2010

WHOLE FARM MODELING OF PRECISION AGRICULTURE TECHNOLOGIES

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WHOLE FARM MODELING OF PRECISION AGRICULTURE TECHNOLOGIES

ABSTRACT OF DISSERTATION

A dissertation submitted in partial fulfillment of the
requirements for the degree of Doctor of Philosophy in the
College of Agriculture at the University of Kentucky

By
Jordan Murphy Shockley

Lexington, Kentucky

Director: Dr. Carl R. Dillon, Professor of Agricultural Economics

Lexington, Kentucky

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ABSTRACT OF DISSERTATION

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This dissertation investigated farm management concerns faced by grain producers due to the acquisition of various precision agriculture technologies. The technologies evaluated in the three manuscripts included 1) auto-steer navigation, 2) automatic section control, and 3) autonomous machinery. Each manuscript utilized a multifaceted economic model in a whole-farm decision-making framework to determine the impact of precision agriculture technology on machinery management, production management, and risk management. This approach allowed for a thorough investigation into various precision agriculture technologies which helped address the relative dearth of economic studies of precision agriculture and farm management. Moreover, the research conducted on the above technologies provided a wide array of economic insight and information for researchers and developers to aid in the advancement of precision agriculture technologies. Such information included the risk management potential of auto-steer navigation and automatic section control, and the impact the technologies had on optimal production strategies. This dissertation was also able to provided information to guide engineers in the development of autonomous machinery by identifying critical characteristics and isolating the most influential operating machine. The inferences from this dissertation intend to be employed in an extension setting with the purpose of educating grain producers on the impacts of implementing such technologies.

KEYWORDS: Farm Management, Mathematical Programming, Economic Optimization, Simulation, Kentucky

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WHOLE FARM MODELING OF PRECISION AGRICULTURE TECHNOLOGIES

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The Graduate School

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CHAPTER ONE

INTRODUCTION

Precision agriculture is the use of technology to assist in optimizing agricultural production by improving the accuracy of existing management activities. One commonly used expression to describe precision agriculture is "Doing the right thing, at the right place, at the right time, and in the right way." An array of state of the art technologies can be utilized to more accurately manage areas within the field. Advancements in these technologies have provided site-specific management options to a broader range of producers. These technologies have evolved such that precision agriculture is no longer considered only practical for the elite farmer. Thus, precision agriculture technologies are well established in mainstream agricultural production. Farm managers are faced with a host of critical decisions as this trend progresses.

The overall objective of this dissertation is to address farm management issues pertaining to the addition, replacement, and selection of precision agriculture technologies. Specifically, this dissertation focuses on machinery, production, and risk management concerns faced by grain producers who adopt selected precision technologies. A hypothetical Kentucky grain producer is used as the case study. This dissertation embodies three separate yet complementary manuscripts. Each manuscript utilizes a multifaceted economic model in a whole-farm decision-making framework to determine if certain precision technologies are economically viable. This approach allows for a thorough investigation into various precision agriculture technologies which helps address the relative dearth of economic studies of precision agriculture and farm management. The anticipated results will provide economic insight into precision agriculture technologies. Moreover, inferences from this dissertation will be employed in an extension setting with the purpose of educating grain producers on the effects of implementing such technologies. Furthermore, the conclusions from the investigations should provide information to researchers and developers to aid in the advancement of precision agriculture technologies.

To accomplish the goals of this dissertation, an appropriate framework must be established. Because of the integrated nature of precision agriculture, a multidisciplinary approach is needed to evaluate the problem. Accordingly, agricultural economics, agricultural engineering, and agronomic principles are employed. Concepts from both disciplines help guide the framework of the dissertation which examines various precision agriculture technologies. This is accomplished with a multifaceted, whole-farm management approach that encompasses enterprise budgets, economic optimization, and risk analysis. Enterprise budgets are used to provide the underlying data necessary for the implementation of the economic optimization models. Additionally, one of the largest factors influencing farm decision making is the farm manager's willingness to bear risk. Various agricultural risks exist: production risk, marketing/price risk, financial risk, legal risk, and human resource management risk. Although consideration of all risks is important, only production risk is incorporated into these analyses to determine the influence on management decisions.

Chapter Initiatives

Chapter One introduces the use of precision agriculture technologies and the evaluation of their economic potential in a whole-farm management setting. The overall problems in acquiring precision technologies are outlined and the framework for addressing these concerns is summarized. In addition, the potential for using the conclusions of this dissertation are explained. These concepts are pursued in Chapters Two, Three, and Four as individual manuscripts with their own objectives, literature review, methods, and conclusions.

Chapter Two establishes a framework to provide a detailed assessment of the economic viability of various auto-steer navigational technologies for grain producers. Specifically, the implementation of both sub-meter and real-time kinematic auto-steer are examined. This chapter addresses established precision agriculture technologies that have already been widely adopted. In addition, various production decisions and the producer's aversion to risk are evaluated. This chapter employs a resource allocation-mean variance quadratic programming formulation to analyze information for a hypothetical Kentucky producer. The hypothetical producer raises corn and soybeans using no-till production practices. The economic, risk, and production impacts of auto-steer are assessed and conclusions are derived in Chapter Two.

The initiatives for Chapter Three are similar in nature to those of Chapter Two. Chapter Three provides a thorough assessment of automatic section control. The incorporation of lightbar navigation with automatic section control is also considered. This chapter addresses precision agriculture technologies that are currently being adopted. Additionally, various production decisions, the producer's aversion to risk, and numerous field shapes are included in the investigation. This chapter also employs a resource allocation-mean variance quadratic programming formulation to analyze information for a hypothetical Kentucky producer. This producer also uses no-till farming practices in the production of corn and soybeans. The economic, risk, and production impacts of automatic section control, with and without lightbar navigation, is assessed in Chapter Three.

Chapter Four develops a unique and multifaceted machinery management model to investigate various factors concerning autonomous machinery. This chapter examines future precision agriculture technologies that are under development but have not been adopted. The model integrates machinery selection, resource allocation, and sequencing theories to compare autonomous and conventional systems. These economic techniques evaluate autonomous machinery to determine whether the technology can replace conventional systems on Kentucky grain farms. Further, this chapter provides engineers and researchers with insight into the development and advancement of autonomous machinery.

Chapter Five presents the collective conclusions of this investigation. It provides a summary of the previous chapters and how they addressed the overall objective of this dissertation. Additionally, this chapter considers areas for future research.

Approach

The overall objectives are addressed using a journal manuscript format. Each manuscript is a separate entity but complement each other with a common theme. This common theme includes a multidisciplinary/whole-farm approach which utilizes mathematical programming and economic optimization to address farm management issues related to the acquisition of precision agricultural technologies. Specifically, the multiple journal manuscript approach addresses established precision agriculture technologies that have already been widely adopted, precision agriculture technologies that are currently being adopted, and future precision agriculture technologies.

CHAPTER TWO

A WHOLE FARM ANALYSIS OF THE INFLUENCE OF AUTO-STEER NAVIGATION ON NET RETURNS, RISK, AND PRODUCTION PRACTICES

Automated steering (auto-steer) is a navigation aid that utilizes the global position system (GPS) to guide agricultural equipment. Auto-steer has been commercially available for many years. There are many combinations of auto-steer systems and GPS receivers available with correspondingly different levels of accuracy. The potential benefits of these systems include reduction of overlaps and skips, the lengthening of operator's workday, accurate placement of inputs, and reduced machinery costs resulting from an increase in machinery field capacity. The increase in machinery field capacity not only could reduce direct costs, but permit more land area to be planted closer to the optimal date. These advantages provide incentive for producers to evaluate the potential of this technology in their farm operation.

Many Kentucky farmers have adopted some form of GPS-enabled navigation technology. The trend for most Kentucky farmers is to first adopt a bolt-on auto-steer system equipped with a sub-meter receiver on the self-propelled sprayer. For the utmost accuracy, a Kentucky farmer upgrades to an integral valve system with a Real Time Kinematic (RTK) GPS receiver on the tractor. Few Kentucky farmers have utilized auto-steer systems on their harvesters, but when they do, it is common to use a bolt-on system. In spite of rapid adoption, the quantitative benefits of auto-steer have been scrutinized by farmers. A thorough investigation by researchers into this technology is long overdue. Issues regarding profitability, interactive effects of production practices, and the often ignored issue of risk are all essential to evaluate.

The majority of existing studies conducted on navigational technologies focused on field performance or general overviews of the technology, which ultimately emphasized engineering concepts. Field performance studies focused on issues regarding accuracy, topography, speed, and evaluation methods (Ehsani, et al., 2002; Gan-Mor, et al., 2007; Stombaugh, et al., 2007; Stombaugh and Shearer, 2001). Research involving the overall status of navigational technologies in North America and Europe had also been reported (Adamchuk, et al., 2008; Keicher and Seufert, 2000; Reid, et al., 2000). Other research previously conducted had focused on the economics of auto-steer.

