP yields and net returns as influenced by weather and farm field soil properties and landscape characteristics.

CHAPTER IV: DATA AND METHODOLOGY

Data

Twenty-nine cotton N fertilizer field experiments were conducted from 2011 to 2014 in Tennessee, Mississippi, Louisiana, and Missouri. Ten of the trials occurred in Tennessee, four in Mississippi, nine in Louisiana, and six in Missouri. The county/parish locations of the farmer fields in each state that were used in the study are presented in Figure 1. The trials tested FP N application versus two VRT N applications on each cotton field. Each EQIP eligible farmer planted cotton across nine strip-plots (referred to as plot for the remainder of this paper) containing 10 sub-plots each that measure roughly 30.5 meters by 11.6 meters with the exception of Missouri where the data was collected by plot, Figure 2.

The experiment was planned as a randomized complete block design with three N fertilizer treatments and three replications. The FP treatment (1) was a uniform-rate N application based on the farmer's current practice. Treatment 2 was a VRT N application calculated using the normalized difference vegetation index (NDVI) via canopy optical-sensing with the Greenseeker™ RT200 Data Collection and Mapping System (NTech Industries, Inc., CA). Treatment 3 was a VRT N application based on actual NDVI readings via canopy optical-sensing with the Greenseeker™ RT200 Data Collection and Mapping System but adjusted based on any combination of historical yield productivity zones, soil imagery, and/or aerial imagery of mid-season crop health. A uniform blanket rate ranging from 33.6 to 78.4 kg N ha^{-1} was applied at (or before) planting to the entire field (covering all three treatment areas) depending on the experiment. Each location provided lint yields harvested, N rates applied, type of N fertilizer used, and latitude and longitudes at the sub-plot level for every participating year. Table 2 includes the average N rate, lint yield, NPU, and net returns by location and year.

To evaluate the net returns inequality in Equation 5, price data, information costs, and application costs were used. Price and budget data are in real 2013 dollars ($), referred to as real dollars, and were indexed using the Bureau of Economic Analysis annual Gross Domestic Product Price Deflator Index (U.S. Department of Commerce 2014). Price data included national average marketing year (August 1-July 31) cotton lint prices received, marketing years 2011 through 2014 (USDA 2014a), adjusted to real \$ kg^{-1}, \$1.84 kg^{-1} in 2014. National prices paid for N fertilizer urea (32% N) were collected for 2011 through 2014 marketing years (USDA 2014d), adjusted to real \$ kg^{-1}, \$0.91 kg^{-1} in 2014. EQIP cost-share payment rates were collected for each of the four states in the experiments for the precision nutrient management payment code 590 for 2011 through 2014 adjusted to real \$ ha^{-1}. Payments for 2014 included \$68.21 ha^{-1} in Mississippi, \$68.46 ha^{-1} in Louisiana, \$65.85 ha^{-1} in Tennessee, and \$32.64 ha^{-1} in Missouri (personal communication with Patricia Turman, Tennessee State Agronomist, 2014, Chris Coreil, Louisiana NRCS Conservation Agronomist, 2014, and Jodie Reisner, Missouri NRCS Conservation Agronomist, 2014; USDA 2014c).

Information and application costs (IAC), including equipment/technology, labor, and other costs, were estimated using partial budgeting methods (Larson et al. 2005) as demonstrated in Equations 4 and 5, Table 3. Two budgets were developed to account for information and application costs: 1) for Greenseeker™ technology (treatment 2) and 2) for Greenseeker™ plus yield monitor information systems (YMIS) (treatment 3). Greenseeker™ was assumed to be retrofitted to an existing boom sprayer measuring 24.7 meters wide and the YMIS was assumed to be retrofitted to an existing 6-row cotton picker measuring 5.8 meters wide. Ownership costs (OC) of equipment/technology for inclusion in IAC for treatments 2 and 3 were estimated using the standards of the American Society of Agricultural and Biological Engineers (ASABE)

(ASABE 2011) similar to Biermacher et al. (2009a), the Agricultural and Applied Economics Association (AAEA) Commodity Costs and Returns Estimation Handbook (AAEA 2000), and equipment costs calculation techniques (Boehlje and Eidman 1984). OC were estimated in Table 3 using the equation:

$$OC_i = [CR_i + TIH_i + RM_i] * H_i, \quad (15)$$

where ownership costs (\$ ha^{-1}) by treatment (i = 2 or 3) were composed of hourly capital recovery (CR_i) by treatment (\$ hour^{-1}), hourly taxes, insurance, and housing (TIH_i) by treatment (\$ hour^{-1}), hourly repairs and maintenance (RM_i) by treatment (\$ hour^{-1}), and hours ha^{-1} (H_i) by treatment. For Greenseeker™, the useful life was assumed to be 5 years or 1500 hours (Gandonou et al. 2006) and the yield monitor information system assumed a useful life of 5 years or 3000 hours (Gandonou et al. 2006; Biermacher et al. 2009a), Table 3. Total Greenseeker™ OC was multiplied by 1.02 to account for calibration using N rich strips (Biermacher et al. 2009a). Information and application cost (real \$ ha^{-1}) for treatment 2 in 2014 was \$2.32 ha^{-1}.

Information and application costs for treatment 3 included the estimated OC for Greenseeker™, estimated OC for yield monitor information system, the cost of a computer, and a consulting fee for technical advice (\$ ha^{-1}), Table 3. The computer was assumed 100% use for the yield monitor system, GPS signal was assumed to be free, and a \$687.08 (2013 real dollars) custom installation fee for retrofitting each technology to existing machinery was assumed for both Greenseeker™ and the yield monitor system (Larson et al. 2005; Gandonou et al. 2006). Computer list price costs were an average of costs for a desktop computer with 8GB memory, 1TB hard drive, and 21" to 23" screen (informal internet survey 2014). In partial budgeting, if information costs were not available ha^{-1} (such as the cost of a computer), costs were spread across the size of a field (Swinton and Lowenberg-DeBoer 1998). Here, the cost of a computer

was allocated across the size of a cotton enterprise in each state (USDA 2012), Table 3. The consulting fee was included due the necessary technical assistance to correctly implement and interpret the technology (McBratney, Whelan, and Ancev 2005). To account for such assistance, an average of 2009 cotton technical advice fees including yield monitor, grid soil sampling, zone soil sampling, and soil survey map fees (Mooney et al. 2010) was normalized to real 2013 dollars, \$12.63 ha^{-1} and added to all years of applicable data. Costs for treatment 3 were \$18.00 ha^{-1} in Tennessee, \$18.06 ha^{-1} in Mississippi, \$18.12 ha^{-1} in Louisiana, and \$17.94 ha^{-1} in Missouri. The 2011, 2012, 2013, and 2014 partial budgets were in real 2013 dollars, 2013 budget example in Table 3.

VRT requires more skilled labor to correctly interpret the technology and compute appropriate N rates. Thus, labor costs for VRT treatments were estimated using custom rate surveys produced by their respective agricultural extension offices (Bowling 2013; Mississippi State University Extension Services 2013; University of Missouri Extension 2012). The 2013 precision fertilizer application labor cost was determined by taking the difference between precision fertilizer application in Tennessee and the average dry bulk fertilizer application in Tennessee, Missouri, and Mississippi[2] (precision fertilizer application such as VRT costs \$6.60 more ha^{-1} in labor to apply dry bulk than FP). The 2013 labor costs were applied to all years of data, 2011-2014. Application costs as well as the other pieces to Equation 5 are included in a partial net returns summary in Table 4.

[2] Tennessee, Mississippi, and Missouri rates were averaged and applied to all locations because Louisiana State University extension office does not produce a custom rate survey.

For each location-year, soil and climate characteristics were collected to determine differences within and between fields (variable names, definitions, and units can be found in Table 5). Soil water holding capacity, organic matter, soil texture, soil depth, field slope, and soil erosion factors were collected from the SSURGO database (USDA 2014f) at the center point of each sub-plot (plot for Missouri locations) using ArcGIS 10.1. A soil erosion index (*SEI*) was estimated using a modified universal soil loss equation to account for the physical factors of the fields:

$$SEI = \frac{KF*LS*R}{TF}, \quad (15)$$

where *KF* is erodibility factor due to water (USDA 2014f) , *LS* is a soil length (*L*) and slope steepness (*S*) factor, calculated as $LS = (0.065 + 0.0456 * S + 0.006541 * S^2)$ at the standard slope length of 22.1 meters (Stone and Hilborn 2012) and percent slope steepness (*S*) (USDA 2014f). *R* is the rainfall and runoff factor from USDA RUSLE2 version 2.5.2.11 (2014), and *TF* is a soil tolerance factor (USDA 2014f). Soil texture percent sand, silt, and clay from SSURGO (USDA 2014f) were used to find the general soil texture name via the USDA soil texture calculator (USDA 2014e). Textures were then narrowed down to four major soil textures and ranked by coarseness: clay (finest), silt, loam, and sand (coarsest). Field elevation was collected from the National Elevation Dataset (U.S. Geology Survey 2014). Climate was measured by temperature (PRISM 2014) as seasonal growing degree days (April 1 through October 31) (Larson, Roberts, and Gwathmey 2007; Wright, Sprenkel, and Marois 2011). To calculate seasonal growing degree days, the daily average temperature minus 15.6 degrees Celsius was summed over April 1 through October 31 per location-year if the daily calculation was greater than zero. Mean farm soil and climate characteristics are presented in Table 6.

Methodology

In addition to soil and weather fixed effects, Equations 16-19 included random variables based on the Schabenberger and Pierce (2002) on-farm experimentation model. Due to the experimental design, Equations 20-23 and 28-31 were each treated like as a meta-analysis similar to Tolliver et al. (2012).

Treatment Effects

The farmer's decision to change his N application technology from FP to VRT is measured by evaluating two aspects of the production decision: 1) net returns per location-year by treatment as driven by yields and N rates and 2) the NPU efficiency.

The following models are estimated with an (ANOVA) using SAS 9.2 (SAS Institute Inc. 2014):

$$Y_{ijktd} = \mu + \delta_t + \lambda_k + \tau_i + \rho_{(j)k} + (\lambda\tau)_{ik} + \omega_{kjid} + \theta_{kjid} + \gamma_{kjid} + \varphi_{kjid} + \beta_{kjid} + \psi_{kjid} + \chi_{kt} + \varepsilon_{ijkt}, \quad (16)$$

$$N_{ijktd} = \mu + \delta_t + \lambda_k + \tau_i + \rho_{(j)k} + (\lambda\tau)_{ik} + \omega_{kjid} + \theta_{kjid} + \gamma_{kjid} + \varphi_{kjid} + \beta_{kjid} + \psi_{kjid} + \chi_{kt} + \varepsilon_{ijkt}, \quad (17)$$

$$NR_{ijktd} = \mu + \delta_t + \lambda_k + \tau_i + \rho_{(j)k} + (\lambda\tau)_{ik} + \omega_{kjid} + \theta_{kjid} + \gamma_{kjid} + \varphi_{kjid} + \beta_{kjid} + \psi_{kjid} + \chi_{kt} + \varepsilon_{ijkt}, \quad (18)$$

$$NPU_{ijktd} = \quad (19)$$

$$\mu + \delta_t + \lambda_k + \tau_i + \rho_{(j)k} + (\lambda\tau)_{ik} + \omega_{kjid} + \theta_{kjid} +$$

$$\gamma_{kjid} + \varphi_{kjid} + \beta_{kjid} + \psi_{kjid} + \chi_{kt} + \varepsilon_{ijkt}.$$

The following is true for all models included for the remainder of this thesis:

Dependent Variables:

Y_{ijktd} is cotton lint yield (kg ha^{-1}),

N_{ijktd} is N rate applied (kg ha^{-1}),

NR_{ijktd} is net returns (\$ ha^{-1}),

NPU_{ijktd} is NPU efficiency,

Explanatory Variables:

μ is the overall mean,

Random Effects:

δ_t is the effect of the t^{th} year (t=2011, 2012, 2013, 2014),

λ_k is the effect of the k^{th} farm location (k=1,…,21),

$\rho_{(j)k}$ is the j^{th} replication (or block) effect nested within k^{th} farm,

$(\lambda\tau)_{ik}$ is the effect of the interaction between the k^{th} farm and the i^{th} treatment,

Fixed Effects:

τ_i is the effect of the i^{th} treatment (i=1, 2, 3),ω_{kjid} is effect of water holding capacity (cm cm^{-1}) by k^{th} farm, j^{th} replication, i^{th} treatment, and d^{th} sub-plot,

θ_{kjid} is effect of organic matter (%) by k^{th} farm, j^{th} replication, i^{th} treatment, and d^{th} sub-plot,

γ_{kjid} is the effect of soil erosion index by k^{th} farm, j^{th} replication, i^{th} treatment, and d^{th} sub-plot,

φ_{kjid} is the effect of soil depth (cm) by k^{th} farm, j^{th} replication, i^{th} treatment, and d^{th} sub-plot,

β_{kjid} is the effect of soil texture by k^{th} farm, jth replication, i^{th} treatment, and d^{th} sub-plot,

ψ_{kjid} is the effect of elevation (meters) by k^{th} farm, j^{th} replication, i^{th} treatment, and d^{th} sub-plot,

χ_{kt} is the effect of seasonal growing degree days by k^{th} farm and t^{th} year,

ε_{ijktd} is the random error associated with the k^{th} farm, j^{th} replication, i^{th} treatment, t^{th} year, and d^{th} sub-plot,

$\delta_t \sim iid(0, \sigma_\delta^2)$ (*iid* refers to independent and identical distribution),

$\lambda_k \sim iid(0, \sigma_\lambda^2)$,

$\rho_{(j)k} \sim iid\left(0, \sigma_\rho^2\right)$,

$(\lambda\tau)_{ik} \sim iid(0, \sigma_{\lambda\tau}^2)$,

$\varepsilon_{ijkt} \sim iid(0, \sigma_\varepsilon^2)$.

The fixed effects are N treatment, soil attributes, and weather, and the random effects are location, year, replication nested in location, and location-treatment interaction. Location was hypothesized to have a significant effect on the dependent variables because every farm was physically different from the next, time in years because the data spans more than one year, treatment because the treatments differ within a farm and between farms, and effects that are within the same farm due to the physical difference between sub-plots from farm to farm. The location-treatment interaction term was expected to be significant but to mask the treatment differences.

The null hypothesis for Equation 16 is that expected lint yields from the VRT N application treatments (i = 2 or 3) per trial will be equal to the expected lint yields from the FP trials was tested in Equation 16. Alternatively, expected VRT lint yields will be greater than expected FP lint yields.

VRT N applications were expected to reduce N use compared to FP. In the special case that the yields are not significantly different across treatments per location-year, revenues (price of cotton times lint yield) will no longer be a factor in net revenues, Equations 1 and 2. The cost side of the equation becomes the driver, as seen in Equation 5. The null hypothesis that VRT by treatment generated no additional N use savings compared to FP, was tested in Equation 17. Alternatively, expected N applied using FP is greater than expected N applied using VRT application.

If yields were not significantly different across treatments per location, N applied was the driving factor. In this case, net returns can be estimated in a similar way to Equations 4 and 5. The null hypothesis that expected net returns from VRT N applications by treatment were the same as expected net returns from FP N application was tested in Equation 18. Alternatively, expected net returns from VRT N applications were greater than expected net returns from FP application.

N rate was also the driver in N use efficiency if yields did not differ. For the same cotton lint yield, a lower N rate would increase the NPU efficiency. The null hypothesis that the expected NPU for VRT N application treatments were equal to expected NPU efficiency for the FP treatment was tested using Model 4. Alternatively, expected NPU efficiency for VRT N application was expected to be greater than NPU for FP N application.

Equations 16, 17, 18, and 19 were first estimated with only treatment as the explanatory variable and again with added soil and weather characteristics. The better fitting models were chosen based on the Akaike information criterion (AIC) and Bayesian information criterion (BIC). Multicollinearity was checked by estimating the variance inflation factor (VIF) using SAS 9.2. The Satterthwaite approximation was used to deal with degrees of freedom.

To determine if the treatments produced significantly different lint yields, N rates, net returns, and NPUs, Dunnett's tests were estimated using SAS 9.2 for Equations 16-19 (Littell et al. 2006). This two-tailed test is useful because multiple treatments can simultaneously be compared to one control while holding the familywise error rate at or below alpha; here, if VRT treatment 2 is significantly different than FP (control) and if VRT treatment 3 is significantly different than FP. This test performs multiple comparisons while holding the familywise error rate at or below an alpha level.

Because the interaction term is random, contrasts between farms were estimated via best linear unbiased predictions using SAS 9.2 for Equations 16-19 to measure the treatment effect at the farm level (Schabenberger and Pierce 2002; Littell et al. 2006). Both VRT treatments were measured separately against FP to see if technology outperformed the current practice. The null hypothesis is that VRT treatments do not differ from FP at the farm level. Alternatively, treatments do differ at the farm level. A Bonferroni correction is a conservative way to handle multiple comparisons and deal with the familywise error rate. Because there are 21 farms, there are 21 separate hypotheses to test for VRT treatment 2 versus FP and VRT treatment 3 versus FP. At a 10% confidence level, the Bonferroni correction is calculated as $\alpha = \frac{0.10}{21} = 0.0047$. Alpha becomes 0.0047 for each hypothesis; at the field level.

Soil, Landscape, and Weather Impacts on Mean Treatment Differences

The soil and climate impacts on mean differences were evaluated by estimating a mixed model ANOVA using SAS 9.2. The mean difference models are:

$$Y\Delta_{ijktd} = \mu + \delta_t + \lambda_k + \rho_{(j)k} + (\lambda\tau)_{ik} + \omega_{kjid} + \theta_{kjid} + \gamma_{kjid} + \varphi_{kjid} + \beta_{kjid} + \psi_{kjid} + \chi_{kt} + \nu_i + \varepsilon_{ijkt} \quad (20)$$

$$N\Delta_{ijktd} = \mu + \delta_t + \lambda_k + \rho_{(j)k} + (\lambda\tau)_{ik} + \omega_{kjid} + \theta_{kjid} + \gamma_{kjid} + \varphi_{kjid} + \beta_{kjid} + \psi_{kjid} + \chi_{kt} + \nu_i + \varepsilon_{ijkt} \quad (21)$$

$$NR\Delta_{ijktd} = \mu + \delta_t + \lambda_k + \rho_{(j)k} + (\lambda\tau)_{ik} + \omega_{kjid} + \theta_{kjid} + \gamma_{kjid} + \varphi_{kjid} + \beta_{kjid} + \psi_{kjid} + \chi_{kt} + \nu_i + \varepsilon_{ijkt} \quad (22)$$

$$NPU\Delta_{ijktd} = \mu + \delta_t + \lambda_k + \rho_{(j)k} + (\lambda\tau)_{ik} + \omega_{kjid} + \theta_{kjid} + \gamma_{kjid} + \varphi_{kjid} + \beta_{kjid} + \psi_{kjid} + \chi_{kt} + \nu_i + \varepsilon_{ijkt} \quad (23)$$

where ν_i is a dummy variable by treatment (*i*); if N management strategy treatment 3 was used in that sub-plot (*d*), then 1; otherwise, 0. Refer to Equations 16-19 for all other explanatory variables. The dependent variable was defined as the difference between *VRT* and *FP* in terms of yields, N rates, NR, and NPU:

$$Y\Delta_{dijkt} = Y_{VRT_i} - Y_{FP} \quad (24)$$

$$N\Delta_{dijkt} = N_{VRT_i} - N_{FP} \quad (25)$$

$$NR\Delta_{dijkt} = NR_{VRT_i} - NR_{FP} \quad (26)$$

$$NPU\Delta_{dijkt} = NPU_{VRT_i} - NPU_{FP} \quad (27)$$

where $Y\Delta$ is the mean difference in cotton lint yields (kg ha^{-1}), $N\Delta$ represents the mean difference in total N rates (kg ha^{-1}), $NR\Delta$ is the mean difference in net returns (\$ ha^{-1}), and $NPU\Delta$ is the mean difference in NPU efficiencies, each between *VRT* technology treatment 2 or 3 and *FP* by the d^{th} sub-plot, i^{th} treatment, j^{th} replication, k^{th} location, and t^{th} year.

The manner in which Equations 20-23 were estimated did not take the FP sub-plot soil explanatory variables into consideration. If the soil characteristics differ from the optical sensing and VRT treatment sub-plots, the integrity of the model may be compromised and what is being measured may not be accurate. To account for this, Equations 20-23 were estimated using a restructured database where a balanced set of replicates for the FP and VRT treatments were used. For example, if the soil texture differed across field 1, replication 1, and sub-plot 1 in treatment 2 versus sub-plot 1 in treatment 1, Figure 1, then the observation was omitted from the dataset; if not, the original observation was used. The models in Equations 20-23 were estimated using the original and restructured datasets and the outputs were evaluated using AIC and BIC statistics to choose the better fitting model. The number of observations omitted ranged from 42 to 105 depending on the variable.

The models were checked for multicollinearity by estimating a regression using SAS 9.2 (PROC REG) and the VIFs. The random effects listed for Equations 16-19 apply here as well.

Models in Equations 20-23 tested the null hypotheses that mean yields, N rates, net returns, and NPUs do not differ between VRT N management strategies and FP due to variability in soils characteristics and climate. Alternatively, soils and climate do generate differences using optical sensing and VRT when compared to FP.

Risk Management Benefits

First degree stochastic dominance of N management treatments was evaluated using the cumulative probability distributions of each treatment. The distributions were calculated by ordering the yields, N rates, NRs, and NPUs from lowest to highest by treatment. The histogram feature in Microsoft Office Excel 2010 was then used to count the number of observations in each pre-determined bin category for every treatment which were used to calculate the respective cumulative probability distributions.

The Kolmogorov-Smirnov (KS) test is a nonparametric test based on the empirical cumulative distribution function and can be used to compare two distributions. The KS statistic D represents the goodness of fit and is based on the vertical difference between the two cumulative probability distributions (Chakravarti, Laha, and Roy 1967). The KS test was estimated using SAS 9.2 as a supplement to the first degree stochastic dominance results due to the criteria that at least one point has to be to the right to show dominance (all others could be equal). The null hypotheses for the KS tests are that the treatment distributions are similar.

Risk management benefits were also assessed using the lower partial moment to evaluate how soil and weather factors affected the probability of the outcomes from the optical sensing and VRT N management treatments being different from the FP N management. The probability of a loss, $n = 0$, Equations 11-14, was measured using a mixed logistic model, and estimated using SAS 9.2:

$$Yprob_{ijktd} = \mu + \delta_t + \lambda_k + \rho_{(j)k} + (\lambda\tau)_{ik} + \omega_{kjid} + \theta_{kjid} + \gamma_{kjid} + \varphi_{kjid} + \beta_{kjid} + \psi_{kjid} + \chi_{kt} + \nu_i + \varepsilon_{ijkt} \quad (28)$$

$$Nprob_{ijktd} = \quad (29)$$

$$\mu + \delta_t + \lambda_k + \rho_{(j)k} + (\lambda\tau)_{ik} + \omega_{kjid} + \theta_{kjid} + \gamma_{kjid} + \varphi_{kjid} + \beta_{kjid} + \psi_{kjid} + \chi_{kt} + \nu_i + \varepsilon_{ijkt}$$

$$NRprob_{ijktd} = \mu + \delta_t + \lambda_k + \rho_{(j)k} + (\lambda\tau)_{ik} + \omega_{kjid} + \theta_{kjid} + \gamma_{kjid} + \varphi_{kjid} + \beta_{kjid} + \psi_{kjid} + \chi_{kt} + \nu_i + \varepsilon_{ijkt} \quad (30)$$

$$NPUprob_{ijktd} = \mu + \delta_t + \lambda_k + \rho_{(j)k} + (\lambda\tau)_{ik} + \omega_{kjid} + \theta_{kjid} + \gamma_{kjid} + \varphi_{kjid} + \beta_{kjid} + \psi_{kjid} + \chi_{kt} + \nu_i + \varepsilon_{ijkt} \quad (31)$$

where *Yprob* is the estimated probability of a VRT treatment producing lower yields than FP, *Nprob* is the estimated probability of the VRT treatment calculating higher N rates than FP, *NRprob* is the probability of VRT net returns being lower than FP, and the *NPUprob* is the probability of VRT treatments calculating lower NPUs than FP. The binary dependent variables are defined in Table 5 as:

If $Y_{VRT} - Y_{FP} < 0$, then $Yprob = 1$; else, $Yprob = 0$; (32)

If $N_{VRT} - N_{FP} > 0$, then $Nprob = 1$; else, $Nprob = 0$; (33)

If $NR_{VRT} - NR_{FP} < 0$, then $NRprob = 1$; else, $NRprob = 0$; (34)

If $NPU_{VRT} - NPU_{FP} < 0$, then $NPUprob = 1$; else, $NPUprob = 0$; (35)

where Y_{VRT} is the VRT yield, Y_{FP} is the current practice yield, N_{VRT} is the VRT N rate applied, N_{FP} is the current practice N rate applied, NR_{VRT} is the VRT net return, NR_{FP} is the current practice net return, NPU_{VRT} is the VRT N use efficiency, and NPU_{FP} is the current practice N use efficiency. If VRT lint yields, net returns, or NPU by treatment (*i*), replication (*j*), farm (*k*), year (*t*), and sub-plot (*d*) were less than the respective FP value, the dependent variable was represented by a 1; otherwise, 0. N rates applied were represented by a 1 if the VRT value

was greater than FP; otherwise 0. Equations 28-31 were estimated using the restructured database. Multicollinearity was checked for the models by estimating the VIF using SAS 9.2. The random variables for these models are specified for Equations 16-19.

A proxy for the estimated marginal probability for each explanatory variable was calculated using the respective odds ratio parameter estimates from SAS 9.2 code ODDSRATIO. The proxy formula used was $100 * [exp(OR) - 1]$ where exp is the exponential and OR is the odds ratio parameter estimate.

Odds ratios were estimated at the restructured database means of the significant variables using the following equation:

$$ODDs = \exp[\widehat{\eta_0} + \widehat{\eta_1} X_1 + \widehat{\eta_2} X_2 + \cdots + \widehat{\eta_e} X_e] \quad (36)$$

where *ODDs* is the yield, N rate, net return, or NPU odds ratio, *exp* represents exponential, $\hat{\eta}$ represents the expected coefficient, *X* is the significant explanatory variable, and e is the last significant explanatory variable for that odds ratio. The odds ratios estimates are used to predict the probability of downside risk, measured by:

$$VRTprob(a = 1) = \frac{ODDs}{1+ODDs} \quad (37)$$

where *VRTprob* is the probability of VRT yields, N rates, net returns, or NPU having a higher chance of being in the lower tail when compared to FP.

The null hypotheses for Equations 28-31 are that N management strategy does not provide yields, N rates, net returns, and NPUs that differ due to soil properties and temperature. Alternatively, soils and temperature do have an effect on yields, N rates, net returns, and NPUs.

CHAPTER IV: RESULTS AND DISCUSSION

Treatment Effects

Using VIF as a measure of multicollinearity, all variables in Equations 16-19 were under a VIF value of five. Equations 16, 17, 18, and 19 were first estimated with only treatment as the explanatory variable. The added soil and climate characteristics generated models that were better fitting using the Akaike information criterion (AIC) and Bayesian information criterion (BIC) best fit criteria without compromising the integrity of the estimation, i.e., the treatment effect for each model did not change when soil properties and temperature were added.

Lint Yields, N Rates, and Net Returns

The estimated cotton lint yield model, Equation 16, produced a better fitting model based on best fit criteria (AIC and BIC), Table 7, than re-estimating the model without the location-treatment interaction term (Schabenberger and Pierce 2002). This indicated that the interaction term was significant. Neither estimation suggested treatment effects. A contrast comparison of the treatments indicated FP lint yields (treatment 1) were not significantly different than VRT treatment 2 or 3, Table 8. A Dunnett's test with the interaction term indicated that treatment 3 was significantly different than the control (FP) but there were no differences in either VRT treatment versus FP with the interaction term, Table 9.

Soil and climate attributes were significant, Table 10. All else equal, soils with a higher percentage of organic matter, greater water holding capacity, coarser soil texture, or deeper soils were positively associated with lint yields. Layers of soil below the surface are more fertile, carrying more organic matter and N available to the plant (Tiessen, Cuevas, and Chacon 1994), and potentially increase yields. Warmer temperatures (i.e., higher growing degree days) were

negatively associated with lint yields. Soil texture significantly impacted yields, meaning that coarser soils were positively related to yields.

The mixed model for N rates applied, Equation 17, showed no significant differences between treatments but indicated that the variance between farms (σ_{λ}^{2} = 242.33) was substantially higher than the variance within farms (σ_{λ}^{2} = 86.83). This means that there was more N rate variation between farms than within farms. Model 2 was re-estimated without the interaction term to see if any effects were being masked, and a Dunnett's test indicated that the VRT treatment 3 was significantly different from the FP treatment, Table 9. Based on the model's best fit criteria, Table 7, the interaction term was significant to the model.

Estimates of VRT treatments (2 and 3) versus FP by location revealed masked treatment effects. Results demonstrated treatments 2 and 3 had significantly lower N rates applied in Lauderdale, TN, Gibson County, TN, and Middle Tensas Parish, LA, using a Bonferroni correction of 0.0047. Northern Leflore County, MS, had N rates lower than FP for only treatment 2. Northern Madison County, TN, and both the northern and southern locations in the Tensas Parish, LA, had estimated N rates that were significantly lower using FP than either VRT treatment (2 and 3). Adams County, MS, experienced lower N rates with FP than VRT treatment 3, Table 8.

The current FP was to apply less N in the locations where FP was significantly lower than VRT by respective state. Tennessee and Louisiana fields have less organic matter as a percentage of the soil where N rates were lower using FP. This could potentially mean that optical sensing of the plant canopy was associated with low organic matter areas in the field and applied more N to the soil. Organic matter, however, was not significant to the N rate model, Table 10. Holding all else constant, soils that were more erodible or had warmer temperatures were positively

associated with N rates. All else equal, more erodible soils or warmer average temperatures had more N applied. Warmer temperatures are correlated with less precipitation (Madden and Williams 1978) and fields with these conditions may get more wind exposure, erosion, and have the potential to lose N applied. Holding all else constant, fields at higher elevations or with coarser soil textures were negatively related to N rates.

On average, farms requiring significantly higher VRT N rates relative to FP (northern Madison County, TN, Adams County, MS, and the northern and southern Tensas Parish locations, LA) had lower elevations, had higher SEI, higher percentages of organic matter, deeper soils, and warmer temperatures than those that had lower VRT N rates (middle Tensas Parish, LA, Gibson and Lauderdale Counties, TN, and northern Leflore County, MS), Table 11. Fields with more erodible soils and warmer temperatures likely require more N because they have the potential to lose N more easily. Fields requiring significantly lower N rates using VRT compared to FP were on average at higher elevations and had lower SEI indexes, lower water holding capacity, lower percentage organic matter, shallower soils, and cooler temperatures.

The net returns Equation 18 estimated with and without the interaction term identified significant treatment differences between net returns, Table 12. Estimating the difference between treatments by farm, however, indicated no treatment differences at Bonferroni correction of 0.0047, Table 8. A Dunnett's test showed net returns to be different between VRT treatment 2 and FP when estimating Equation 18. When re-estimating the model without the interaction term, the Dunnett's test revealed significant differences between VRT treatment 2 versus the control (FP) and VRT treatment 3 versus control, Table 9.