Economic studies regarding auto-steer often utilized simple techniques which failed to encompass all benefits and costs of the technology. A limited number of whole farm economic studies of auto-steer had been conducted (Griffin, et al., 2008; Griffin, et al., 2005). These economic studies had not included a farm manager's ability to exploit the technology by altering production practices to increase profitability or reduce risk. While some of these studies were helpful, the economic potential of the technology may be understated to the extent that substitution of inputs and alteration of production practices were not addressed in these models. Widespread interest, coupled with the scarcity of studies, motivates the incorporation this technology into a more complete whole farm planning model. By including alternative production practices, economic optimization can be achieved. In turn, this allows investigation into the full potential of auto-steer on the farm. Furthermore, opportunities to exploit auto-steer technology for reducing production risk may also be explored.

Few researchers conducted in-depth risk analyses of precision agriculture technologies, beyond the present focus of this study. Dillon, et al. (2007) conducted educational workshops to inform farmers of the risk management potential of precision agriculture. Oriade and Popp (2000) conducted a whole farm planning model of precision agriculture technology where risk was incorporated. However, the lack of yield data, and the interactive effects of production practices necessarily led to overly restrictive assumptions and results. Others have developed theoretical models that suggested variable rate technology could be utilized in managing production risk (Lowenberg-DeBoer, 1999). The investigation into auto-steer as a risk management tool was meager, therefore became an objective of this study.

The objectives of this study are to: (1) determine profitability of auto-steer under various scenarios, (2) determine if auto-steer can be utilized as a tool for risk management, (3) determine optimal production practices under various scenarios with and without auto-steer, (4) determine the break-even acreage level, payback period, and return on investment for the adoption of auto-steer, and (5) determine the impact of input price on the profitability of auto-steer. A whole farm economic model is used to provide a detailed assessment of auto-steer options for a hypothetical commercial grain farm in Kentucky. Due to the adoption trend for auto-steer by Kentucky farmers, investigations are undertaken considering three scenarios: (1) the addition of a bolt-on auto-steer system with a sub-meter receiver on a self-propelled sprayer, (2) the addition of an integral valve auto-steer system with a RTK GPS receiver on a tractor, and (3) the addition of both auto-steer systems to the farm enterprise. Scenario three investigates the situation in which a farmer is utilizing sub-meter auto-steer on the sprayer and a RTK auto-steer on the tractor. Hence, the benefits and costs of both systems are incorporated into the model. All five of the above objectives are investigated for each of the above scenarios as well as incorporating four farmer risk aversion attitudes: neutral, low, medium, and high risk aversion for objectives one through four.[1]

Analytical Procedure

The experimental framework for this study includes the production environment, the economic optimization whole farm model, and the specific conditions and resource base of the hypothetical farm that represents the study focus. These are each discussed in turn to establish the analytical framework of the study.

The Production Environment

Production data estimates were determined using Decision Support System for Agrotechnology Transfer (DSSAT v4), a biophysical simulation model (Hoogenboom, et al., 2004). DSSAT has provided underlying production data for almost 15 years in studies covering a multitude of geographic locations and experimental requirements as evidenced by relevant refereed publications in numerous journals. When coupled with the validation specific to the study at hand, as discussed later, DSSAT was determined to be an appropriate model for this study.

The minimum input required to develop yield estimates in DSSAT includes site weather data for the duration of the growing season, site soil data, and definition of production practices. Site weather data were obtained from the University of Kentucky Agricultural Weather Center (2008). Daily climatology data were collected for 30 years in Henderson County, Kentucky. Soil data were obtained from a National Cooperative

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[1] The four risk aversion levels reported are neutral, low, medium and high which represent a desire to maximize net returns that 50, 60, 75, and 85 percent likely to be achieved.

Soil Survey of Henderson County, Kentucky from the Natural Resources Conservation Service (NRCS). After identifying all soil series located in Henderson County, information on those soil series was gathered using the NRCS Official Soil Series Description from their website. Four representative soils (deep silty loam, deep silty clay, shallow silty loam, and shallow silty clay) were utilized in the biophysical simulation models. Finally, numerous production practices were defined to complete the minimum requirements to operate DSSAT. Production practices were identified for both corn and full season soybeans in accordance with the University of Kentucky Cooperative Extension Service Bulletins (2008). Varying production practices utilized in this study included planting date, crop variety, plant density, row spacing, and fertilizer practices (Table 2.1.1 and Table 2.1.2).

A comprehensive validation was performed on the response of yield estimates to varying production practices and compared to pertinent literature. For instance, the response of corn yield to nitrogen rates exhibited a quadratic response which was consistent with previous studies (e.g. Schmidt, et al., 2002; Cerrato and Blackmer, 1990). Also, comparisons of simulated to actual historical yield trends were made for Henderson County, Kentucky. Regression analyses were conducted, in which t-tests confirmed that the simulated yields for both corn and soybeans were not statistically different from the actual historical yields, with a significance of 99%.[2] Discussions with specialists were also conducted to confirm that the simulated yield results were reasonable. For more information with regard to the validation process, refer to the appendix. Overall, yield estimates were believed to be representative of production in Henderson County, Kentucky. These yield data were a key element of the economic model.

The Economic Model

The economic framework of a commercial Kentucky corn and soybean producer under no-till conditions was embodied in a resource allocation model employed within a mean-variance (E-V) quadratic programming formulation. Mathematical details of the model can be found in Appendix 1. The model incorporated risk, as measured by the variance of net returns across years, which was consistent with formulations developed by Freund (1956). Specifically, the model was modified from Dillon's (1999) risk

[2] The R^2 for corn and soybean regression analyses were 0.22 and 0.46 respectively.

management model to include additional production practices such as nitrogen rate and row spacing. The model was also modified by allowing multiple weeks for harvesting. In addition, four land types were incorporated within the model. Finally, the inclusion of various auto-steer scenarios distinguished this model from Dillon's (1999) model.

The objective of this model was to maximize net returns less the Pratt risk aversion function coefficient multiplied by the variance of net returns. The Pratt risk aversion coefficient measured a hypothetical producer's aversion to risk and was in accordance with the method developed by McCarl and Bessler (1989). Intuitively, the model represented the typical risk-return tradeoff in which the model discounts the expected net returns by the variance of net returns.

The economic model included decision variables, constraints, and other data and coefficients. The decision variables for the model were the land area in corn and soybean production. These were identified by alternative production possibilities and soil types.[3] Based on the decision variables, expected average yields and net returns were calculated. For the model to determine these decision variables, constraints were required within the model.

Constraints included land available, labor, crop rotation, and ratio of soil type. The land constraint guaranteed that the combined production of corn and soybeans did not exceed the available land assumed for this study. In addition, agricultural tasks performed in the production of both corn and soybeans were required. These tasks included: planting, spraying, fertilizing, and harvesting which were constrained by the estimated suitable field hours per week available for performing each operation. The rotation constraint required 50% of the land to produce corn and 50% to produce soybeans. This represented a two year crop rotation typical of a Kentucky grain producer. Furthermore, constraints were required to ensure that production practices were uniformly distributed across all soil types. This implied that variable rate by soil types could not occur.

Besides the constraints, additional information required within the model included establishing the coefficients, data, and further assumptions of the model. The

[3] The economic model had the ability to choose various production alternatives across the allotted acres for all scenarios including the base case with no auto-steer technologies.

coefficients necessary for this investigation included labor hours and the prices for corn and soybeans. Labor hours for producing corn or soybeans were based on the field capacities of the operating machines. To determine the total labor required for each operation, a ten percent increase in field capacities was employed. This reflected additional labor required for performing other tasks such as travelling from field to field, refilling the seed bins and sprayer tanks, and unloading the grain bin. Furthermore, the prices of corn and soybeans were also necessary for this analysis. Prices for corn and soybeans were determined from the World Agricultural Outlook Board (2008). Prices used were the 2009 median estimates less Kentucky's basis, which resulted in $9.75/bu and $4.25/bu for soybeans and corn respectively.

Supplementary data crucial for this investigation included the proper land area, suitable field hours, and the cost of auto-steer. The land area chosen for this study was reflective of Henderson County, Kentucky. Henderson County ranks second in the state in both corn and soybean production (Kentucky Agriculture Statistics, 2007-2008). According to the Kentucky Farm Business Management Program, a 2600 acre farm corresponded to the upper one third of all farms in management returns as represented by net farm income in the Ohio Valley region of Kentucky, where Henderson County is located (Pierce, 2008). Therefore, the acreage level assumed for this investigation was deemed an appropriate size. Suitable field days were calculated based on probabilities of it not raining 0.15 inches or more per day over a period of a month.[4] This was determined from the 30 year historical climatological dataset previously mentioned. The probabilities were multiplied by the days worked in a week and hours worked in a day to determine expected suitable field hours per week. Moreover, the annualized ownership cost of both auto-steer systems included depreciation and the opportunity cost of capital invested. Depreciation of the auto-steer technologies were calculated using the straight-line method with an assumed 10 year useful life and no salvage value. The opportunity cost of capital investment was calculated using an 8% interest rate. A total investment of $7,000 for auto-steer with a sub-meter receiver and $35,000 for auto-steer with a RTK

[4] An example for determining suitable field days is given for clarification. Over the 30 year timeframe, the median days in January that it rained 0.15 inches or more was 5. Therefore, the probability of it NOT raining .15 inches per day in January was (1-(days rained/days in the month)). This probability was used to estimate the number of suitable field days for the model.

receiver was assumed. As a result, the annualized costs of sub-meter and RTK auto-steer were \$980 and \$4,900, respectively.[5] For the addition of both auto-steer systems, the costs were added together for a total investment of \$42,000, with an annualized cost of \$5,880.