All else equal, coarser soil textures, soils with a higher percentage of organic matter, or deeper soils were positively associated with net returns. The significant and positive soil texture

coefficient estimate indicates that coarser soil textures had a positive effect on net returns. Greater water holding capacity was negatively associated with net returns. *Ceteris paribus*, fields with higher percentages of organic matter, coarser soils, or deeper soils had positive associations with yields and, in turn, profits. In the same respect, fields at higher elevations or that were warmer had negative associations with yields and profits.

N Production Use Efficiency

Results from the NPU mixed model, Equation 19, indicated that the treatment means were not significantly different, Table 12. The variation between farms (σ_{λ}^{2} = 131.75) was greater than within the farms (σ_{λ}^{2}= 0.92). Equation 19 was re-estimated without the interaction term to determine if farm effects were being masked and results indicated treatment differences, Table 12. NPU means were significantly different between both VRT treatments and the control FP treatment as estimated by the Dunnett's test, Table 9. The AIC and BIC criteria indicated that the original model was a better fit than dropping the interaction term, Table 7. Thus, the interaction term was significant to the model but was masking the treatment effect.

Estimating the mean treatment differences at the farm level resulted in significantly higher FP N use efficiency than either of the VRT treatments in northern Madison County, TN, and northern Tensas Parish, LA. Adams County, MS, experienced a FP N use efficiency that was significantly higher than VRT treatment 3. These three farms experienced more efficient N use when determining their own rates than when using VRT. No farms exhibited more efficient N use with VRT when compared to FP, Table 8.

Elevation, water holding capacity, organic matter, soil texture, soil depth, and growing degree days had significant effects on NPU, Table 10. Fields at higher elevations, with greater water holding capacity, or warmer temperatures, all else equal, were negatively associated with

N use efficiency. Fields with a higher percentage of organic matter, coarser soil textures, or deeper soils had positive effects on N use efficiency. Soil texture also had a positive association with NPU, meaning that coarser soils in reference to sand promoted more efficient use of N. Holding all else constant, soils with relatively more organic matter, coarser soils, and deeper soils were associated with low enough N rates to increase N efficiency. *Ceteris paribus*, high elevation fields with greater water holding capacity, or warmer average days had a negative relationship with N use efficiency. Soils with these conditions may have higher tendencies for erosion and, therefore, may require more N applied.

Soil, Landscape, and Weather Impacts on Mean Treatment Differences

The VIF test for multicollinearity indicated all factors were under a value of five when estimated for equations 20-23. In each case, the model estimated from the restructured database was the better fitting model than using the entire database, i.e. had lower AIC and BIC values.

Lint Yields, N Rates, and Net Returns

Several soil attributes were statistically significant in the lint yield mean difference model, Equation 20 and Table 13. Soils classified as having a silt or loam soil texture relative to sand (intercept) were negative in relation to VRT yields when compared to FP. Deeper soils or more erodible soils were positively associated with VRT yields relative to FP. Higher temperatures or fields at higher elevations had a negative relationship with VRT yields compared to FP. Coarser soils, fields at higher elevations, or fields in locations with warmer temperatures were negatively associated with VRT yields when compared to FP, all other factors being equal. Thus, VRT may not be a good option on fields with these conditions. Soils that have a higher percentage of organic matter, deeper soils, and more erodible soils had positive associations with lint yields

using VRT compared to FP, all else equal. This could be due to organic matter carrying natural N and has nutrients available to the plant (Tiessen, Cuevas, and Chacon 1994). Soils with a higher erosion index had a positive association to lint yields potentially because more N was applied, Table 13.

Many of the soil attributes had a significant impacts on N rate differences between technology generated N rates and FP, Equation 21. N rate differences were significantly and negatively associated with sand (intercept), silt, or loam soil textures and positively with clay when VRT was compared to FP. Finer soils tend to need more N applied due to the lack of natural N while coarser soils need less N applied. Greater water holding capacity, more erodible soils, and higher growing degree days were positive in relation to VRT N rates. Deeper soils had a negative association to VRT N rate compared to FP. All else equal, more N was applied using VRT compared to FP on fields with a greater water holding capacity, more erodible soil, or warmer temperatures. The estimated VRT treatment 3 dummy variable indicated significantly higher N rates, indicating that Greenseeker™ plus YMIS calculated higher mean N rates than FP.

While soil attributes had significant impacts on mean differences in lint yields and N rates between N management strategies, they had less of an impact on net returns Equation 22. Silt soil textures had a negative impact on VRT net returns when compared to FP. As noted above, the silt texture also had a negative association to VRT yields and VRT N rates. The N rates savings may not have been enough to increase the net return for that soil type, holding all else constant. The soil texture reference variable sand, however, experienced positive associations with VRT net returns compared to FP, Table 13. A higher percentage of organic matter or deeper soils were positively associated with VRT net returns compared to FP. Higher elevation fields had a negative association with VRT net returns compared to FP. Higher

elevations may be more exposed to wind and rain and therefore have more erosion. Higher temperatures had a negative relation to VRT net returns. All else equal, warmer climates were negatively associated with VRT yields compared to FP, positively with N rates and, thus, negatively with NR. Warmer temperatures are correlated with dryer climates, particularly during the summer months in the United States (Madden and Williams 1978), which may cause the need for higher N rates. N applied was not high enough to increase yields such that net returns were increased.

N Production Use Efficiency

Results from Equation 23 indicated that soil and climate characteristics play a significant role in N use efficiency. NPU was negatively associated with clay soil texture compared to sand and positively associated with loam soil texture. Soils that were richer in organic matter had a positive association with VRT N use efficiency compared to FP. More erodible soils or fields with warmer temperatures had negative associations to VRT N efficiency. While a higher percentage of organic matter had a positive relation to N use efficiency of VRT compared to FP, all else equal, the more erodible fields and warmer climates had negative associations to N use efficiency, likely due to the need for higher N rates.

Risk Management Benefits

Stochastic Dominance

Results presented above for mean differences among the N management treatments are applicable to risk-neutral producers who makes decisions based on expected net returns. Risk averse farmers are not only concerned about expected net returns but also the dispersion of net returns—particularly net returns that fall below the expected value. The cumulative probability

distributions for net return displayed at the sub-plot level and at the location-year (also referred to as field) level in Figure 2 were used to evaluate the risk management benefits of optical sensing and VRT for N management in cotton. In addition, cumulative probability distributions for yield, N rate, and N use efficiency at the sub-plot and field levels are presented in Figures 3-10.

At the sub-plot level, the net return distributions crossed when all treatments were examined together, but treatment 2 compared to FP exhibited first degree stochastic dominance, Figure 7. However, the net return distribution for treatment 2 was not first degree stochastic dominant over the FP at the field level. Thus, a farmer using first degree stochastic dominance as the decision rule for field level data could not make a decision on whether to adopt VRT based on first degree stochastic dominance criterion. At the sub-plot and field levels, yield, N rate, and NPU distributions crossed at least once, indicating that VRT did not provide consistently higher yields, lower N rates, or higher NPU across the different field locations in the study, respective Figures 3-4, 5-6, and 9-10.

Based on the mean-variance rule, the farmer could not make a decision as the highest mean net return occurred in treatment 2 and the lowest variance occurred in treatment 3, Table 14. Further investigation was needed to know if the treatments were significantly different. The lint yield KS statistics indicated that the treatments did not differ at the sub-plot or field level, Table 15. Both VRT net return distributions were respectively different when compared to the FP at the sub-plot level. When tested to see if the two VRT treatments were different from each other, the KS results indicated that net return distributions were not significantly different between the two VRT treatments at both the sub-plot and field levels.

Downside Risk – Lint Yields, N Rates, and Net Returns

When equations 28-31 were tested for multicollinearity, the VIF for each variable was under a value of five. The significant explanatory variables were evaluated at their means to determine the potential risk management benefit of using VRT. Table 16 includes the estimated coefficients for Equations 28-31. Marginal effects of soil characteristics and weather on VRT risk management benefits are shown in Table 17.

The significant soil and weather factors associated with lint yields in the estimated logit model were silt soil texture ($Pr \leq 0.01$), loam soil texture ($Pr \leq 0.01$), water holding capacity ($Pr \leq 0.10$), organic matter ($Pr \leq 0.05$), soil depth ($Pr \leq 0.05$), and growing degree days ($Pr \leq 0.01$). Yield marginal changes indicate coarser soils or warmer temperatures are positively attributed with the probability of lower VRT yields than FP. Greater water holding capacity, higher percentages of organic matter, or deeper soils are negatively associated with the probability of lower VRT yields than FP. All else equal, increases in organic matter could potentially lower the probability of yield loss enough to warrant VRT adoption for some.

Odds ratios were evaluated at the means of the significant variables in the cotton lint yield model for the two significant soil texture variables, Equation 36. At the silt soil texture, the lint yields odds ratio indicated that VRT treatment yields were 3.6 times as likely to be lower than FP yields under these conditions. There was a 78.11% probability of VRT yields being lower than FP yields, Equation 37. A field with a silt soil texture had a high probability of lower yields with VRT and could potentially benefit from a keeping the farmer's current practice N rate.

Estimating the odds ratio at the loam soil texture indicated that VRT treatments on loam fields were 2.3 times as likely to have lower yields than with FP. Evaluating Equation 36 for the

loam soil texture, there was a 69.44% probability that VRT yields were lower than FP yields. Loamy fields with the same mean soil conditions and climate would also likely benefit from FP in terms of yields.

The significant soil and weather variables related with N rates in the estimated logit model were silt soil texture ($Pr \leq 0.01$), loam soil texture ($Pr \leq 0.01$), elevation ($Pr \leq 0.01$), water holding capacity ($Pr \leq 0.01$), treatment 3 dummy variable ($Pr \leq 0.01$), and soil erosion index ($Pr \leq 0.01$). Evaluating the marginal changes in soil and weather attributes at the means indicated that coarser soils or soils at higher elevations are negatively associated with the probability that FP generates lower N rates than VRT, Table 17. Greater water holding capacity, more erodible soils, or treatment 3 were positively associated with the probability that FP generates lower N rates than VRT.

N rate odds ratios were estimated at the means of the significant variables for the soil textures silt and loam. N rate odds ratio for silt indicated that FP N rates were 0.32 times as likely to be lower than VRT N rates. There was a 24.21% probability that the FP N rates were lower than VRT N rates. Silt fields with the mean soil conditions would likely benefit from VRT in terms of N cost savings and environmental benefits due to the 75.79% chance of VRT generating lower N rates than FP.

Evaluating the odds ratio at the loam soil texture indicated that the FP N rates were 0.27 as likely to be lower than the VRT N rates, Equation 36. The probability of FP N rates being lower than VRT N rates, Equation 37, was 26.68%. Under these conditions, there was a relatively small chance that FP was applying less N than the VRT technology calculated as necessary. A field with these conditions may benefit from VRT use for environmental benefits.

Parameter estimates from the net returns logit model Equation 30 are in Table 16. The significant soil and weather variables associated with net returns in the estimated logit model were silt soil texture (Pr≤0.01), loam soil texture (Pr≤0.06), organic matter (Pr≤0.10), and growing degree days (Pr≤0.01). Evaluating soil property and weather marginal changes in relation to net returns indicated that coarser soil textures and warmer temperatures were positively associated with the probability of lower net returns using VRT compared to FP, Table 17.

Evaluating the NR odds ratio at the means of the significant variables for the soil texture silt indicated that VRT net returns were 3.3 times as likely to be lower than FP net returns There was a 76.6% chance that VRT had lower net returns than FP. Field with these conditions would not benefit from VRT adoption in terms of profits.

The odds ratio evaluated at the loam soil texture indicated that VRT net returns were 3.0 times as likely to be less than FP. The probability of downside risk under these conditions was 74.91%, Equation 27. Fields with these soil conditions would be better suited to continue using the current FP N management in place.

Downside Risk – N Production Use Efficiency

Significant soil and weather variables related with N production use were sand soil texture (Pr≤0.10), clay soil texture (Pr≤0.01), loam soil texture (Pr≤0.05), soil depth (Pr≤0.05), soil erosion index (Pr≤0.05), and growing degree days (Pr≤0.01).The marginal changes in soil properties and weather in relation to NPU indicated that finer soil textures or warmer temperatures were positively associated with the probability of a lower VRT N use efficiency compared to FP, Table 17. Deeper soils or coarser soil textures were negatively related to the probability of lower N use efficiency of VRT compared to FP.

NPU efficiency odds ratio estimated at the clay soil texture indicated that VRT N use efficiency was 79.9 times as likely to be lower than FP. There was a 98.76% probability of VRT NPU being lower than FP, Equation 37. Using VRT on clay fields with the mean depth, erosion index, and temperature such as these would be inefficient in terms of N use relative to the FP.

At soil texture loam the odds ratio indicated that VRT N use efficiency was 0.5 times as likely to be lower than FP. Evaluating Equation 37 at this odds ratio, there was a 32.08% probability that VRT N efficiency was lower than FP on loam fields with these conditions. This means there is a 67.92% chance of higher N use efficiency using VRT compared to FP.

CHAPTER V: CONCLUSIONS AND RECOMMENDATIONS

The objective of this study was to determine the effect of optical sensing and VRT on profitability, N use/NPU efficiency, and risk management in cotton production. Field trials were conducted in Tennessee, Mississippi, Louisiana, and Missouri from 2011 to 2014 that provided cotton yield and N rates applied per technology, Table 2. Two VRT treatments were compared to the FP using methods that included an ANOVA to determine mean treatment differences, an ANOVA to determine soil and weather effects on treatment mean differences, and a logistic analysis to identify risk management benefits.

Two main conclusions were drawn from this study. First, the VRT treatments indicated some N savings but were not profitable compared to FP. There was some evidence of significantly higher mean net returns using VRT with Greenseeker™ compared to the current practice at the sub-plot level, but the field level showed no difference. Second, there were profit risk management benefits identified at the field level using Greenseeker™ compared to FP.

Other inferred conclusions that can aid in the cotton farmer's decision making are: 1) the VRT treatments may not apply enough N to significantly increase yields; 2) four locations realized significantly lower N rates applied in at least one form of VRT N fertilizer application and four had higher N rates; and 3) N rates were not low enough to increase N use efficiency and encourage environmental benefits.. The fields tested in the experiments likely had limited enough spatial and temporal variability within the field that VRT treatments did not make a difference in net returns.

Cotton farmers in Tennessee, Louisiana, Mississippi, and Missouri states can use this information as a decision aid when considering switching to VRT. Mean net returns were positive across locations (for all technologies), Table 2, but N savings and EQIP incentive

payments did not offset the cost of the technology enough to justify the adoption of VRT in the MRB states. Policy makers are also interested in these results as EQIP payments did not increase net returns enough to justify the adoption of VRT. This can be considered when deciding nutrient management cost-share payments for the future in Tennessee, Mississippi, Missouri and Louisiana.

Areas for potential further research on net returns with this data include incentive payments and price sensitivity. Determining the precision nutrient management EQIP payment that would make optical sensing and VRT more profitable than FP by state would be of interest to policy makers. Research on net return sensitivity to cotton lint price could indicate the threshold where VRT becomes statistically more profitable than FP. Additional studies on fields with more spatial and temporal variability could also be conducted for further research in this discipline.

LIST OF REFERENCES

American Agricultural Economics Association. 2000. *Commodity Costs and Returns Estimation Handbook: A Report of the AAEA Task Force on Commodity Costs and Returns*. Ames, IA.

American Society of Agricultural and Biological Engineers. 2011. *Agricultural Machinery Management Data*. St. Joseph, Michigan: ASABE.

Antle, J.M. 1987. Econometric Estimation of Producers' Risk Attitudes. *American Journal of Agricultural Economics* 69:509-22.

Babcock, B.A., and G.R. Pautsch. 1998. Moving from Uniform to Variable Fertilizer Rates on Iowa Corn: Effects on Rates and Returns. *Journal of Agriculture and Resource Economics* 23(2): 385-400.

Babcock, B.A., and J.F. Shogren. 1995. The Cost of Agricultural Production Risk. *Agricultural Economics* 12:141-50.

Biermacher, J.T., B.W. Brorsen, F.M. Epplin, J.B. Solie, and W.R. Raun. 2009a. Economic Feasibility of Site-Specific Optical Sensing for Managing Nitrogen Fertilizer for Growing Wheat. *Precision Agriculture* 10:213-30.

———. 2009b.The Economic Potential of Precision Nitrogen Application with Wheat Based on Plant Sensing. *Agricultural Economics* 40:397-407.

Biermacher, J.T., F.M. Epplin, B.W. Brorsen, J.B. Solie, and W.R. Raun. 2006. Maximum Benefit of a Precise Nitrogen Application System for Wheat. *Precision Agriculture* 7:193-204.

Binswanger, H.P. 1981. Attitudes Towards Risk: Theoretical Implications of an Experiment in Rural India. *Economic Journal* 91:867-90.

Boehlje, M.D., and V.R. Eidman. 1984. *Farm Management*. New York, NY: John Wiley & Sons, Inc.

Bongiovanni, R., and J. Lowenberg-DeBoer. 2000. Economics of Variable Rate Lime in Indiana. *Precision Agriculture* 2:55-70.

Bowling, B. 2013. Custom Rates Survey, 2013. Department of Agriculture and Resource Economics, University of Tennessee Extension. http://economics.ag.utk.edu/extension/pubs/CustomRates2013-rev.pdf.

Boyer, C.N., B.W. Brorsen, J.B. Solie, and W.R. Raun. 2011. Profitability of Variable Rate Nitrogen Application in Wheat Production. *Precision Agriculture* 12:473-87.

Bradley, J.F., and D.D. Tyler. 1996. No-Till: Sparing the Plow to Save the Soil. *Tennessee Agri Science* 179:7-11.

Bullock, D.G., and D.S. Bullock. 1994. Quadratic and Quadratic-Plus-Plateau Models for Predicting Optimal Nitrogen Rate of Corn: A Comparison. *Agronomy Journal* 86:191-5.

Butchee, K.S., J. May, and B. Arnall. 2011. Sensor Based Nitrogen Management Reduced Nitrogen and Maintained Yield. *Crop Management* 10(1).

Carr, P.M., G.R. Carlson, J.S. Jacobson, G.A. Nielsen, and E.O. Skogley. 1991. Farming Soils, Not Fields: A Strategy for Increasing Fertilizer Profitability. *Journal of Production Agriculture* 4:57-61.

Cassman, K.G., G.C. Gines, M.A. Dizon, M.I. Samson, and J.M. Alcantara. 1996. Nitrogen-Use Efficiency in Tropical Lowland Rice Systems: Contributions from Indigenous and Applied Nitrogen. *Field Crops Research* 47:1-12.

Cassman, K.G., S. Peng, D.C. Olk, J.K. Ladha, W. Reichardt, A. Dobermann, U. Singh. 1998. Opportunities for Increased Nitrogen-Use Efficiency From Improved Resource Management in Irrigated Rice Systems. *Field Crops Research* 56:7-39.

Chakravarti, I.M., R.G. Laha, and J. Roy. 1967. *Handbook of Methods of Applied Statistics: Techniques of Computation, Descriptive Methods, and Statistical Inference, Volume I.* New York, NY: John Wiley & Sons, Inc.

Chavas, J. P. 2004. *Risk Analysis in Theory and Practice*. San Diego, CA: Elsevier Academic Press.

Dhompongsa, S., H.T. Nguyen, and S. Sriboonchita. 2010. *Stochastic Dominance and Applications to Finance, Risk and Economics*. Boca Raton, FL: Chapman & Hall.

Elms, M.K., C.J. Green, and P.N. Johnson. 2001. Variability of Cotton Yield and Quality. *Communications in Soil Science and Plant Analysis* 32(3): 351-68.

Fishburn, P.C. 1977. Mean-Risk Analysis with Risk Associated with Below-Target Returns. *The American Economic Review* 67:116-26.

Gandonou, J-M. A., C.R. Dillion, S.A. Shearer, and T. Stombaugh. 2006. Precision Agriculture Equipment Ownership versus Custom Hire: A Break-even Land Area Analysis. *Journal of the American Society of Farm Managers and Rural Appraisers*.

Hu, R.., J. Cao, J. Huang, S. Peng, J. Huang, X. Zhong, Y. Zou, J. Yang, and R.J. Buresh. 2007. Farmer Participatory Testing of Standard and Modified Site-Specific Nitrogen Management for Irrigated Rice in China. *Agricultural Systems* 94:331-40.

Isik, M., and M. Khanna. 2003. Stochastic Technology, Risk Preferences, and Adoption of Site-Specific Technologies. *American Journal of Agricultural Economics* 85(2):305-17.

Koch, B., R. Khosla, W.M. Frasier, D.G. Westfall, and D. Inman. 2004. Economic Feasibility of Variable-Rate Nitrogen Application Utilizing Site-Specific Management Zones. *Agronomy Journal* 96:1572-80.

Lambert, D., and J. Lowenberg-DeBoer. 2000. Precision Agriculture Profitability Review. Purdue Agriculture Site-Specific Management Center. http://www.agriculture.purdue.edu/ssmc/Frames/newsoilsX.pdf.

Lambert, D.M., J. Lowenberg-DeBoer, and G.L. Malzer. 2006. Economic Analysis of Spatial-Temporal Patterns in Corn and Soybean Response to Nitrogen and Phosphorus. *Agronomy Journal*. 98:43-54.

Lambert, D., J. Lowenberg-DeBoer, and R. Bongiovanni. 2004. Comparison of Four Spatial Regression Models for Yield Monitor Data: A Case Study from Argentina. *Precision Agriculture* 5:579-600.

Larkin, S.L., L. Perruso, M.C. Marra, R.K. Roberts, B.C. English, J.A. Larson, R.L. Cochran, and S.W. Martin. 2005. Factors Affecting Perceived Improvements in Environmental Quality from Precision Farming. *Journal of Agricultural and Applied Economics* 37(3):577-88.

Larson, J.A., B.C. English, and R.K. Roberts. 2002. Precision Farming Technology and Risk Management. *A Comprehensive Assessment of the Role of Risk in U.S. Agriculture.* R.E. Just and R.D. Pope (Eds.). Norwell, MA: Kluwer Academic Publishers.

Larson, J.A., E.C. Jaenicke, R.K. Roberts, and D.D. Tyler. 2001. Risk Effects of Alternative Winter Cover Crop, Tillage, and Nitrogen Fertilization Systems in Cotton Production. *Journal of Agricultural and Applied Economics* 33(3):445-57.

Larson, J.A., R.K. Roberts, B.C. English, R.L Cochran, and B.S. Wilson. 2005. A Computer Decision Aid for the Cotton Yield Monitor Investment Decision. *Computers and Electronics in Agriculture* 48:216-34.

Larson, J.A., R.K. Roberts, and C.O. Gwathmey. 2007. Herbicide-Resistant Technology Price Effects on the Plant Density Decision for Ultra-Narrow-Row Cotton. *Journal of Agricultural and Resource Economics* 32(2):383-401.

Littell, R.C., G.A. Milliken, W.W. Stroup, R.D. Wolfinger, O. Schabenberger. 2006. *SAS® for Mixed Models Second Edition*. Cary, NC: SAS Institute Inc.

Lowenberg-DeBoer, J., and S.M. Swinton. 1997. Economics of Site-Specific Management in Agronomic Crops. *The State of Site Specific Management for Agriculture*. Washington, D.C.: National Academy Press.

Lowenberg-DeBoer, J. 1999. Risk Management Potential of Precision Farming Technologies. *Journal of Agriculture and Applied Economics* 31(2):275-85.

Madden, R.A., and J. Williams. 1978. The Correlation Between Temperature and Precipitation in the United States and Europe. *Monthly Weather Review* 106:142-7.

Maine, N., W.T. Nell, J. Lowenberg-DeBoer, and Z.G. Alemu. 2007. Economic Analysis of Phosphorus Application under Variable and Single-Rate Applications in the Bothaville District. *Agrekon* 46(4):532-47.

———. 2010. Impact of Variable-rate Application of Nitrogen on Yield and Profit: A Case Study from South Africa. *Precision Agriculture* 11:448-63.

McBratney, A., B. Whelan, and T. Ancev. 2005. Future Directions of Precision Agriculture. *Precision Agriculture* 6:7-23.

Mississippi State University Extension Service. 2013. Custom Rates for Farm and Ranch Services in Mississippi. http://msucares.com/pubs/publications/p2776.pdf.

Mooney, D.F., R.K. Roberts, B.C. English, D.M. Lambert, J.A. Larson, M.Velandia, S.L. Larkin, M.C. Marra, S.W. Martin, A. Mishra, K.W. Paxton, R. Rejesus, E. Segarra, C. Wang, and J.M. Reeves. 2010. Precision Farming by Cotton Producers in Twelve Southern States: Results from the 2009 Southern Cotton Precision Farming Survey. Department of Agricultural and Resource Economics, University of Tennessee.

National Research Council. 1997. *Precision Agriculture in the 21st Century: Geospatial and Information Technologies in Crop Management*. Washington, DC: The National Academies Press.

Ortiz-Monasterio, J.I., and W.R. Raun. 2007. Reduced Nitrogen and Improved Farm Income for Irrigated Spring Wheat in the Yaqui Valley, Mexico, Using Sensor Based Nitrogen Management. *Journal of Agricultural Science* 145:1-8.

Peng, S., R.J. Buresh, J. Huang, J. Yang, Y. Zou, X. Zhong, G. Wang, and F. Zhang. 2006. *Field Crops Research* 96:37-47.

Post, T., and M. Kopa. 2013. General Linear Formulations of Stochastic Dominance Criteria. *European Journal of Operational Research* 230:321-32.

PRISM, Climate Group. 2014. Northwest Alliance for Computational Science and Engineering. Oregon State University. http://www.prism.oregonstate.edu/recent/.

Raun, W.R., and G.V. Johnson. 1999. Improving Nitrogen Use Efficiency for Cereal Production. *Agronomy Journal* 91:131-78.

Raun, W.R., J.B. Solie, G.V. Johnson, M.L. Stone, R.W. Mullen, K.W. Freeman, W.E. Thomason, and E.V. Lukina. 2002. Improving Nitrogen Use Efficiency in Cereal Grain Production with Optical Sensing and Variable Rate Application. *Agronomy Journal* 94:815-20.

Raun, W.R., J.B. Solie, M.L. Stone, K.L. Martin, K.W. Freeman, R.W. Mullen, H. Zhang, J.S. Schepers, and G.V. Johnson. 2005. Optical Sensor-Based Algorithm for Crop Nitrogen Fertilization. *Communications in Soil Science and Plant Analysis* 36:2759-81.

Roberts, A.D., and S.D. Prince. 2010. Effects of Urban and Non-Urban Land Cover on Nitrogen and Phosphorus Runoff to Chesapeake Bay. *Ecological Indicators* 10(2): 459-74.

Roberts, R.K., S.B. Mahajanashetti, B.C. English, J.A. Larson, and D.D. Tyler. 2002. Variable Rate Nitrogen Application on Corn Fields: The Role of Spatial Variability and Weather. *Journal of Agricultural and Applied Economics* 34(1):111-29.

Sawyer, J.E. 1994. Concepts of Variable Rate Technology with Considerations for Fertilizer Application. *Journal of Production Agriculture* 7(2):195-201.

Schabenberger, O., and F.J. Pierce. 2002. Contemporary Statistical Models for the Plant and Soil Sciences. Boca Raton, FL: CRC Press LLCC, pp 474-479.

Scharf, P.C., D.K. Shannon, H.L. Palm, K.A. Sudduth, S.T. Drummond, N.R. Kitchen, L.J. Mueller, V.C. Hubbard, and L.F. Oliveira. 2011. Sensor-Based Nitrogen Applications Out-Performed Producer-Chosen Rates for Corn in On-Farm Demonstrations. *Agronomy Journal* 103:1683-91.

Scharf, P.C., N.R. Kitchen, K.A. Sudduth, J.G. Davis, V.C. Hubbard, and J.A, Lory. 2005. Nitrogen Management. *Agronomy Journal* 97:452-61.

Selley, R. 1984. Decision Rules in Risk Analysis. *Risk Management in Agriculture*. P.J. Barry (Ed.). Ames, IA: Iowa State University Press.

Stone, R.P., and D. Hilborn. 2012. Universal Soil Loss Equation (USLE) Factsheet. Ministry of Agriculture, Food and Rural Affairs. http://www.omafra.gov.on.ca/english/engineer/facts/12-051.pdf.

Swinton, S.M., and J. Lowenberg-DeBoer. 1998. Evaluating the Profitability of Site-Specific Farming. *Journal of Production Agriculture* 11(4):439-46.

Thrikawala, S., A Weersink, G. Kachnoski, and G. Fox. 1999. Economic Feasibility of Variable Rate Technology for Nitrogen on Corn. *American Journal of Agricultural Economics* 81:914-27.

Tiessen, H., E. Cuevas, and P. Chacon. 1994. The Role of Soil Organic Matter in Sustaining Soil Fertility. *Nature* 371:783-5.

Tolliver, D.K., J.A. Larson, R.K. Roberts, B.C. English, D.G. De La Torre Ugarte, and T.O. West. 2012. Effects of No-Till on Yields as Influenced by Crop and Environmental Factors. *Agronomy Journal* 104(2):530-541.

Tubaña, B.S., D.B. Arnall, O. Walsh, B. Chung, J.B. Solie, K. Girma, and W.R. Raun. 2008. Adjusting Midseason Nitrogen Rate Using a Sensor-Based Optimization Algorithm to Increase Use Efficiency in Corn. *Journal of Plant Nutrition* 31:1975-98.

Turner, R.E., and N.N. Rabalais. 1991. Changes in Mississippi River Water Quality this Century. *BioScience* 41(3):140-7.

University of Missouri, Extension. 2012. 2012 Custom Rates for Farm Services in Missouri. http://agebb.missouri.edu/mgt/custrate/customrate2012.pdf.

U.S. Department of Agriculture. 2012. Census of Agriculture. 2012 Census Volume 1, Chapter 1: State Level Data. http://www.agcensus.usda.gov/Publications/2012/Full_Report/Census_by_State/.

———. 2013. Economic Research Service. Fertilizer Use and Price. http://www.ers.usda.gov/data-products/fertilizer-use-and-price.aspx#.UyuJZfldVdU.

———. 2014a. National Agriculture Statistics Service. Cotton, Price Received, Measured in $/lb. http://quickstats.nass.usda.gov/#CB852E7A-A8A7-3C8D-8C18-B0244CC64A8F.

_____. 2014b. National Resources Conservation Service. Environmental Quality Incentives Program. http://www.nrcs.usda.gov/wps/portal/nrcs/main/national/programs/financial/eqip/.

_____. 2014c. National Agriculture Statistics Service: Mississippi. 2014 Statewide EQIP Practice, Ranking and Rate Information. http://www.nrcs.usda.gov/wps/portal/nrcs/detail/ms/programs/financial/eqip/?cid=stelprdb1193441.

———. 2014d. National Agriculture Statistics Service. Nitrogen, Price Paid, Measured in $/ton. http://quickstats.nass.usda.gov/#CB852E7A-A8A7-3C8D-8C18-B0244CC64A8F.

_____. 2014e. National Resources Conservation Service: Soils. Soil Texture Calculator. http://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/?cid=nrcs142p2_054167.

_____. 2014f. Natural Resources Conservation Service: Soils. SSURGO Database. http://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/?cid=nrcs142p2_053627.

U.S. Department of Commerce. 2014. Bureau of Economic Analysis. *Implicit Price Deflators for Gross Domestic Product*. NIPA Table 1.1.9 Implicit Price Deflators for Gross Domestic Product.