Finally, there were two assumptions within the model in need of clarification. First, the amount of area initially overlapped by the equipment without using auto-steer was assumed. Secondly, there was an increase in the operators work day due to the adoption of auto-steer. Unfortunately, scientific research pertaining to these factors was lacking since each was operator dependent. Therefore, these factors were evaluated over a range to provide general economic insight into the profitability of auto-steer under two technological scenarios. The technical coefficients of the model were varied to reflect various overlap scenarios. The overlap scenarios were varied from 5 feet to 10 feet overlap for the sprayer and 0.5 feet to 3 feet overlap for tractor operations. By doing so, both field capacity and cost (inputs, labor, and fuel) for the relative machinery operations were affected. The operator's work day was also evaluated for various increases in hours worked per day which reflected the operator's ability to work further into the night with less fatigue. It was determined that varying the hours worked per day had no impact on profitability unless the farmer worked below the original hours assumed for the base case of 13 hours per day. On the other hand, the results from varying the overlapped area were provided in the results section. To address the specific objectives of this study, inquires into the appropriate overlap and workday scenario were required to represent a typical Kentucky farmer, and discussed in the following section.

The Hypothetical Model Farm

A base machinery complement was determined for a hypothetical commercial grain farm in Henderson County which practices no-till farming. The machinery set included one 250-hp 4WD tractor with the following implements: a split row no-till planter (16 rows), a 42-ft anhydrous applicator, a grain cart with 500 bushel capacity, and a 20-ft stalk shredder for corn. A 300-hp harvester was also utilized with an 8 row header

[5] The annualized cost of an auto-steer technology was calculated using the following equation for the straight-line depreciation method plus the opportunity cost of capital represented by the average value times the interest rate. [((Total Investment – Salvage Value)/(Useful Life)) + ((Total Investment + Salvage Value)*Interest Rate)/2].

for corn and a 25-ft flex header for soybeans. A self propelled sprayer with an 80-ft boom that applied herbicides on corn (Glyphosate, Bicep II, and Roundup), herbicides on soybeans (Roundup and 2, 4-D, B) and insecticide on soybeans (Acephate) completed the equipment set. All equipment specifications (e.g. speed, width, and efficiency) were from the Mississippi State Budget Generator (MSBG), which complies with the ASABE Standards (Laughlin and Spurlock, 2007). However, both the planter and applicator were added into MSBG with the appropriate data, which were compiled from the Illinois Farm Business Management (2008) machinery operation specifications. For the base case, no machines were equipped with any GPS-enabled navigation technologies.

It was recognized for the base machinery set that, due to operator error and/or fatigue and lack of navigational technologies, varying overlaps occurred. The degree of overlap depended on machinery and the timing of application (i.e. pre-plant or post-plant). For this study, the focus was on the self-propelled sprayer and the implements attached to the tractor since those machines would be impacted by auto-steer. First, an overlap of 10% of the equipment width was assumed for the pre-planting operations of the self propelled sprayer, hence eight feet of overlap (Griffin, et al., 2008; Palmer, 1989). Next, it was assumed that the planter passes would overlap by one foot. Therefore, all operations following planting would be overlapped by one foot since the implements would follow the enterprise row (Stombaugh, 2009). By adopting auto-steer navigation the above overlaps could potentially be reduced.

The potential benefits of auto-steer not only included a reduction in overlap but also an increase in field speed and length of operator's work day. When adopting bolt-on auto-steer with a sub-meter receiver on the self-propelled sprayer, a reduction in overlap from eight feet to three feet for pre-planting operations was utilized (Stombaugh, et al., 2005). There was no reduction in overlaps for post-planting operations due to the base accuracy of the planter (one foot overlap) since post planting operations would follow the enterprise row. When adopting an integral valve auto-steer system with an RTK base station, reductions in overlap from one foot to one inch were utilized for tractor operations (Stombaugh, et al., 2005).

Another benefit from auto-steer was an increase in field speed. For the sprayer, it was assumed field speeds increased 20% for pre-planting applications and 10% for post-planting applications. An increase in speeds during post-planting application were assumed because of the ability to drive faster during headland turns and the ability to quickly determine which row to enter to continue operating. Speed increases of 5% for planting and 10% for both fertilizer application and stalk shredding were also assumed (Stombaugh, 2009). With the above benefits of both auto-steer systems quantified, a percent multiplier was computed and implemented to calculate the new field capacities for the appropriate machines (Table 2.2). The calculated multiplier was also utilized in determining the reduced costs associated with implementing auto-steer.

In addition, suitable field days were altered to represent the adoption of auto-steer by increasing the operator's workday from 13 hours to 15 hours. This was attributed to the ability of the operator to work further into the night with less fatigue (Griffin, et al., 2008).[6] To determine the influence of auto-steer on net returns, risk, and production practices, both old and new field capacities, as well as suitable field days, were utilized in the economic model.

Results and Discussion

Three auto-steer scenarios were investigated and then compared to the base scenario without auto-steer navigation: (1) the addition of a bolt-on auto-steer system with a sub-meter receiver on a self-propelled sprayer, (2) the addition of an integral valve auto-steer system with a RTK GPS receiver on a tractor, and (3) the addition of both auto-steer systems to the operation.

Sub-Meter Auto-Steer Results

The economic, risk, and production impacts of sub-meter auto-steer were first investigated. The addition of sub-meter auto-steer increased expected net returns under all four risk scenarios compared to the base without navigational technology (Table 2.3). Across all risk aversion levels, the average increase in expected net returns was 1.08%

[6] Scientific research for determining increased work hours is non-existent since it is the farmer's preference on how many hours are worked each day, but it is known that farmers have the ability to work longer hours due to auto-steer if they wish. Therefore, alterations in suitable field days were modeled after the cited study.

($4.05/acre)[7]. Also, the minimum and maximum net returns were both higher compared to the base scenario for all risk aversion levels.

The break-even acreage level, payback period, and the return on investment for the adoption of sub-meter auto-steer were also determined. To spread out the fixed cost associated with sub-meter auto-steer, a land area of 222 acres was required under the risk neutral scenario.[8] Also, the payback period was calculated under the risk neutral scenario, and sub-meter auto-steer was able to pay for itself in 0.61 years for farms with 2600 acres. Furthermore, sub-meter auto-steer had a 153.73% return on investment[9].

In addition to determining the economic impact of sub-meter auto-steer, investigating its potential to become a tool for risk management was also an objective. For this study, production risk was measured by the coefficient of variation (C.V) of net returns across years. If the adoption of sub-meter auto-steer decreased the C.V. as well as increased expected net returns when compared to the base scenario, it could be inferred that the technology could be used to manage production risk. Evidence of reduced risk through sub-meter auto-steer was displayed by more favorable C.V. across risk aversion levels when compared to the base scenario. In addition, an increase in expected net returns occurred under all risk scenarios when compared to the base scenario (e.g. 17.63[10] and $1,030,817 under risk neutrality compared to 17.81 and $1,020,336). The average decrease in C.V. due to the adoption of sub-meter auto-steer was 0.16%. As a result, it was determined that sub-meter auto-steer could be used as a tool for risk management. The farm manager's capability to alter production practices was a large contributor in reducing the C.V.

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[7] For the risk neutral scenario, if the operator overlapped by only 5ft, net returns increased by 0.94% with a return on investment of 141.59%. On the other hand, if the operator overlapped by 10ft, the net returns increased by 1.08% with a return on investment of 161.96%. Note: Base overlap for the self-propelled sprayer was 8ft.

[8] Break-even acreage level could not be determined based solely on a calculation. Both the base scenario and the specific auto-steer scenarios acreage level were varied within the model such that both their expected net returns converged. Once the net returns for each model converged, the break-even acreage level was determined.

[9] The following formula was utilized to calculate the returns on investment: [(Net returns gained from technology)+(Opportunity cost of capital)] / (Total investment in the technology). The opportunity cost of capital was calculated using the following formula: (Interest rate*Total investment/2). The return on invest was adjusted such that the opportunity cost of capital was not accounted for twice. Therefore, the percentages appropriately reflected the return on the capital invested.

[10] +/- 17.63% of mean net returns occur in about 2/3 of the years. C.V. is a relative measure of risk with a decrease representing a reduction in risk.