U.S. Geology Survey. 2014. National Elevation Dataset: Metadata. http://ned.usgs.gov/.

Vetsch, J.A., G.L. Malzer, P.C. Robert, and D.R. Huggins. 1995. Nitrogen Specific Management by Soil Condition: Managing Fertilizer Nitrogen in Corn. In Robert et al., ed., *Site-*

Specific Management for Agricultural Systems. Madison, WI: ASA, CSSA, SSSA, pp. 465-473.

Wang, D., T. Prato, Z. Qiu, N.R. Kitchen, and K.A. Sudduth. 2003. Economic and Environmental Evaluation of Variable Rate Nitrogen and Lime Application for Claypan Soil Fields. *Precision Agriculture* 4:35-52.

Watkins, B.K., Y. Lu, and W. Huang. 1998. Economic and Environmental Feasibility of Variable Rate Nitrogen Fertilizer Application with Carry-Over Effects. *Journal of Agricultural and Resource Economics* 23(2):401-26.

Whelan, B.M., and A.B. McBratney. 2000. The "Null Hypothesis" of Precision Agriculture Management. *Precision Agriculture* 2:265-79.

Wibawa, W.D., D.L. Dludlu, L.J. Swenson, D.G. Hopkis, and W.C. Dahnke. 1993. Variable Fertilizer Application Based on Yield Goal, Soil Fertility, and Soil Map Unit. *Journal of Production Agriculture* 6:255-61.

Wright, D.L., R.K. Sprenkel, and J.J. Marois. 2011. Cotton Growth and Development. *University of Florida IFAS Extension*. http://edis.ifas.ufl.edu/ag235.

Zhang, N., M. Wang, and N. Wang. 2002. Precision Agriculture – A Worldwide Overview. *Computer and Electronics in Agriculture* 36:113-32.

APPENDIX

Tables

Table 1. Literature review summary

				Profitability			Excess N			Risk Management Benefits
Author	Year	Fertilizer	Crop	VRT	URT	FP	VRT	URT	FP	VRT
Watkins, Lu, and Huang	1998	N	seed potato	$1 per ha	$2 per ha		same to reduced	same to reduced		
Roberts et al.	2002	N	corn				reduced more	Reduced		
Hu et al.	2007	N	rice	$63 to $82 per ha			+NUE			
Peng et al.	2006	N	rice	similar to higher		X	- N/+ NUE		X	
Lambert, Lowenberg-DeBoer, and Bongiovanni	2004	N	corn	0 or $1 to $2 per ha	X					
Wang et al.	2003	N	corn	++	X		reduced	X		
Maine et al.	2010	N	corn	++ overall	X					
Biermacher et al.	2006	N	winter wheat	$21.80 to $24.30 per ha	X		N by -59% by -82%	X		
Biermacher et al.	2009	N	winter wheat	$16 per ha	$9 per ha					
Butchee, May, and Arnall	2011	N	spring wheat				-22.4 kg N per ha		X	
Ortiz-Monasterio and Raun	2007	N	spring wheat	$56 per ha		X	-69 kg N per ha		X	
Raun et al.	2002	N	winter wheat	$4 to $5 per ha			NUE +15%			
Raun et al.	2005	N	winter wheat				NUE +15%			
Scharf et al.	2011	N	corn	$42 per ha	X		- 15 kg N per ha	X		
Lowenberg-DeBoer	1999	P&K	corn*							X
Isik and Khanna	2003	N&P	corn							X
Larson, English, and Roberts	2002	N	corn							X

*Corn-soybean or corn-soybean-wheat rotation.
X represents VRT in relation to either URT or FP.
++ represents that VRT was overall more profitable than either URT or FP.

Table 2. Mean cotton lint yields (kg ha^{-1}), N rates (kg ha^{-1}), NPU efficiency, and net returns ($ ha^{-1}) by location and year

County/Parish	State	Year	N	Cotton Lint Yield (kg ha^{-1})	N rates (kg ha^{-1})	NPU Efficiency	Net Returns ($ ha^{-1})
Research Station	LA	2012	89	941.14	101.65	9.44	1476.63
Tensas Parish Middle	LA	2012	90	1742.67	122.48	14.63	2787.45
		2013	90	1850.73	142.23	13.06	3162.93
Tensas Parish Middle low	LA	2014	90	1524.16	113.43	14.00	2675.18
Tensas Parish North	LA	2012	90	2307.38	102.33	28.33	3789.34
		2013	100	1329.18	132.35	10.97	2235.61
Tensas Parish South	LA	2012	90	1197.45	135.29	9.07	1835.10
		2013	90	1980.03	109.57	18.23	3463.60
		2014	80	1755.68	125.27	13.92	3077.85
Dunklin	MO	2013	12	887.22	99.29	9.29	1484.72
New Madrid East	MO	2012	24	1318.00	75.12	17.68	2151.04
New Madrid North	MO	2012	33	1247.82	75.62	16.67	2031.05
New Madrid South	MO	2012	12	1042.00	83.33	12.55	1665.04
Pemiscot North	MO	2013	6	1313.41	91.08	15.46	2273.55
Pemiscot South	MO	2013	6	1180.49	103.58	11.58	2007.44
Adams	MS	2012	107	1010.71	78.49	14.86	1647.00
Leflore East	MS	2014	35	1761.77	143.45	12.33	3047.17
Leflore North	MS	2013	60	1742.37	119.19	15.23	3013.67
Leflore South	MS	2013	48	1952.37	142.55	13.93	3437.51
Carroll	TN	2014	72	836.96	93.32	9.25	1451.90
Gibson	TN	2011	72	760.35	179.23	4.82	1570.31
		2012	88	1160.80	93.96	13.00	1849.92
Lauderdale	TN	2012	90	1485.86	114.22	13.09	2369.38
		2013	90	869.03	98.29	23.37	1474.07
		2014	90	722.41	92.69	8.28	1242.81
Madison North	TN	2012	72	959.41	88.81	11.77	1543.11
		2013	72	1168.91	72.79	55.53	2068.93
Madison South	TN	2014	72	1189.96	91.29	13.61	2104.08
Tipton	TN	2012	72	1286.63	93.94	13.93	2077.64

N represents the number of observations.

Table 3. 2013 Ownership Cost Budgets for Greenseeker™, Yield Monitor Information Systems (YMIS), a Computer, and Technical Assistance

	Green-seeker™	YMIS	Computer		Technical Advice[10]
Ownership Cost	Dollars	Dollars	Dollars	Cost by State	Dollars
Capital Recovery (annual) [2]	$13,622.38	$ 3,232.99	$ 224.90		
Purchase/list price[1,6,7] (2013 dollars)	$60,684.08	$14,421.08	$1,001.24		
Salvage value[3] (2013 dollars)	$ 48.27	$ 34.52	$ -		
Capital recovery factor	0.22	0.22	0.22		
Real interest rate[4] (%)	4%	4%	4%		
Useful life (years)[5]	5	5	3		
Average hours of use per year[5]	300	600			
Taxes, Insurance, and Housing[2]	$ 606.36	$ 143.87	$ 10.01		
Interest rate (%)	2%	2%	2%		
Repairs and Maintenance[2]	$42,478.86	$11,536.86	$ 0.00		
Repairs as % of list price[3] (%)	70%	80%			
Useful life[5] (hours)	1500	3000			
Hectares per Hour[2]	16.86	1.82			
Speed (km hour^{-1})[3]	10.5	4.5			
Width (m)[3]	24.7	5.7912			
Meters per kilometer (m km^{-1})	1,000	1,000			
Efficiency (%)[3]	65%	70%			
Meters^2 ha^{-1}	10,000	10,000			
Hours ha^{-1}	0.059	0.548			
Cotton Enterprise Size[8]					
Tennessee farm (ha)			279.42	$ 0.28	
Mississippi farm (ha)			231.10	$ 0.34	
Louisiana farm (ha)			196.47	$ 0.40	
Missouri farm (ha)			347.08	$ 0.23	
Total ownership costs hour^{-1}	$ 37.81	$ 4.97	$ 78.31		
Total costs (2013 dollars ha^{-1})	$ 2.25	$ 2.73			$ 12.63
Greenseeker™ costs * 1.02[9]	$ 2.29				

[1]Includes $500 (684.08 in 2013 dollars) to retrofit (Larson et al. 2005)

[2]Formula given in Boehlje and Eidman (1984)

[3]ASABE Standards (2011)

[4]American Agricultural Economics Association (2000)

[5]Gandonou et al. (2006)

[6]List Price for Yield Monitoring is the average of Case IH and John Deere plus $500 (684.08 in 2013 dollars) (Larson et al. 2005)

[7]Average cost for desktop computer and color printer (informal survey 2014)

[8]Average area (ha) in cotton on a farm categorized as a cotton farm per state as given by 2012 Census of Agriculture (USDA 2012)

[9]Greenseeker™ multiplied by 1.02 to account for N rich strip calibration (Biermacher et al. 2009a).

[10]Mooney et al. 2010

Table 4. Partial budget summary for VRT treaments: Greenseeker™ (treatment 2) and Greenseeker™ plus YMIS (treatment 3)

Net Return Component	Treatment 2	Treatment 3
Revenue ($ ha^{-1})		
Cotton Revenue ($ ha^{-1})	$ 2,530.27	$ 2,509.08
Cotton lint price[1] ($ kg^{-1})	$ 1.86	$ 1.86
Cotton lint yield[1] (kg ha^{-1})	1360.36	1348.97
2013 EQIP Payment ($ ha^{-1})		
Tennessee	$ 63.99	$ 63.99
Louisiana	$ 66.53	$ 66.53
Mississippi	$ 66.28	$ 66.28
Missouri	$ 33.61	$ 33.61
Costs ($ ha^{-1})		
N applied ($ ha^{-1})	$ 66.55	$ 71.51
Urea N price[1] ($ kg^{-1})	$ 0.93	$ 0.93
In-season N rate[1] (kg ha^{-1})	71.56	76.89
N fertilizer application[3] ($ ha^{-1})	$ 6.60	$ 6.60
Information/operating costs[2] ($ ha^{-1})		
Tennessee	$ 2.29	$ 12.91
Louisiana	$ 2.29	$ 13.03
Mississippi	$ 2.29	$ 12.97
Missouri	$ 2.29	$ 12.86
Net Returns ($ ha^{-1})		
Tennessee	$ 2,518.82	$ 2,508.20
Louisiana	$ 2,521.36	$ 2,510.62
Mississippi	$ 2,521.11	$ 2,510.43
Missouri	$ 2,488.44	$ 2,477.87

[1]Prices, yields, and N rates are averages of the years included in this study (2013 real $).

[2]Operating costs for treatment 3 include cost of computer and technical assistance (see table 3).

[3]N fertilizer application is the labor cost for dry bulk only.

Table 5. Dependent and explanatory variable names, definitions, and means

Variable Name	Variable Definition	Mean	Min	Max	N
Dependent Variable					
Y	Cotton lint yields (kg ha^{-1})	1347.07	133.25	2585.06	1942
N	Total nitrogen rates applied (kg ha^{-1})	109.74	33.59	252.83	1953
NR	Net returns (\$ ha^{-1})	2268.57	239.25	4232.64	1942
NPU	Nitrogen production use efficiency (Y/N)	13.43	0.61	119.56	1942
YΔ	VRT_i-FP yields (kg ha^{-1})	37.05	-1941.20	2077.53	1263
NΔ	VRT_i-FP N rates (kg ha^{-1})	4.95	-67.59	125.36	1263
NRΔ	VRT_i-FP NR (\$ ha^{-1})	102.37	-3630.32	3668.06	1263
NPUΔ	VRT_i-FP NPU	-3.21	-96.52	20.18	1263
Yprob	If VRT_i<FP, 1; otherwise, 0	0.45	0	1	1263
Nprob	If VRT_i>FP, 1; otherwise, 0	0.55	0	1	1263
NRprob	If VRT_i<FP, 1; otherwise, 0	0.37	0	1	1263
NPUprob	If VRT_i<FP, 1; otherwise, 0	0.47	0	1	1263
Explanatory Variables					
Treatment	Treatment dummy 1 Farmer practice 2 VRT Greenseeker™ 3 VRT Greenseeker™ + yield monitor information systems (YMIS)[1]				
Soil texture index	Soil texture ranked by coarseness (4 being the coarsest) 1 Clay 2 Silt 3 Loam 4 Sand[1]	2.13	1	4	1935
Elevation	Vertical distance above sea-level (meters)	64.40	21.64	136.36	1953
Water holding capacity[2]	Water holding capacity (cm cm^{-1}) – "the amount of water that an increment of soil depth, inclusive of fragments, can store that is available to plants"	0.21	0.08	0.23	1935
Organic matter[2]	Organic matter (%) – "the amount by weight of decomposed plant and animal residue expressed as a weight percentage of the less than 2 mm soil material"	1.84	0.52	2.50	1935
Soil erosion index	Soil erosion index	7.35	0.21	39.13	1935
Depth[2]	Soil depth (cm) – "Distance from the top of the soil to the base of the soil horizon"	21.53	8.00	64.00	1935
Growing degree days	Seasonal growing degree days (Celsius)	1574.3	1025.93	1943.27	1953
Treatment 3	If treatment 3 (Greenseeker™ plus YMIS), then 1; otherwise, 0	0.33	0	1	1953

[1]Reference variable

[2]Definition taken directly from SSURGO (USDA 2014f).

Table 6. Mean elevation (meters), soil texture(s), mean SEI, mean water holding capacity (cm cm^{-1}), mean organic matter (%), mean soil depth, and mean growing degree days (Celsius) by county/parish and state

County/Parish	State	N	Elevation (meters)[4]	Soil Texture(s)[2]	SEI	Water Holding Capacity (cm cm^{-1})[1]	Organic Matter (%)[1]	Soil Depth (cm)[1]	Growing Degree Days (Celsius)[3]
Research Station	LA	90	21.64	Sand	7.53	0.22	2.20	18.00	1938.34
Tensas Middle	LA	180	21.64	Silt	3.59	0.21	2.23	22.29	1846.54
Tensas Middle low	LA	90	21.64	Silt	3.69	0.22	2.20	28.00	1346.87
Tensas North	LA	190	23.46	Clay; Silt	3.15	0.18	2.15	15.96	1830.56
Tensas South	LA	270	21.64	Clay; Silt	7.26	0.22	2.20	28.00	1731.71
Dunklin	MO	12	82.09	Loam; Sand	0.31	0.09	1.01	19.67	1439.52
New Madrid East	MO	24	92.99	Loam; Sand	2.06	0.21	1.35	22.75	1682.86
New Madrid North	MO	33	89.74	Loam	1.92	0.21	1.23	19.61	1682.86
New Madrid South	MO	12	89.74	Sand	1.00	0.17	0.75	20.00	1682.86
Pemiscot North	MO	6	85.12	Silt; Sand	2.53	0.19	1.13	17.33	1377.81
Pemiscot South	MO	6	83.86	Silt	3.85	0.23	2.00	18.00	1377.81
Adams	MS	107	55.17	Silt	6.87	0.22	1.89	27.03	1856.31
Leflore East	MS	35	43.07	Clay; Silt; Loam	6.91	0.20	1.49	20.00	1211.69
Leflore North	MS	60	43.07	Silt; Loam	6.59	0.19	1.75	23.00	1648.79
Leflore South	MS	48	43.07	Silt; Loam	6.86	0.20	1.60	21.54	1648.79
Carroll	TN	72	123.22	Silt	11.41	0.21	1.45	17.49	1025.93
Gibson	TN	160	130.72	Silt	19.60	0.22	1.38	21.32	1464.16
Lauderdale	TN	270	90.32	Silt	3.22	0.21	1.93	13.18	1337.34
Madison North	TN	144	117.25	Silt	16.12	0.22	1.33	20.06	1404.96
Madison South	TN	72	136.36	Silt	12.79	0.22	1.41	18.72	1063.23
Tipton	TN	72	89.70	Silt	5.02	0.22	1.25	40.51	1584.43

[1] Source: SSURGO (USDA 2014f).

[2] Source: Soil texture triangle (USDA 2014e).

[3] Source: PRISM (PRISM 2014).

[4] Source: National Elevation Data (U.S. Geology Survey 2014).

N represents number of observations.

Table 7. Best fit criteria for treatment effect models, Equations 16-19

	Yields		N Rate		NPU		NR	
	With	Without	With	Without	With	Without	With	Without
-2 LL	27181.0	27187.8	17617.0	18274.3	12695.8	12886.7	29433.0	29435.2
AIC	27195.0	27199.8	17625.0	18280.3	12709.8	12898.7	29447.0	29447.2
BIC	27190.7	27196.1	17629.2	18283.5	12705.5	12895.0	29442.7	29443.6
N used	1924	1924	1935	1935	1924	1924	1924	1924

N represents number of observations.
AIC is the Akaike information criterion, BIC is the Bayesian information criterion, and the -2LL is the -2 Log Likelihood.

Table 8. Treatment effect estimates of VRT treatments 2 and 3 versus FP by location on lint yield (kg ha^{-1}), N rate (kg ha^{-1}), NPU, and net returns (NR) ($ ha^{-1})

			Cotton Lint Yield (kg ha^{-1})		Total N Rates (kg ha^{-1})		NPU Efficiency (kg kg-^{1})		Net Returns ($ ha^{-1})	
County/Parish	State	N	2 vs 1	3 vs 1	2 vs 1	3 vs 1	2 vs 1	3 vs 1	2 vs 1	3 vs 1
Research Station	LA	30	211.71	271.85	37.54	32.26	-1.11	-0.33	339.48	446.59
			(284.71)	(237.62)	(17.91)	(16.69)	(3.66)	(2.76)	(471.11)	(394.46)
Tensas Middle	LA	60	-26.53	-42.19	-26.10	-14.23	2.91	1.18	73.13	15.77
			(183.39)	(171.05)	(21.71)*	(13.73)*	(2.95)	(2.06)	(335.51)	(313.35)
Tensas Middle low	LA	30	67.05	19.65	-45.90	-50.52	5.45	5.72	276.87	195.90
			(103.57)	(126.16)	(5.90)	(6.06)	(1.21)	(1.40)	(190.26)	(232.52)
Tensas North	LA	60	153.95	120.37	79.22	84.33	-17.15	-17.91	163.19	90.22
			(119.97)	(181.58)	(12.57)*	(19.52)*	(11.69)*	(12.43)*	(226.68)	(332.13)
Tensas South	LA	90	234.03	219.22	9.50	24.69	1.50	-0.08	452.83	390.41
			(593.14)	(574.53)	(16.89)*	(24.76)*	(4.93)	(5.22)	(1031.12)	(1010.62)
Dunklin	MO	4	-82.30	-92.51	-18.48	-23.80	0.95	1.88	-84.03	-94.68
			(44.57)	(73.65)	(13.11)	(21.10)	(1.18)	(3.39)	(62.69)	(136.49)
New Madrid East	MO	8	-18.59	-27.52	-6.02	-3.78	1.33	0.67	8.23	-14.94
			(37.84)	(35.32)	(6.69)	(6.80)	(1.43)	(1.56)	(59.65)	(63.17)
New Madrid North	MO	11	19.02	12.00	-3.97	-4.72	1.28	1.45	67.30	54.11
			(71.34)	(81.91)	(9.26)	(10.46)	(2.27)	(2.26)	(121.03)	(132.36)
New Madrid South	MO	4	51.00	61.57	6.44	8.40	-0.29	-0.50	98.01	108.52
			(26.14)	(34.75)	(7.94)	(5.67)	(1.53)	(1.10)	(60.66)	(66.31)
Pemiscot North	MO	3	55.27		-41.81		7.95		212.60	
			(129.95)		(8.40)		(4.06)		(250.70)	
Pemiscot South	MO	3	-20.94		-16.80		1.89		23.61	
			(288.35)		(16.95)		(3.07)		(510.74)	
Adams	MS	29	117.77	57.66	17.25	26.71	-6.74	-8.58	222.35	96.12
			(58.26)	(75.84)	(39.40)	(54.08)*	(8.87)	(11.30)*	(27.51)	(30.40)
Leflore East	MS	17	20.10		17.38		-1.33		64.03	
			(306.27)		(6.85)		(2.09)		(559.30)	

Table 8. Continued

			Cotton Lint Yield (kg ha^{-1})		Total N Rates (kg ha^{-1})		NPU Efficiency (kg kg^{-1})		Net Returns ($ ha^{-1})	
County/Parish	State	N	2 vs 1	3 vs 1	2 vs 1	3 vs 1	2 vs 1	3 vs 1	2 vs 1	3 vs 1
Leflore North	MS	20	-22.93	-54.22	-31.07	-14.47	4.16	2.04	81.82	-11.77
			(54.67)	(132.68)	(18.95)*	(25.57)	(3.06)	(3.82)	(101.80)	(236.09)
Leflore South	MS	16	103.06	38.91	11.27	13.24	-0.14	-0.61	223.42	100.24
			(98.79)	(92.19)	(18.12)	(23.81)	(2.18)	(2.80)	(177.21)	(193.01)
Carroll	TN	24	30.69	134.90	-16.80	-5.60	2.31	2.16	149.39	315.32
			(246.94)	(150.60)	(15.84)	(20.36)	(3.60)	(2.87)	(462.84)	(285.18)
Gibson	TN	48	-11.03	-4.42	-14.65	-16.42	1.20	1.56	-2.92	-15.29
			(303.57)	(286.92)	(19.42)*	(22.30)*	(3.94)	(3.04)	(576.54)	(532.59)
Lauderdale	TN	90	-12.88	45.84	-18.66	-12.07	2.45	2.86	76.83	165.33
			(391.78)	(360.03)	(18.84)*	(20.85)*	(5.03)	(5.54)	(718.42)	(657.46)
Madison North	TN	48	-360.74	-286.99	18.90	21.93	-32.88	-34.34	-641.41	-521.44
			(608.74)	(533.45)	(38.80)*	(49.86)*	(37.10)*	(40.98)*	(1148.18)	(1010.12)
Madison South	TN	24	-83.65	-65.59	-12.60	-15.86	1.33	2.59	-68.93	-32.30
			(301.44)	(231.69)	(15.60)	(21.88)	(4.33)	(5.00)	(573.11)	(424.55)
Tipton	TN	24	11.04	-50.89	-6.53	-14.00	1.20	1.89	92.83	1.70
			(182.06)	(194.22)	(10.40)	(14.11)	(2.15)	(3.05)	(305.61)	(327.91)

* Significant differences using the Bonferroni correction to deal with multiple comparisons.

Standard errors are in parentheses.

N is the number of observations; the Pemiscot, MO, locations did not have a treatment 3.

Table 9. Differences of least squares means and Dunnett's test results, with (With) and without (Without) the location-treatment interaction term

		F Observed Estimate	
Variable	Effect	With	Without
Yield	Treatment 2 vs 1	29.96	28.68
		(21.50)	(15.69)
Yield	Treatment 3 vs 1	38.39	35.82
		(21.92)	(15.84)$^{++}$
N rate	Treatment 2 vs 1	-2.20	2.32
		(5.50)	(1.46)
N rate	Treatment 3 vs 1	1.35	7.95
		(5.73)	(1.50)$^{+++}$
NPU	Treatment 2 vs 1	-1.86	-3.21
		(1.72)	(0.67)$^{+++}$
NPU	Treatment 3 vs 1	-2.15	-3.70
		(1.77)	(0.66)$^{+++}$
Net Returns	Treatment 2 vs 1	90.73	89.59
		(34.33)$^{++}$	(28.27)$^{+++}$
Net Returns	Treatment 3 vs 1	76.03	72.09
		(34.92)$^{+}$	(28.56)$^{++}$

Note: Standard error in parentheses.

$^{+,++,+++}$ Dunnett's adjusted probability significant at the 10%, 5%, or 1% level.

Table 10. Treatment, soil attribute, and climate effects on lint yields (kg ha^{-1}), N rates (kg ha^{-1}), NPU, and net returns (NR) ($ ha^{-1})

	Cotton lint yields (kg ha^{-1})	N rates (kg ha^{-1})	NPU	NR ($ ha^{-1})
N	1924	1935	1924	1924
Intercept[1] (μ)	1872.41	133.85	159.15	2730.60
	(467.32)***	(15.82)***	(14.68)***	(739.26)***
Treatment 1 (τ_1)	-38.39	-1.35	2.15	-76.86
	(21.92)*	(5.73)	(1.77)	(48.83)**
Treatment 2 (τ_2)	-8.42	-3.55	0.29	-14.27
	(21.62)	(5.73)	(1.66)	(34.67)
Elevation (ψ)	-5.53	-0.35	-0.27	-8.30
	(2.66)*	(0.12)***	(0.07)***	(4.62)*
WHC[2] (ω)	29.72	0.98	-0.51	-53.20
	(5.10)***	(0.38)***	(0.09)***	(9.19)***
OM[3] (θ)	1.64	-0.05	0.03	3.01
	(0.36)***	(0.03)*	(0.01)***	(0.65)***
Soil Texture[4,1] (β)	26.44	-1.52	0.69	48.64
	(3.78)***	(0.27)***	(0.72)***	(6.78)***
SEI (γ)	0.78	0.87	-0.04	1.33
	(2.18)	(0.18)***	(0.04)	(3.93)
Depth (φ)	5.33	-0.01	0.05	9.58
	(1.01)***	(0.08)	(0.02)***	(1.83)***
GDD (χ)	-0.44	0.01	-0.09	-0.52
	(0.21)**	(0.00)***	(0.00)***	(0.32)

*,**,*** Significant at the 10%, 5%, and 1% level.

Standard error in parentheses.
WHC is water holding capacity, OM is organic matter, SEI is soil erosion index, GDD is growing degree days, and N is number of observations.

[1]Treatment 3 and soil texture 'sand' are in intercept.

[2] WHC scaled by 100 cm cm^{-1}.

[3] OM scaled by 100%.

[4] Soil texture scaled by 10%

Table 11. Soil and climate property means by farm with significant N rate differences using VRT versus FP

N Rate	County/Parish	State	Elevation (meters)[4]	Soil Texture(s)[2]	SEI	Water Holding Capacity (cm cm^{-1})[1]	Organic Matter (%)[1]	Soil Depth (cm)[1]	Growing Degree Days (Celsius)[3]
VRT<FP	Tensas Middle	LA	21.64	Silt	3.59	0.21	2.23	22.29	1846.54
	Gibson	TN	130.72	Silt	19.6	0.22	1.38	21.32	1464.16
	Lauderdale	TN	90.32	Silt	3.22	0.21	1.93	13.18	1337.34
	Leflore North	MS	43.07	Silt; Loam	6.59	0.19	1.75	23	1648.79
	average		*71.44*		*8.25*	*0.21*	*1.82*	*19.95*	*1574.21*
VRT>FP	Madison North	TN	117.25	Silt	16.12	0.22	1.33	20.06	1404.96
	Adams	MS	55.17	Silt	6.87	0.22	1.89	27.03	1856.31
	Tensas North	LA	23.46	Clay; Silt	3.15	0.18	2.15	15.96	1830.56
	Tensas South	LA	21.64	Clay; Silt	7.26	0.22	2.20	28.00	1731.71
	average		*54.38*		*8.35*	*0.21*	*1.89*	*22.76*	*1705.89*

[1] Source: SSURGO (USDA 2014f).

[2] Source: Soil texture triangle (USDA 2014e).

[3] Source: PRISM (PRISM 2014).

[4] Source: National Elevation Data (U.S. Geology Survey 2014).

Table 12. Type 3 fixed effects, Equations 16-19, (With) and without (Without) the location-treatment interaction term

	Treatment F Value Estimate	
Variable	With	Without
Yield[1,2]	1.71	2.84*
N rate[1]	0.2	14.8***
NPU[1,2]	0.86	16.44***
Net Returns[1,2]	3.90**	5.52***

*** Significant at the 1% level.

[1]Model included Satterthwaite approximation to deal with degrees of freedom.

[2]Model included a repeat statement with group treatment to deal with unequal variances.

Table 13. Soil and climate attribute effects on lint yield (kg ha^{-1}), N rate (kg ha^{-1}), net returns (NR) ($ ha^{-1}), and NPU mean differences

Effect	Yield (kg ha^{1})	N rate (kg ha^{1})	NR ($ ha^{1})	NPU
Intercept[1,2] (μ)	32.54	-7.77	856.58	-9.87
	-20.83	(1.91)***	(372.90)**	(8.78)
Clay[2] (β_1)	-4.63	6.33	-195.82	-12.41
	-6.61	(0.61)***	(118.31)*	(2.77)***
Silt[2] (β_2)	-24.45	-1.68	-376.13	-2.67
	(4.92)***	(0.45)***	(87.97)***	(2.08)
Loam[2] (β_3)	-14	-2.41	-190.16	6.19
	(6.15)**	(0.56)***	(110.02)*	(2.59)**
Elevation (ψ)	-1.98	-0.05	-3.80	0.03
	(0.53)***	-0.05	(0.95)***	(0.02)
WHC[2] (ω)	6.74	1.92	929.64	6.54
	-6.41	(0.59)***	(1148.78)	(26.80)
OM[3] (θ)	1.71	-0.03	297.60	8.39
	(0.48)***	-4.44	(86.15)***	(2.01)***
Depth (φ)	3.76	-0.27	6.58	0.08
	(1.26)***	(0.12)**	(2.27)***	(0.05)
VRT3 (ν)	24.82	5.81	26.02	0.02
	-20.59	(1.91)***	(36.90)	(0.86)
SEI (γ)	5.89	0.90	6.62	-0.43
	(2.09)***	(0.19)***	(3.75)*	(0.09)***
GDD (χ)	-0.34	0.04	-0.71	-0.01
	(0.05)***	(0.00)***	(0.09)***	(0.00)***

*,**,*** 10, 5, and 1 percent significance.

Standard error in parentheses.
WHC is water holding capacity, OM is organic matter, VRT3 is the variable rate dummy for treatment 3, SEI is soil erosion index, and GDD is growing degree days.

The number of observations for each model is 1140.

[1] Intercept contains soil texture sand.

[2] Textures scaled by 10%.

[3] WHC scaled by 100 cm cm^{-1}.

[4] OM scaled by 100%.

Table 14. Treatment summary statistics for lint yields (kg ha^{-1}), N rates (kg ha^{-1}), net returns (NR) ($ ha^{-1}), and NPU efficiency

Variable	Summary Statistics	Treatment 1	2	3
Lint Yield (kg ha^{-1})				
	Max	2,397	2,585	2,565
	Min	226	133	204
	Mean	1,332	1,360	1,349
	Std Dev	463	472	457
	CV	34.75	34.72	33.91
	N	649	658	635
N Rate (kg ha^{-1})				
	Max	244	226	253
	Min	34	54	34
	Mean	107	109	114
	Std Dev	35	31	35
	CV	32.48	28.73	30.93
	N	660	659	635
NR ($ ha^{-1})				
	Max	4,081	4,233	4,167
	Min	481	239	333
	Mean	2,226	2,315	2,264
	Std Dev	805	816	782
	CV	36.14	35.25	34.56
	N	649	658	635
NPU				
	Max	120	54	40
	Min	1	1	1
	Mean	18	14	14
	Std Dev	19	7	6
	CV	107.38	46.07	44.86
	N	649	658	635

Table 15. Kolmogorov-Smirnov Statistics, D Statistic (D Stat) and P value (P) by lint yield, N rate, net returns (NR), and NPU and treatment at the sub-plot and field levels

			Cotton Lint Yield		N Rate		NR		NPU	
Comparison Level	Treatment Comparison	N	D Stat	P value	D Stat	P value	D Stat	P value	D Stat	P value
Sub-plot	2 versus 1	1307	0.0576	0.2275	0.2128	<0.0001	0.0852	0.0173	0.1107	0.0007
	3 versus 1	1284	0.0675	0.1075	0.1895	<0.0001	0.0798	0.0334	0.0832	0.0235
	2 versus 3	1293	0.0392	0.7035	0.0849	0.0190	0.0692	0.0906	0.0946	0.0062
Field	2 versus 1	58	0.1379	0.9455	0.3103	0.1224	0.1379	0.9455	0.1724	0.7818
	3 versus 1	55	0.1896	0.7075	0.2626	0.3009	0.1605	0.8719	0.1631	0.8589
	2 versus 3	55	0.0981	0.9994	0.1260	0.9815	0.1256	0.9815	0.1552	0.8961

Note: The null hypothesis is that the treatments are similar.
N represents the number of observations.