It was also determined that the optimal production practices for the base scenario (Table 2.4) were altered when sub-meter auto-steer was adopted (Table 2.5). This demonstrated the importance of a whole farm analysis and the need to adjust production practices to take full advantage of the new technology. The majority of changes occurred in the production of soybeans. For example, there was a removal of planting on April 29th with maturity group four under risk neutrality. This was due to the competition for suitable field hours during the planting of soybeans on the week of April 22nd with spraying post-emergence herbicide on corn planted on March 25th. With the ability to spray more effectively with sub-meter auto-steer, more suitable field hours were available for planting the highest yielding soybean planting date/maturity group combination.

The largest change that occurred due to the adoption of sub-meter auto-steer was for medium risk aversion. Planting the week of May 6th with maturity group four was removed from the optimal production set and the acres redistributed to planting the week of May 13th with maturity group four. This was due to the competition of suitable field hours during the week of spraying insecticide on soybeans planted on the week of May 13th with harvesting the corn planted on March 25th with maturity group 2600. Similar to what occurred under risk neutrality, the adoption of sub-meter auto-steer provided a more efficient means of spraying insecticide. This allowed for more acres of soybeans planted on the week of May 13th. Even though there were modification to the optimal production set when compared to the base scenario with no auto-steer navigation, the average yields of soybeans were not altered.

Unlike soybeans, corn production practices in the optimal set were not change compared to the base scenario without sub-meter auto-steer. There was a redistribution of acres within the optimal set for all risk aversions, but no more than 25 acres were reallocated. Since there was no considerable change in the production of corn, average yields remained the same.

RTK Auto-Steer Results

The economic, risk, and production implications of adopting an integral valve auto-steer system with an RTK GPS receiver on a tractor was also examined. This study occurred while the tractor was planting, fertilizing, and stalk shredding. With the adoption of RTK, expected net returns increased under all four risk scenarios when compared with the base (Table 2.3). Across all risk aversion levels, the average increase in expected net returns was 1.95% ($7.36/acre)[11]. When compared to the addition of a bolt-on auto-steer system with a sub-meter receiver on a self-propelled sprayer, the average increase in expected net returns across all risk levels was 0.87% ($3.31/acre). Also, the minimum and maximum net returns were higher compared to the base scenario for all risk aversion levels, except for the minimum net returns under risk neutrality.

The break-even acreage level, payback period, and the return on investment for the adoption of RTK auto-steer were also determined. The break-even acreage under the risk neutral scenario was 521 acres. Also, the payback period was calculated under the risk neutral scenario and was determined that RTK auto-steer would pay for itself in 1.45 years for farms with 2600 acres. In addition, RTK auto-steer had a 59.19% return on investment. While these numbers still seem favorable, they were higher than the less expensive sub-meter auto-steer option except for the payback period and return on investment.

The possibility of RTK auto-steer to reduce production risk was also examined. Similar to the sub-meter auto-steer scenarios, RTK exhibited the ability to reduce risk by exemplifying a more favorable coefficient of variation across risk aversion levels when compared to the base scenario except for the low risk aversion level. In addition, an increase in expected net returns occurred under all risk scenarios (e.g. 17.46 and $1,309,654 under risk neutrality compared to 17.81 and $1,020,336). The average C.V across 30 years increased under the low risk aversion scenario. However, after investigating the risk-adjusted net returns (Z-Value), results indicated that RTK auto-steer had superior risk reducing properties compared to the base and sub-meter auto-steer. The higher C.V. indicated that the producer was willing to experience greater variability to achieve the higher expected net returns. For the scenarios where C.V. decreased, the average was 0.20%. As a result, it was determined that RTK auto-steer could be used as a tool for risk management for farmers. The farm manager's capability to alter

[11] For the risk neutral scenario, if the operator overlapped by only 0.5ft, net returns increased by 1.61% with a return on investment of 49.25%. On the other hand, if the operator overlapped by 3ft, the net returns increased by 5.20% with a return on investment of 155.72%. Note: Base overlap for the tractor was 1ft.

production practices was a large contributor in reducing the C.V., hence the possibility to managing production risk.

Production practices under the base scenario (Table 2.4) were also altered due to the adoption of RTK auto-steer (Table 2.6). Unlike sub-meter auto-steer, RTK impacted optimal corn production practices as well as soybean production practices. Interestingly, multiple factors contributed to the optimal nitrogen fertilizer results. Specifically, a reduced expense attributed to RTK auto-steer led to a heightened derived quantity demanded for its use. Thus, for a given planting date and plant population, a higher optimal nitrogen rate was often consequential. Furthermore, risk averse behavior coupled with adjustments in planting date and plant population ultimately increased the average optimal nitrogen rate. Notably, under risk neutrality, everything stayed constant except for the amount of nitrogen applied. When comparing other risk aversion levels with the base scenario without auto-steer, planting dates and maturity groups remained the same but more acres were allocated towards higher nitrogen rates, seeding rates, or a combination of both. For example, under high risk aversion, 600 acres of corn were planted with 100 lbs/N without RTK. However, only 460 acres of corn were planted with the same nitrogen rate once RTK was incorporated within the model. Also for high risk aversion, 570 acres of corn was planted without RTK at a seeding rate of 24,000 and only 430 acres were planted with RTK at the same seeding rate. These changes were attributed directly to the reduction in overlap that RTK auto-steer provided. Specifically, RTK auto-steer increased the efficiency of planting and nitrogen application through enhanced performance rates and the amount of suitable field time available. This allowed for shifts towards higher optimal plant populations which corresponded to a greater desired nitrogen rate.

While the desired optimal nitrogen rate therefore increased, it was interesting to note that the greater efficiency of nitrogen application associated with RTK auto-steer was responsible for reduced nitrogen purchased. Thus, the precise application of nitrogen reduced the cost to deliver the same quantity of fertilizer to the corn plant. For the base scenario, a total of 270,518 lbs of nitrogen was applied to farm. With RTK auto-steer and the reduction in overlap, only 268,978 lbs of nitrogen was applied to the farm. Therefore, production economic theory supported the observed increase in recommended rates of nitrogen made available to the corn plant while the total nitrogen purchased actually declined because of reduced overlaps. The observed increase in nitrogen rate and plant population resulted in a moderate increase in average corn yields of one or two bushels per acre depending on risk behavior.

Unlike corn, soybean production practices remained relatively constant when compared to the base scenario. The largest change in the production of soybeans was the reallocation of acres under the low risk aversion level. Two interesting results occurred under risk neutrality and medium risk aversion. Similar to sub-meter auto-steer, planting the week of April 29th was also removed from the optimal set under risk neutrality. This was attributed to the competition for suitable field hours during the week of planting soybeans and spraying corn. The difference was that RTK increased the efficiency of planting whereas sub-meter auto-steer increased the efficiency of spraying. However, the change in the production of soybeans remained the same. For medium risk aversion, planting the week of May 6th with maturity group four was not removed from the optimal set like the occurrence with the adoption of sub-meter auto-steer. This was because the competition for suitable field days was between spraying soybeans and harvesting corn, neither of which were influenced by RTK in this study. In addition, soybean yields were not impacted by the utilization of RTK.

Sub-Meter and RTK Auto-Steer Results

Similar to the first two investigations, the economic, risk, and production impacts were analyzed for both auto-steer systems operating together. The adoption of both auto-steer systems increased the expected net returns under all four risk scenarios when compared to the base scenario (Table 2.3). Across all risk aversion levels, the average increase in expected net returns was 3.03% ($11.30/acre). When compared with the addition of a bolt-on auto-steer system with a sub-meter receiver on a self-propelled sprayer, the average increase in expected net returns across all risk levels was 1.93% ($7.35/acre). When compared with the addition of an integral valve auto-steer system with an RTK GPS receiver on a tractor, the average increase in expected net returns across all risk levels was 1.05% ($4.04/acre). Also, the minimum and maximum net returns were higher compared to the base scenario for all risk aversion levels.

The break-even acreage level, payback period, and the return on investment for the adoption of both auto-steer systems were also determined. The break-even acreage under the risk neutral scenario was 425 acres. Also, the payback period was calculated under the risk neutral scenario and it was determined that the addition of both auto-steer systems would pay for themselves in 1.18 years for farms with 2600 acres. Furthermore, the addition of both auto-steer systems had a 74.93% return on investment. These results were less than operating solely RTK auto-steer but still greater than sub-meter auto-steer alone.

The possibility of utilizing both auto-steer systems for reducing production risk was also an objective. The addition of both auto-steer systems exhibited the greatest ability to reduce risk. When compared to other auto-steer scenarios, both coefficient of variations and expected net returns were favored. The average decrease in the C.V. was 0.29%; therefore the addition of both auto-steer systems could be used as a tool for risk management. Similar to the first two investigations, the farm manager's capability to alter production practices was a large contributor in reducing the C.V., hence the possibility to managing production risk.