Table 16. Soil and climate attribute effects on lint yield, N rate, net returns (NR), and NPU, logistic coefficient estimates

Effect	Yield (kg ha^{-1})	N rate (kg ha^{-1})	NR ($ ha^{-1})	NPU
Intercept[1,2] (μ)	-0.91	-1.19	-1.31	-2.51
	(1.22)	(1.48)	(1.30)	(1.30)*
Clay[2] (β_1)	-0.27	1.91	0.10	4.15
	(0.47)	(1.18)	(0.45)	(1.06)***
Silt[2] (β_2)	1.75	-3.86	0.98	-0.13
	(0.36)***	(0.69)***	(0.35)***	(0.30)
Loam[2] (β_3)	1.29	-3.72	0.88	-0.98
	(0.39)***	(0.65)***	(0.41)**	(0.39)**
Elevation (ψ)	0.00	-0.02	0.00	0.00
	(0.00)	(0.00)***	(0.00)	(0.00)
WHC[2] (ω)	-7.00	17.71	-3.21	3.29
	(3.93)*	(5.30)***	(4.01)	(4.50)
OM[3] (θ)	-0.61	0.41	-0.51	-0.38
	(0.29)**	(0.38)	(0.29)*	(0.31)
Depth (φ)	-0.02	0.00	-0.01	-0.02
	(0.01)**	(0.01)	(0.01)	(0.01)**
VRT3 (ν)	0.11	0.46	0.14	0.03
	(0.12)	(0.14)***	(0.13)	(0.13)
SEI (γ)	-0.02	0.12	0.00	0.03
	(0.01)	(0.02)***	(0.01)	(0.01)**
GDD (χ)	0.00	0.00	0.00	0.00
	(0.00)***	(0.00)	(0.00)***	(0.00)***

[1] Intercept contains soil texture category 'sand'

*,**,*** 10, 5, and 1 percent significance

Standard error in parentheses.

Number of observations per model is 1140.

Table 17. Marginal effects of soil and climate properties in yields, N rates, net returns (NR), and NPU

Effect	Lint Yield Estimate	N Rate Estimate	NR Estimate	NPU Estimate
Intercept[1,2]	-5.9623	-6.9554	-7.2956	-9.1885*
Clay[2]	-2.3616	57.4634	1.1004	622.3134***
Silt[2]	47.2877***	-9.7883***	16.5568***	-1.2462
Loam[2]	26.4844***	-9.7566***	14.1669**	-6.2626**
Elevation	0.4425	-1.75443***	0.498338	-0.24969
WHC[2]	-0.9991*	0.0000***	-0.9596	25.8859
OM[3]	-0.4567**	0.5132	-0.4017	-0.3185
Depth	-1.8546**	0.3996	-1.2057	-1.7200**
VRT3	11.9184	59.0423***	14.7746	3.2590
SEI	-1.7672	12.9867***	0.0348	3.0898**
GDD	0.1248***	0.0249	0.0965***	0.1845***

*,**,*** 10, 5, and 1 percent significance to logit models.

[1] Intercept contains soil texture category sand.

[2] Texture scaled by 10%.

[3] WHC scaled by 100 cm cm^{-1}.

[4] OM scaled by 100%.

Figures

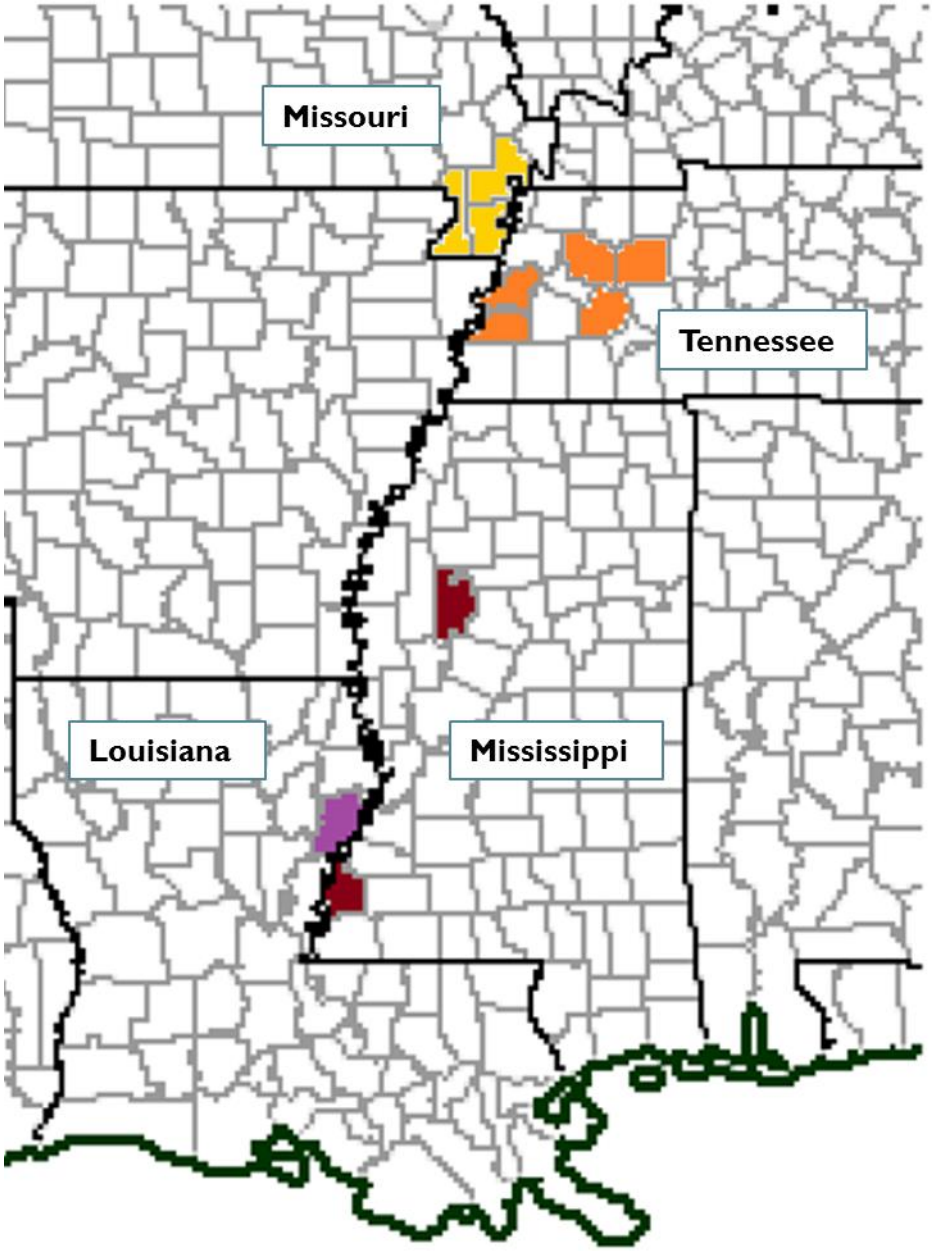


Figure 1. County/Parish locations of the experiment fields designated by color

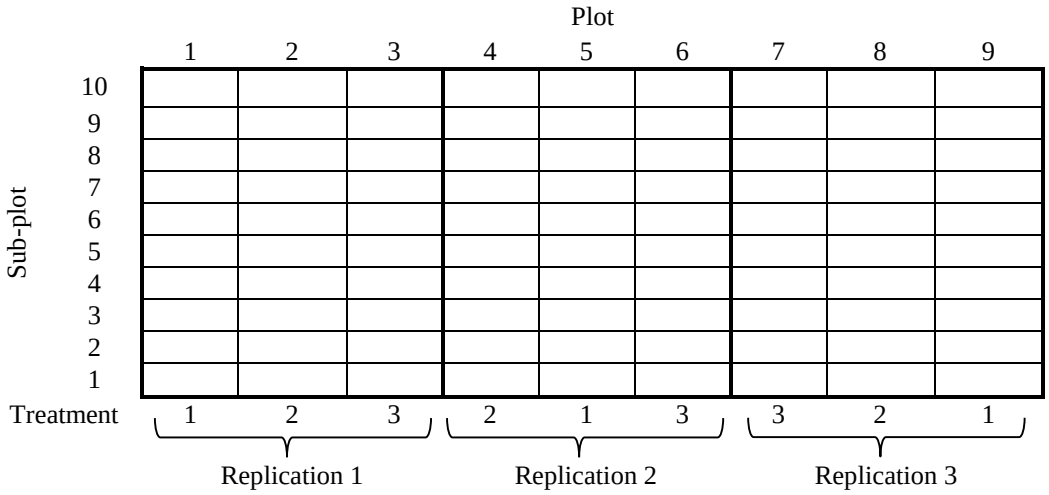


Figure 2. Example of a location's randomized complete block design: 9 plots, 10 sub-plots per plot (totaling 90), and 3 replications of random treatments

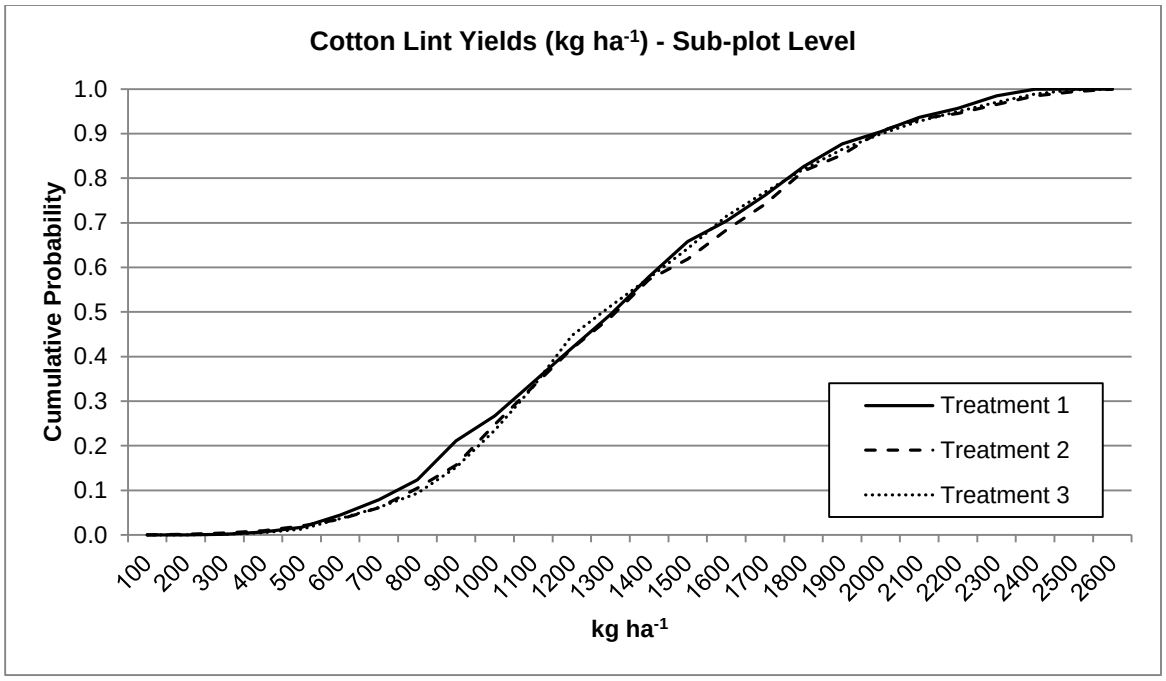


Figure 3. Sub-plot level cotton lint yields (kg ha^{-1}) cumulative probability distributions

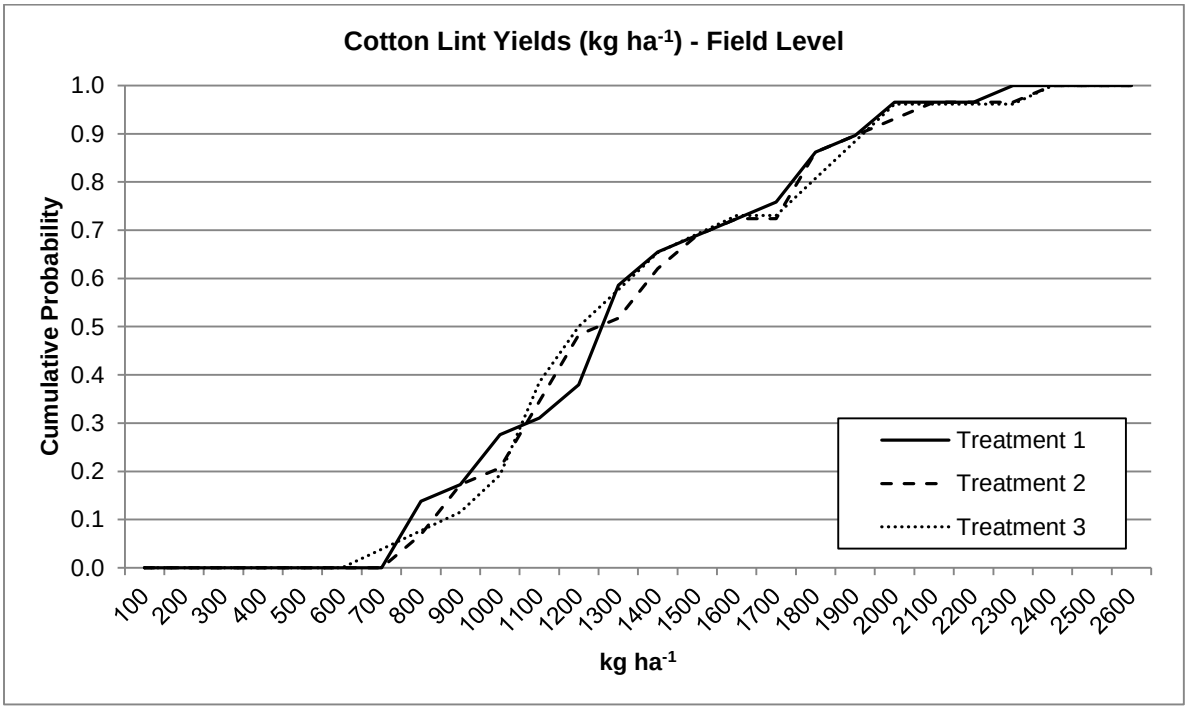


Figure 4. Field level cotton lint yields (kg ha^{-1}) cumulative probability distributions