Alterations in production practices for corn and soybeans were also investigated. When adding both auto-steer systems, production practices and division of acres were similar as the scenario when adding just RTK auto-steer. Only a few differences occurred within the optimal production set. The alterations in production practices when using both systems independently were seen when joined together in this analysis. Notably, results were similar to RTK auto-steer but there was the removal of May 6th from the optimal production set which occurred when adding just sub-meter auto-steer alone. This was due to utilizing each auto-steer system in the production of corn and soybeans.

Impact of Input Price on the Profitability of Auto-Steer

Sensitivity analyses were conducted to determine the impact of input price fluctuations on the net returns and profitability of auto-steer under the risk neutral scenario. Three inputs were investigated, herbicide, nitrogen, and seed prices. However, only the inputs that each auto-steer scenario impacted were analyzed. Specifically, sub-meter auto-steer influences herbicide costs because it was on the sprayer. Additionally, RTK auto-steer influences nitrogen and seed cost because it was on the tractor. When the technologies were combined, they influenced all three inputs. Each input price was varied from -20% to 20% of the base, ceteris paribus. Net returns for the base case and all three auto-steer scenarios were observed when input prices were varied (Table 2.7). As input prices were varied, the percent increase in profitability above the base case due to the adoption of auto-steer was also calculated. For example, when herbicide price increased by 20%, there was an increase of 1.25% in profitability over the base scenario due to the adoption of sub-meter auto-steer. As the appropriate input price increased, auto-steer became more profitable. Also, as input price decreased, auto-steer became less profitable. When operating with both auto-steer systems, herbicide price increases provided greater potential for profitability than nitrogen price increases. Conversely, nitrogen price decreases provided greater potential for profitability than herbicide price decreases.

Conclusion

A whole farm economic model is used to assess three auto-steer scenarios for various risk aversion levels. First, a general investigation into the increase in net returns and return on investment for auto-steer under various overlap scenarios and hours worked per week are conducted. Results indicate that at the lowest overlap scenario, both sub-meter and RTK auto-steer systems are profitable and the return on investment is always substantially larger than the interest rate. A base overlap and hours worked per day are assumed and a more thorough investigation is then conducted.

The objectives of this study are to determine the economic, risk, and production implications due to the adoption of auto-steer. For all risk levels, results indicate that all three auto-steer scenarios are profitable, with the greatest average increase in expected net returns of 3.03% ($11.30/acre) for the scenario with both auto-steer systems. In addition, the minimum and maximum net returns that occur over thirty years are both higher due to the adoption of auto-steer except for RTK under risk neutrality. Furthermore, the break-even acreages under all scenarios are less than 525 acres, with a payback period of no more than 1.5 years. Also, the largest return on investment is 153.73% for sub-meter auto-steer.

The results also demonstrate that regardless of the auto-steer scenario or risk aversion level, the coefficient of variation decreases in all but one scenario. None the less, when coupled with an increase in net returns, auto-steer can be used to manage production risk. However, reduced production risk is based mainly on the farm manager's capability to alter production practices.

The results of this investigation also indicate that the adoption of auto-steer can impact optimal corn and soybean production practices. Corn production is impacted the most by the addition of RTK auto-steer navigation. This is due to the reduced overlap which results in an overall decrease in the total amount of fertilizer applied to the field despite an increase in the optimal nitrogen rate that the corn plant actually receives. In addition, the increase in efficiency results in a higher plant population, which also corresponds to the increase in optimal nitrogen rates. Soybeans are impacted the most due to the addition of sub-meter auto-steer, and its influence on the competition between resources, specifically suitable field hours. Finally, changes in the input price directly affect the expected net returns and the profitability of auto-steer.

Table 2.1.1. Summary of corn production practices utilized within this study.

Planting Date: March 25, April 1, April 8, April 15, April 22, April 29, May 6, May 13, May 20
Maturity Group (GDD): 2600-2650, 2650-2700, 2700-2750
Plant Population (plants/acre): 24,000, 28,000, 32,000
Row Spacing: 30”
Plant Depth: 1.5”
Nitrogen Rate (actual lbs/acre): 100, 150, 175, 200, 225

Table 2.1.2. Summary of soybean production practices utilized within this study.

Planting Date: April 22, April 29, May 6, May 13, May 20, May 27, June 3, June 10, June 17
Maturity Group: MG2, MG3, MG4
Plant Population (plants/acre): 111,000, 139,000, 167,000
Row Spacing: 15”, 30”
Plant Depth: 1.25”

Table 2.2. Base field capacities, as well as new field capacities when auto-steer is adopted on the self-propelled sprayer and tractor

Implement	Old Field Capacity (hr/ac)	New Field Capacity (hr/ac)[1]	Multiplicative Factor[2]
Sprayer: Pre-Plant	0.0132	0.0103	0.7792
Sprayer: Post-Plant	0.0132	0.0120	0.9090
Planter	0.0491	0.0457	0.9305
Anhydrous Applicator	0.0491	0.0437	0.8892
Stalk Shred	0.0825	0.0715	0.8672

[1]New field capacities are calculated according to the changes in width and speed due to the adoption of auto-steer.
[2]The multiplicative factor represents the percent change between the new and old field capacities. For example, sub-meter auto-steer decreased the hours per acre for pre-planting application of chemicals by approximately 22%.

Table 2.3. Economics of auto-steer navigation under various risk aversion scenarios

	Risk Aversion Levels			
Base[1]	Neutral	Low	Medium	High
Expected Net Returns	$1,020,336	$1,007,871	$979,545	$913,621
Percent Optimal	100.00%	100.00%	100.00%	100.00%
C.V. (%)	17.81	15.66	13.79	11.06
Minimum Net Returns	$658,928	$666,801	$680,614	$701,470
Maximum Net Returns	$1,364,489	$1,341,037	$1,276,158	$1,136,768
Sub-Meter[2]				
Expected Net Returns	$1,030,817	$1,018,353	$990,004	$924,306
Percent Optimal	101.03%	101.04%	101.07%	101.17%
C.V. (%)	17.63	15.50	13.63	10.94
Minimum Net Returns	$669,333	$677,251	$689,454	$712,151
Maximum Net Returns	$1,375,037	$1,351,584	$1,285,587	$1,148,208
RTK[3]				
Expected Net Returns	$1,039,654	$1,029,945	$997,029	$931,284
Percent Optimal	101.89%	102.19%	101.78%	101.93%
C.V. (%)	17.46	15.71	13.62	10.97
Minimum Net Returns	$657,201	$684,554	$696,721	$717,024
Maximum Net Returns	$1,374,844	$1,364,430	$1,294,246	$1,159,634
Both[4]				
Expected Net Returns	$1,050,126	$1,040,424	$1,007,642	$941,757
Percent Optimal	102.92%	103.23%	102.87%	103.08%
C.V. (%)	17.29	15.56	13.47	10.85
Minimum Net Returns	$667,673	$694,905	$705,437	$727,494
Maximum Net Returns	$1,385,317	$1,375,126	$1,304,026	$1,170,109

[1]Base refers to operating without any auto-guidance systems.
[2]Sub-Meter refers to the adoption of a bolt-on auto-steer system with a sub-meter receiver on a self propelled sprayer.
[3]RTK refers to the adoption of an integral valve auto-steer system with a RTK GPS receiver on a tractor.
[4]Both refers to the adoption of both auto-steer systems above and operating together.

Table 2.4. Production results and acres planted for various risk aversion levels under the base scenario with no auto-steer navigational technologies

Section 1. Corn Management Practices				Risk Aversion Levels			
Planting Date	Maturity Group	Plant Pop	Nitrogen Rate	Neutral	Low	Medium	High
March 25	2600	28000	150	0	0	333	485
March 25	2650	28000	150	0	362	0	0
March 25	2650	32000	150	362	0	0	0
March 25	2700	24000	100	0	0	0	148
March 25	2700	24000	150	0	0	413	0
March 25	2700	28000	175	0	293	0	0
March 25	2700	32000	175	722	272	0	0
April 1	2700	24000	100	0	0	0	183
April 1	2700	28000	100	0	0	0	30
April 1	2700	28000	150	0	0	142	0
April 1	2700	32000	150	0	157	65	0
April 8	2600	24000	100	0	0	0	238
April 8	2700	28000	150	0	0	103	0
April 15	2700	28000	225	216	0	0	0
April 22	2650	28000	150	0	216	244	216
			Yields[1]	163	159	153	147

Section 2. Soybean Management Practices[2]			Risk Aversion Levels			
Planting Date	Maturity Group		Neutral	Low	Medium	High
April 22	MG3		0	0	731	0
April 22	MG4		1290	0	0	0
April 29	MG2		0	0	0	804
April 29	MG3		0	0	0	91
April 29	MG4		10	616	0	0
May 6	MG4		0	684	50	0
May 13	MG4		0	0	519	0
June 17	MG4		0	0	0	405
		Yields	62	62	61	57

[1]Yields for both corn and soybeans are in bu/Acre.
[2]Optimal plant population and row spacing was the same for all risk scenarios of 111,000 plants per acre and 15 inch row spacing.

Table 2.5. Production results and land area planted for various risk aversion levels under sub-meter auto-steer

Section 1. Corn Management Practices				Risk Aversion Levels			
Planting Date	Maturity Group	Plant Pop	Nitrogen Rate	Neutral	Low	Medium	High
March 25	2600	28000	150	0	0	338	489
March 25	2650	28000	150	0	362	0	0
March 25	2650	32000	150	362	0	0	0
March 25	2700	24000	100	0	0	0	148
March 25	2700	24000	150	0	0	408	0
March 25	2700	28000	175	0	291	0	0
March 25	2700	32000	175	722	272	0	0
April 1	2700	24000	100	0	0	0	181
April 1	2700	28000	100	0	0	0	31
April 1	2700	28000	150	0	0	167	0
April 1	2700	32000	150	0	159	43	0
April 8	2600	24000	100	0	0	0	235
April 8	2700	28000	150	0	0	104	0
April 15	2700	28000	225	216	0	0	0
April 22	2650	28000	150	0	216	240	216
			Yields[1]	163	159	153	147

Section 2. Soybean Management Practices[2]			Risk Aversion Levels			
Planting Date	Maturity Group		Neutral	Low	Medium	High
April 22	MG3		0	0	720	0
April 22	MG4		1300	0	0	0
April 29	MG2		0	0	0	804
April 29	MG3		0	0	0	97
April 29	MG4		0	628	0	0
May 6	MG4		0	672	0	0
May 13	MG4		0	0	580	0
June 17	MG4		0	0	0	399
		Yields	62	62	61	57

[1]Yields for both corn and soybeans are in bu/Acre.
[2]Optimal plant population and row spacing was the same for all risk scenarios of 111,000 plants per acre and 15 inch row spacing.

Table 2.6. Production results and land area planted for various risk aversion levels under RTK auto-steer

Section 1. Corn Management Practices					Risk Aversion Levels			
Planting Date	Maturity Group	Plant Pop	Nitrogen Rate		Neutral	Low	Medium	High
March 25	2600	28000	150		0	0	334	515
March 25	2650	28000	150		0	362	0	0
March 25	2650	32000	175		362	0	0	0
March 25	2700	24000	100		0	0	0	117
March 25	2700	24000	150		0	0	362	40
March 25	2700	28000	175		0	0	45	0
March 25	2700	32000	175		0	42	0	0
March 25	2700	32000	200		722	559	0	0
April 1	2700	24000	100		0	0	0	66
April 1	2700	28000	100		0	0	0	137
April 1	2700	32000	150		0	121	203	0
April 8	2600	24000	100		0	0	0	209
April 8	2700	28000	150		0	0	112	0
April 15	2700	28000	225		216	0	0	0
April 22	2650	28000	150		0	135	244	216
April 22	2700	28000	175		0	81	0	0
				Yields[1]	165	161	154	148

Section 2. Soybean Management Practices[2]			Risk Aversion Levels			
Planting Date	Maturity Group		Neutral	Low	Medium	High
April 22	MG3		0	0	734	0
April 22	MG4		1300	0	0	0
April 29	MG2		0	0	0	798
April 29	MG3		0	0	0	98
April 29	MG4		0	988	0	0
May 6	MG4		0	312	53	0
May 13	MG4		0	0	513	0
June 17	MG4		0	0	0	403
		Yields	62	62	61	57

[1]Yields for both corn and soybeans are in bu/Acre.
[2]Optimal plant population and row spacing was the same for all risk scenarios of 111,000 plants per acre and 15 inch row spacing.

Table 2.7. Expected net returns as well as profitability of auto-steer above the base case (%) as input prices fluctuate by the percentages indicated.[1]

	Sub-Meter[2]	RTK[3]		Both[4]		
	Herbicide	Nitrogen	Seed	Herbicide	Nitrogen	Seed
20%	1.25	2.07	2.23	3.17	3.11	3.29
10%	1.14	1.96	2.06	3.04	3.00	3.10
0%	1.03	1.89	1.89	2.92	2.92	2.92
-10%	0.92	1.85	1.74	2.80	2.87	2.74
-20%	0.82	1.73	1.59	2.68	2.74	2.58

[1] The percentages indicate the increase in net returns above the base scenario with the same increase in input price.
[2] The impact of herbicide price fluctuations on the profitability of sub-meter auto-steer on the self-propelled sprayer when compared to the base case.
[3] The impact of nitrogen and seed price fluctuations on the profitability of RTK auto-steer on the tractor when compared to the base case.
[4] The impact of herbicide, nitrogen, and seed price fluctuations on the profitability of both sub-meter auto-steer on the self-propelled and RTK auto-steer on the tractor when compared to the base case.

CHAPTER THREE

WHOLE FARM ANALYSIS OF AUTOMATIC SECTION CONTROL FOR SELF-PROPELLED AGRICULTURAL SPRAYERS

Precision agriculture technology has evolved in such a manner that it provides farmers with new and innovative ways to possibly improve profitability. One of these ways is a new approach to the application of liquid chemicals known as automatic section control. Automatic section control on a sprayer has the ability to selectively manage input application across the spray boom. This technology utilizes a global positioning system (GPS) to locate the position of the sprayer within the field, and then records the areas covered. If the sprayer traverses an area previously covered it can automatically turn the appropriate section off, therefore eliminating over application. In addition, automatic section control can manage chemical application in undesirable areas such as point rows, waterways, and during headland turns. Currently, automatic section control is available by many manufacturers and has the ability to control up to 48 sections of the spray boom. With this capability, numerous benefits are possible.

The largest benefit associated with automatic section control is the reduction in overlapped areas especially prevalent on irregular shaped fields. As a result, this new technology has the potential to increase profits due to reducing input costs. Specifically, automatic section control can reduce the cost of any chemical application applied with the self-propelled sprayer (e.g. herbicide and pesticide). Environmental benefits are also possible due to the ability to manage buffer zones and protect sensitive areas in and around the field. Furthermore, improved efficiency can occur if coupled with a navigational aide such as lightbar or auto-steer. To evaluate automatic section control as a viable replacement for standard uniform sprayers, economic analyses must be conducted.

Batte and Ehsani (2006) began investigating the possible economic benefits of this technology. They concluded that input savings alone from the technology could be substantial if automatic section control could be developed. Once a prototype was created and farm trials conducted, Dillon, et al. (2007) examined the economic implications of utilizing automatic section control. They determined that input expense savings from the application of herbicide alone would justify adoption. In addition, results indicated a break-even area of 785 acres and a payback period of 3.19 years based on herbicide alone. Shockley, et al. (2008) expanded the above study to include additional inputs and benefits associated with navigational technologies. Results from the study indicated a break-even area as low as 403 acres and payback period of less than one year for high rates of herbicide applications. Mooney, et al. (2009) conducted the most recent economic analysis and determined automatic section control became profitable at input saving levels of 11% or above.

Even though previous economic studies have provided valuable insight of automatic section control, numerous shortcomings exist. The previous analyses utilized simple techniques and only focused on cost savings. Moreover, the results understated the economic potential to the extent that substitution of inputs and the ability to alter production strategies were not considered within these models. In addition, field shape could have a substantial impact on the economic viability of automatic section control, which was not investigated in previous studies. Furthermore, previous research into automatic section control has excluded other issues such as the economic impact of including navigational aids and the impact on risk.

The addition of navigational aids to automatic section control can have substantial economic implications. By utilizing navigation aids such as lightbar with automatic section control, improved performance rates of the sprayer can occur. In turn, this can impact the optimal production strategies. As a result, opportunities to exploit automatic section control to reduce production risk should also be examined. Lowenberg-DeBoer (1999) developed theoretical models suggesting variable rate technologies could be used to manage risk. Therefore, the potential for automatic section control to manage production risk is an objective of this investigation.

The objectives of this study are to: (1) determine the impact of automatic section control on expected net returns under various scenarios, (2) determine if automatic section control can be used to manage production risk, (3) determine the impact of automatic section control on optimal production strategies under various scenarios, (4) determine the break-even acreage level, percent overlap, payback period, and return on investment required to justify the implementation of automatic section control, and (5) determine the influence of input price fluctuations on the profitability of automatic section control.

To provide a detailed assessment of automatic section control for a hypothetical grain farmer in Kentucky, a whole farm economic model is utilized. This study investigates automatic section control with and without lightbar navigation. In addition, three different field shapes with corresponding overlap scenarios as well as four farmer risk aversion attitudes (neutral, low, medium, and high) are included into the whole farm model to accomplish the above objectives.

Analytical Procedure

The analytical framework of this study embodies the production environment, economic model, and explicit conditions pertaining to the hypothetical farm that represents the study focus and are detailed in the follow sections. This section has a high degree of similarity to Chapter 2 and presented again due to the journal article approach of this dissertation.