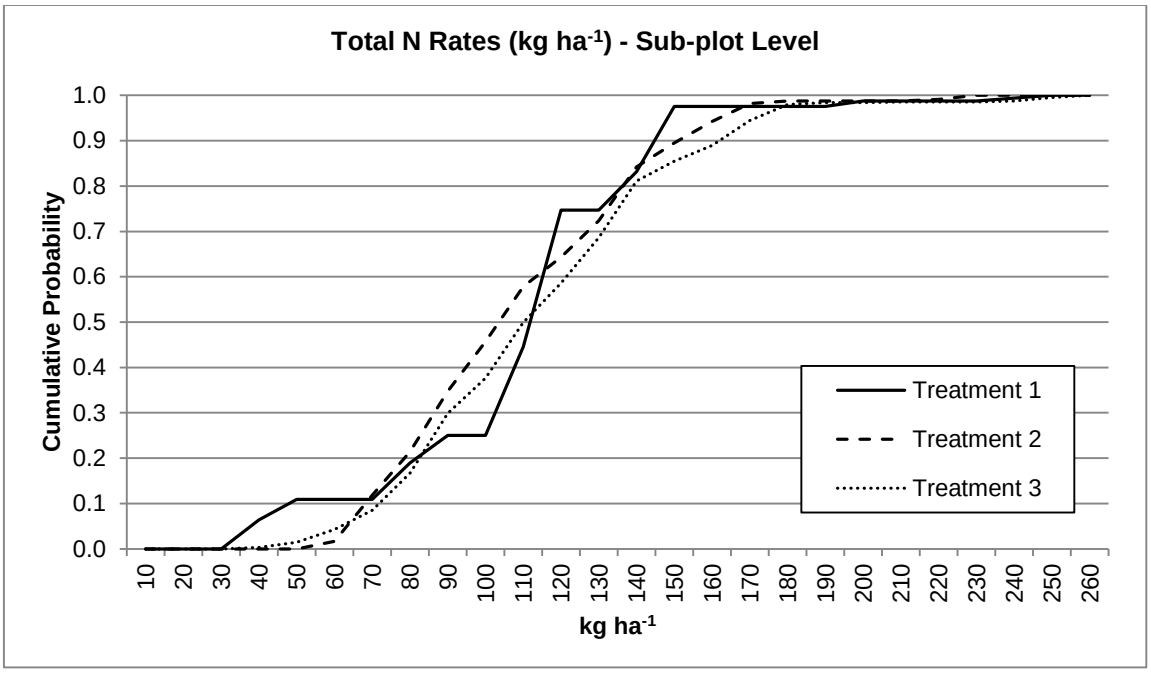


Figure 5. Sub-plot level total N rate (kg ha^{-1}) cumulative probability distributions

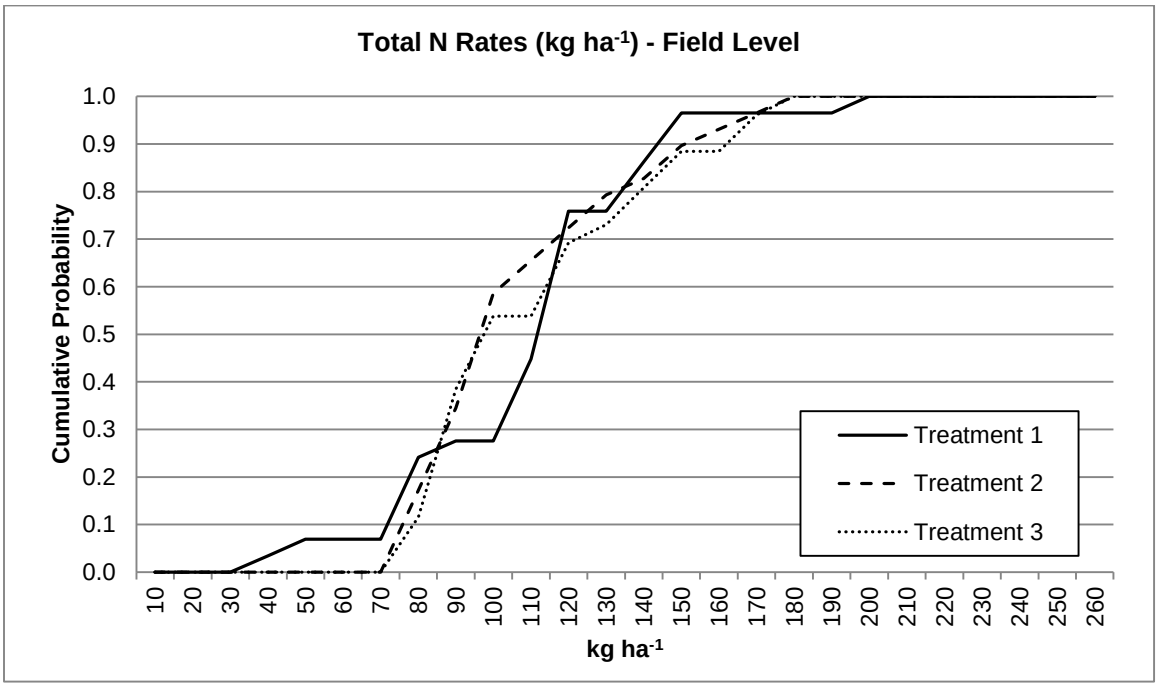


Figure 6. Field level total N rates (kg ha^{-1}) cumulative probability distributions

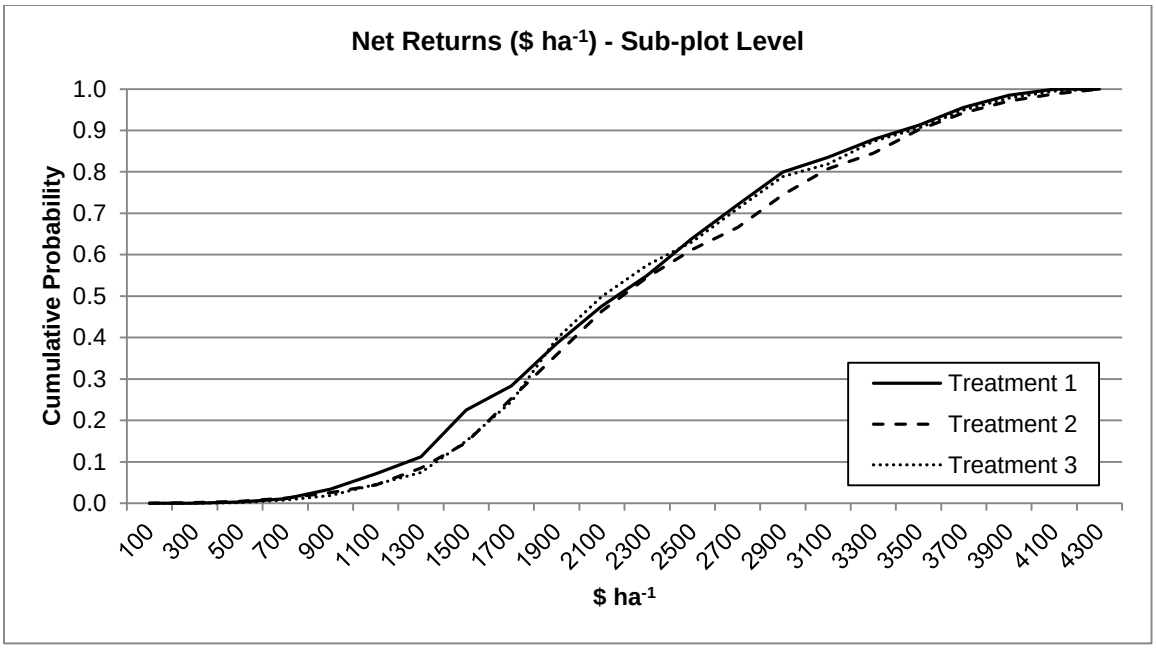


Figure 7. Sub-plot level net return ($ ha^{-1}) cumulative probability distributions

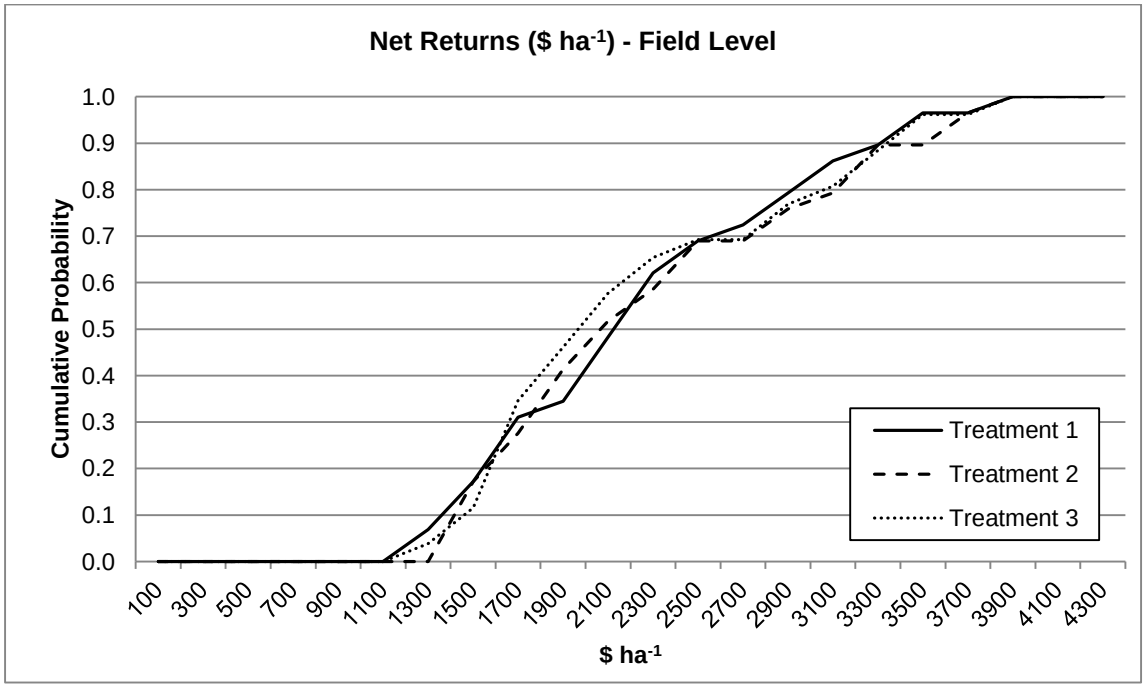


Figure 8. Field level net return ($ ha^{-1}) cumulative probability distributions

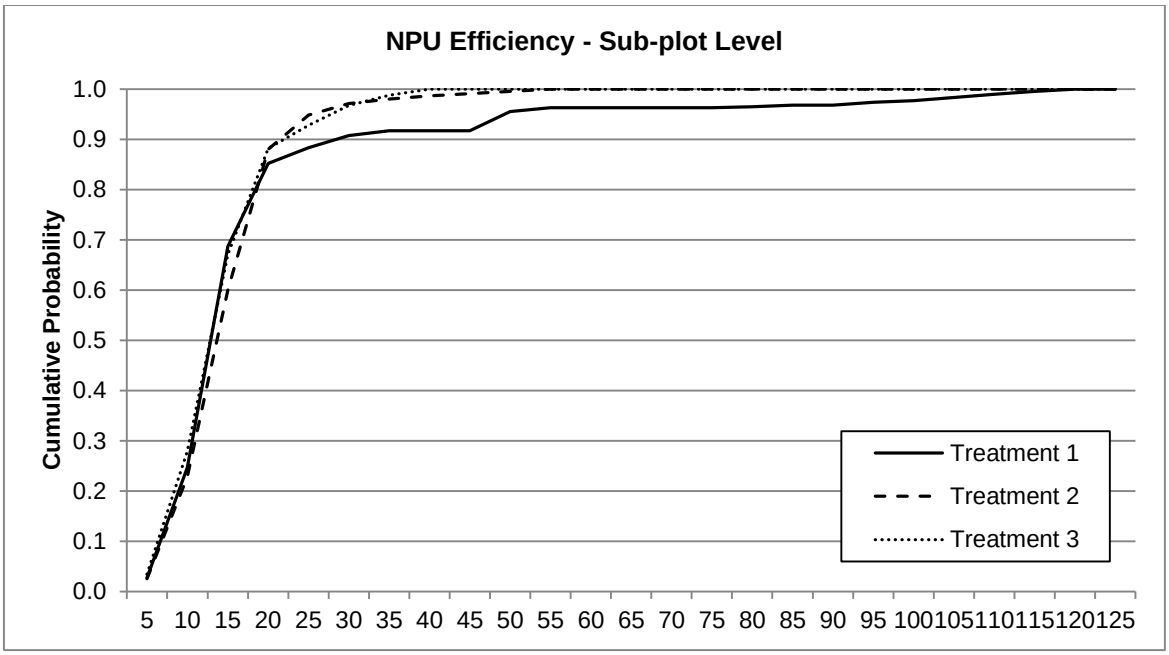


Figure 9. Sub-plot level NPU efficiency cumulative probability distributions

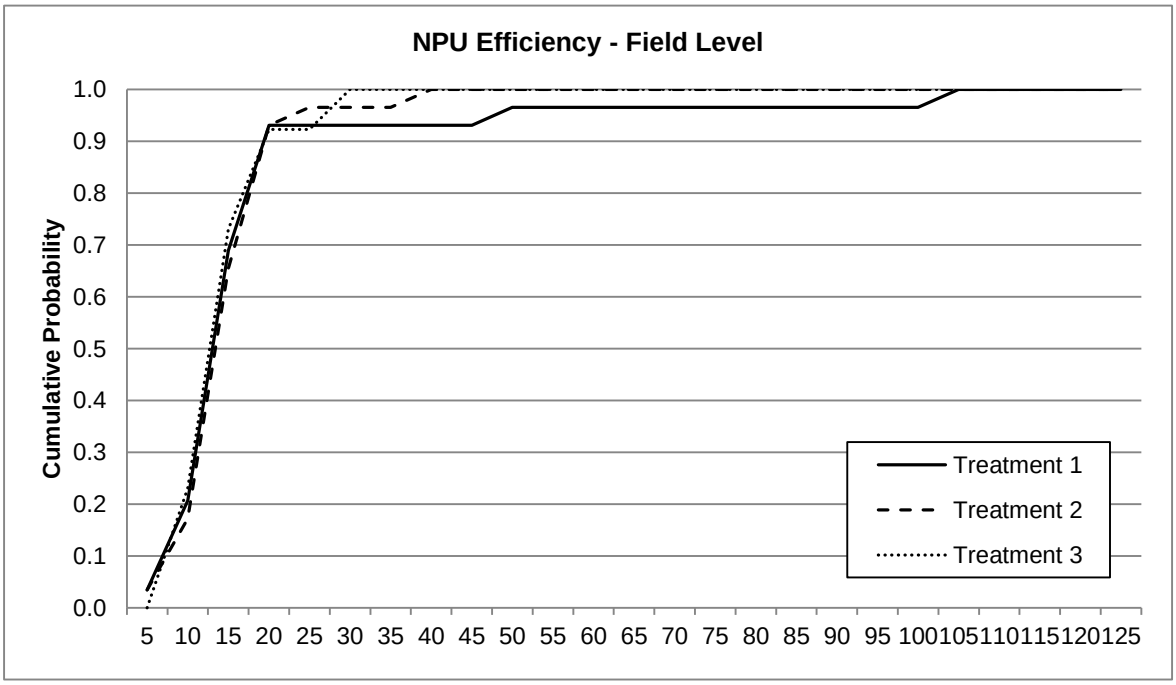


Figure 10. Field level NPU efficiency cumulative probability distributions

VITA

Melissa Reynolds Stefanini was born in Gainesville, Florida, to Pam Trigiano and John Reynolds. She has one brother, Bryan Reynolds, one step-brother, Andrew Trigiano and step-father Robert Trigiano. Melissa is the wife of Joel Victor Stefanini and they together have two dogs, Ari and Mylo. She grew up in Tennessee, attending Maryville High School in Maryville, TN. She left the state to pursue a Bachelor of Arts in Economics with a minor in Business from Winthrop University in Rock Hill, South Carolina. She returned home after graduating in December of 2007 and worked for the University of Tennessee as a Research Associate with the Center for Business and Economic Research for five and a half years. Melissa continued her education with a Masters of Science degree in Agricultural and Natural Resource Economics at the University of Tennessee at Knoxville, TN. She graduated in August of 2015 and is employed with the Center for Business and Economic Research as the Director of the Tennessee State Data Center.