The Production Environment

The Decision Support System for Agrotechnology Transfer (DSSAT v4), a biophysical simulation model, was utilized to estimate the production data for this study (Hoogenboom, 2004). For almost 15 years, DSSAT has provided production data for refereed studies in numerous journal articles that encompassed various geographic locations. DSSAT was determined to be an appropriate model for this study after a comprehensive validation specific to this study was performed and discussed later in this section.

Developing yield estimates in DSSAT required input data that included site weather data for the duration of the growing season, site soil data, and a description of the production practices. Daily climatology data were accumulated for 30 years in Henderson County, Kentucky and obtained through the University of Kentucky Agricultural Weather Center (2008). To acquire the necessary soil data, a National Cooperative Soil Survey of Henderson County, Kentucky was developed from the Natural Resources Conservation Service (NRCS). From the soil survey, it was determined that four representative soils (deep silty loam, deep silty clay, shallow silty loam, and shallow silty clay) would be utilized in the biophysical simulation models. Finally, production practices were ascertained for corn and full season soybeans in accordance with the University of Kentucky Cooperative Extension Service Bulletins (2008). These included a range of planting date, crop variety, plant density, row spacing, and fertilizer practices (Table 3.1).

The estimated yields were validated by analyzing their response to varying production practices, and then compared to relevant literature. For example, corn yields exhibited a quadratic response to nitrogen rates, which is consistent with previous literature (e.g. Schmidt, et al., 2002; Cerrato and Blackmer, 1990). Furthermore, regression analysis was conducted to compare the estimated yields from DSSAT to actual historical yield trends for Henderson County, Kentucky. Performing a t-test confirmed that the estimated yields were not statistically different from actual yields with a significance of 99% for both corn and soybeans.[12] Refer to the appendix for more details with regard to the validation of the estimated yields. In general, the simulated yields were thought to be typical of grain production in Henderson County, Kentucky. The estimated yield data provided an essential element to be utilized within the economic model.

The Economic Model

A resource allocation model was employed within a mean variance (E-V) quadratic programming formulation to represent a commercial Kentucky corn and soybean producer operating under no-till farming conditions. The mathematical details of the model can be found in the Appendix 1. Freund (1956) developed the formulation to incorporate risk measured by the variance of net returns across years. Dillon (1999) modeled risk within an E-V framework which has been modified for this study. Specifically, additional production practices, the incorporation of different land types, allowing for multiple harvest weeks, and the inclusion of automatic section control technology with and without lightbar navigation distinguished this model from Dillon's (1999) model.

The objective of the model was to maximize net returns less the product of the Pratt risk aversion coefficient and the variance of net returns. The Pratt risk aversion

[12] Corn and soybean regressions resulted in an R^2 of 0.22 and 0.46 respectively.

coefficient was developed by McCarl and Bessler (1989) as a measure of a hypothetical producer's aversion to risk. By utilizing this coefficient, the model exhibited the classic risk-return tradeoff by penalizing net returns by its variance. Four risk aversion levels were modeled within the E-V framework.[13]

Various decision variables, constraints, and supplementary coefficients and data comprised the economic framework of this study. Variables decided within the economic model include the production of corn and soybeans. These are identified by the amount of acres produced by various production practices on the respected soil type.[14] From the decision variables, the expected net returns and average yields could be determined. To formulate the model and provide insights into the above decision variables, appropriate constraints were required.

To provide insight into the above decision variables, the appropriate constraints were required which included land available, labor, crop rotation, and ratio of soil type. The land area constraint limited the total production of corn and soybeans by the available acres assumed for this investigation. Additionally, the estimated suitable field hours per week bounded the operating hours of the machines required to perform the activities necessary in the production of corn and soybeans. Since a Kentucky grain producer often utilizes a two year crop rotation, a constraint was required such that 50% of the land available was in corn production and 50% was in soybean production. Furthermore, it was assumed that the producer would not be utilizing variable rate applications based on soil type. As a result, constraints requiring uniformity of production practices across soil types were required. In addition to the constraints, establishing the proper coefficients and data were essential in the framework of the economic model.

The coefficients required for this study consisted of the labor hours and the prices for corn and soybeans. Field capacity of the machines provided the basis for determining the labor required to perform the agricultural tasks. A ten percent increase in hours per

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[13]Risk aversion levels were given by percentages representing the desire of net returns likely to be achieved. Percentages of 50, 60, 70, and 85 were modeled and were labeled as neutral, low, medium, and high risk aversion respectively.

[14] The various production practices and their respective allotted acres were decided within the model for all scenarios investigated including the base case without automatic section control.

acre was utilized to represent the total labor required to complete specific operations. The extra labor occurs from performing such tasks as refilling the sprayer tanks and seed bins, unloading the grain tank and any other labor tasks required. In addition, the price for corn and soybeans also needed to be established. The World Agricultural Outlook Board (2008) estimated the median 2009 prices for corn and soybeans, after adjusting for Kentucky basis, at $4.25/bu and $9.75/bu respectively.

Accompanying data critical to this study included of the appropriate land area, suitable field hours, and the costs of automatic section control and lightbar navigation. Because of the nature of this investigation, the land area chosen reflected a farm size located in Henderson County, Kentucky that supported the ownership of a self-propelled sprayer. According to the Kentucky Agricultural Statistics (2008), Henderson County was the second largest corn and soybean producer in the state. Henderson County is located in the Ohio Valley region of Kentucky where farm sizes of 2600 acres are representative of the upper one third of net farm income for farms registered into the Kentucky Farm Business Management program (Pierce, 2008). This was deemed an appropriate size to support the ownership of a self-propelled sprayer. Suitable field days were also determined from 30 years of historical climatological data. They were estimated based on probabilities of it not raining 0.15 inches or more per day over a period of a month.[15] The calculated probabilities were utilized to determine expected suitable field hours per week. Finally, the cost of automatic section control was annualized and incorporated both depreciation and the opportunity cost of capital invested. Depreciation was calculated using the straight-line method with an assumed eight year useful life and an 8% interest rate on capital investment. With the adoption of automatic section control technology, additional costs included a Zynx-20 controller at $4750, a 30 channel spray ECU at $3100, 54 solenoid valves at $159 each and $470 for wiring and harness. Notably this allowed the replacement of the standard spray controller which was assumed to have a salvage value of $1050. This consequently nets a total investment outlay of $15,856 and an annualized cost of $2,616 per year. With the

[15] For clarification, an example was given for determining suitable field days. If the median days in January that it rained 0.15 inches or more was 5 over 30 years, the probability of it NOT raining .15 inches per day in January was (1-(days rained/days in the month)).

addition of lightbar with sub-meter accuracy, the total investment outlay was $18,856 and an annualized cost of $3,111 (Dillon, et al., 2007; Shockley, et al., 2008; Stombaugh, 2009). With this technology, perfect control (i.e. zero overlap) was assumed for this investigation.

The Hypothetical Model Farm

A collection of machines was established that corresponded to a hypothetical farm located in Henderson County that operated under no-till farming conditions. The collection of machines comprised one 250-hp 4WD tractor with the following implements: a 42-ft anhydrous applicator, a split row no-till planter (16 rows), a grain cart with 500 bu capacity, and a 20-ft stalk shredder for corn. Also included was a 300-hp harvester with an 8 row header for corn and a 25-ft flex header for soybeans. Additionally, a self propelled sprayer with a 90-ft boom that applied herbicides on corn (Glyphosate, Bicep II, and Roundup), herbicides on soybeans (Roundup and 2, 4-D, B) and insecticide on soybeans (Acephate) was the equipment set assumed. Mississippi State Budget Generator (MSBG) was utilized to compile the ASABE Standard specifications for the above equipment set (i.e. speed, width, and efficiency). However, the addition of the no-till split row planter and the anhydrous applicator was required (Laughlin and Spurlock, 2007). Illinois Farm Business Management (2008) machinery specifications were utilized to gather appropriate data for the planter and anhydrous applicator.

The benefits acquired by equipping the above self-propelled sprayer with automatic section control were influenced by whether or not lightbar navigation was also utilized. For the scenarios that incorporated solely automatic section control, only direct input cost savings were reflected in the coefficients. These variations in cost savings were dependent on which crop, input, and field shape the autonomous section control was operating on (Table 3.2). When utilizing a sub-meter receiver with a navigational aid, such as lightbar, an enhanced performance rate of the sprayer occurred. This was due to the ability to use GPS navigation to reduce overlaps within the field. A reduction in overlap to three feet for the self-propelled sprayer due to the addition of lightbar to the self-propelled sprayer was assumed (Stombaugh, 2005). Besides the technology, field shape could also influence the analysis.

The profitability of automatic section control could vary greatly depending on the field shape on which the sprayer was being used. This was due to the differences in potential overlap. Therefore, three different field shapes were chosen for this study that represented the breadth of Kentucky grain farms. The three farms were chosen from a study conducted by Stombaugh et al. (2009). The study collected data from numerous farms throughout Kentucky and were utilized in the development of a computational method and software tool. The program had the ability to estimate the overlapped area in a particular field as it was affected by automatic section control. By utilizing field boundary shape files, implement width, and number of sections controlled across the spray boom, the program could calculate the percentage overlapped area for a given field. The program generated field coverage using straight parallel paths in which overlaps occurred only due to headland encroachment and point row areas. Obstacles within the field boundary were not considered in the model. Three field shapes and corresponding percentage of overlapped area were chosen as base scenarios for this investigation. In particular, fields with a low (5%), medium (16.5%), and high (25.5%) percentage of overlapped area were chosen (Figures 1).

Results and Discussion

Three base scenarios with the aforementioned differing percentage of overlapped area were investigated and then compared to the addition of automatic section control with and without lightbar navigation. Table 3.3 presents the economic impact of the various base overlap scenarios.

Automatic Section Control without Lightbar

The addition of automatic section control without lightbar was examined to determine the economic, risk, and production impacts due to adoption. When compared to the three base cases, expected net returns increased under every risk aversion level with the adoption of automatic section control (Table 3.3). The increase in expected net returns varied from 0.16% ($0.60/acre) for a low overlap field (5% overlap) to an increase of 2.35% ($8.11/acre) in net returns for a high overlap field (25.5% overlap). The average increase in expected net returns across all three base scenarios under risk neutrality was 1.17% ($3.40/acre). As risk aversion increased, results indicated the profitability of automatic section control without lightbar increased when compared to the base scenarios. In addition, as the overlapped area increased, profits increased due to the addition of automatic section control without lightbar when compared to the base scenarios. Additionally, the results indicated the average percent decrease in expected total variable cost across all base scenarios for risk neutrality was 2.24%. This was considerably less than the 11% which Mooney, et al. (2009) determined was needed for automatic boom section control to become profitable. Furthermore, for all base overlap scenarios and risk aversion levels, both the minimum and maximum net returns were greater when incorporating section control.

The break-even acreage level, percent overlap, payback period, and return on investment for the adoption of automatic section control without lightbar were also determined. For each overlap scenario under risk neutrality, break even acreage levels were calculated to determine the approximate land area necessary to justify the adoption of automatic section control[16]. Results indicated that land areas of 1535, 428, and 279 acres for low, medium, and high overlaps, respectively, were needed to distribute the fixed cost associated with adoption. Furthermore, an overlap of 4% or more was needed for automatic section control to be profitable with a farm size of 2600 acres. The payback periods were calculated under risk neutral scenarios and results indicated that automatic section control was able to pay for itself in 3.75, 1.04, and 0.67 years for low, medium, and high overlaps, respectively, for farms with 2600 acres. In addition, the return on investment for automated section control was 14.19%, 83.60%, and 137.00% for low, medium, and high overlaps respectively[17]. As the overlap area increases, the input savings that occurred begins to dominate the depreciation of automatic section control, resulting in the above return on investments. In addition, all three returns on investment were greater than the opportunity cost of capital (8%). Therefore, automatic section control without lightbar was deemed a sound investment for the scenarios evaluated.

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[16] Break-even acreage levels could not be determined from a simple calculation. Both the base and technology scenarios acreage levels must be varied accordingly such that both base and technology scenario converge to the same expected net return.

[17] The return on invest was adjusted such that the opportunity cost of capital was not accounted for twice. Therefore, the percentages appropriately reflected the return on the capital invested. Specifically, the following formula was utilized to calculate the returns on investment: [(Net returns gained from technology)+(Opportunity cost of capital)] / (Total investment in the technology). The opportunity cost of capital was calculated using the following formula: (Interest rate*Total investment/2).

The potential of automatic section control to assist in managing production risk was also an objective. It could be inferred that automatic section control reduces production risk if both the coefficient of variation (C.V.) decrease and expected net returns increase, when compared to a base scenario.[18] For this investigation, automatic section control exhibited more favorable coefficients of variation and expected net returns when compared to all base overlap scenarios and risk aversion levels (e.g. 17.67 and $1,026,270 under risk neutrality with automatic section control compared to 18.04 and $1,005,182 for high overlap without automatic section control). The average decreases in C.V. across risk levels were 0.16%, 0.99%, and 2.12% for low, medium, and high overlap, respectively. As a result, automatic section control without lightbar could be utilized for managing production risk.

Optimal production practices with and without automatic section control were also determined for this study. Since automatic section control without lightbar only affected direct input cost savings, optimal production practices were not altered. Therefore, detailed production results were discussed in the following section.

Automatic Section Control with Lightbar

The addition of automatic section control with lightbar was also examined to determine the economic, risk, and production impacts due to adoption. Overall economic results were similar to the addition of automatic section control without lightbar (Table 3.4). When compared to the base overlap scenarios, for all risk aversion levels, automatic section control with lightbar was profitable. In addition, both minimum and maximum net returns were higher than the base overlap scenarios. Even though net returns were above the base overlap scenarios, the addition of lightbar to automatic section control was only justified for medium and high overlap scenarios. This observation was a result of the whole farm approach that was utilized. Specifically, this investigation was able to capture the effect lightbar had on input cost savings and the performance rate of the sprayer based on the various overlap scenarios. Therefore, this study was able to explain the full impact automatic section control with lightbar had on expected net returns.

Additionally, the break-even acres, payback period, and the return on investment under risk neutrality were determined. Land areas of 1893, 513 and 328 acres for low,

[18] The C.V is a relative measure of risk and any decrease indicates a possibility of risk reduction

medium, and high overlaps, respectively, were needed to distribute the fixed cost associated with the adoption of automatic section control with lightbar. The amount of acres required above to justify the addition of automatic section control with lightbar was considerably higher than without lightbar. The greatest increase in acres occurred for the low overlap scenario in which an additional 358 acres were required due to the addition of lightbar to automatic section control. Also, the payback periods for low, medium, and high overlap scenarios were 4.41, 1.19, and 0.76 years, respectively. These were also greater than automatic section control without lightbar. In addition, the returns on investment were lower than without lightbar of 10.18%, 71.71%, and 118.74% for low, medium, and high overlap, respectively. Similar to automatic section control without lightbar, as the overlapped area increases, the input savings that occurred began to dominate the depreciation costs of automatic section control, resulting in the above return on investments. However, the percentage of overlap required to justify the adoption of automatic section control with lightbar was 4%, the same as without lightbar. Furthermore, results indicated that an overlap of 14% or more was needed before a farmer would prefer the addition of lightbar to automatic section control. The above percentages of overlaps calculated were determined through numerous investigations within the model. Even though the returns on investment and payback periods for automatic section control without lightbar were greater, the returns on the investment with lightbar were still above the opportunity cost of capital and the payback periods never differed more than one year. Therefore, automatic section control with lightbar was still considered a sound investment.

The potential of automatic section control with lightbar to assist in managing production risk was also an objective. Similarly, automatic section control with lightbar exhibited more favorable coefficients of variation and expected net returns when comparing all base overlap scenarios and risk aversion levels. Therefore, automatic section control with lightbar could become a tool for managing production risk. The addition of a lightbar to automatic section control had a greater impact on the reduction of C.V. than without lightbar for medium and high overlap scenarios. The average decreases in C.V. across risk levels were 0.14%, 1.38%, and 2.32% for low, medium, and high overlap, respectively.

Determining the impact on production practices from utilizing automatic section control with lightbar was also an objective. Unlike before, operating section control with lightbar did influence the optimal production practices when compared to the base overlap scenarios. As sprayer overlap increased, the performance rate of spraying operations decreased. Therefore, when operations were competing for suitable field hours, the optimal production decisions were influenced by this constraint. As sprayer overlap increased, the majority of change occurred in the production of soybeans (Tables 3.5-3.7). Conversely, corn production practices remained relatively unaffected. This was attributed to the competition for suitable field hours with other production practices. For example, under risk neutrality, planting corn on the week of March 25th occurred during the same week as the burn down herbicide application for soybeans planted on April 22nd. Therefore, as the performance rate of the sprayer decreased, more acres of soybeans must be planted at an alternative production combination (in this case planting the week of April 29th with maturity group IV). For each risk aversion level, a different conflict occurred between production practices. Examples included spraying corn while planting soybeans and harvesting corn while spraying beans during the same week.

When analyzing the impact automatic section control with lightbar had on optimal production practices, results indicated that the same optimal production practices occurred as the low overlap scenario (Table 3.8). Since the percent overlaps between the two scenarios only differed by less than two percent, there were no changes in production practices. When compared to the other overlap scenarios, automatic section control with lightbar provided the sprayer with an enhanced performance rate. This allowed for additional acres to be produced on previously bound production practices. Since automatic section control with and without lightbar did not alter the production practice for the low overlap scenario, the additional cost of utilizing lightbar with automatic section control was not justified for the scenario.

Impact of Input Price on the Profitability of Automatic Section Control

Sensitivity analyses were conducted to establish the influence of input price on the profitability of automatic section control under the risk neutral scenario for all three overlap scenarios. Since automatic section control influences the chemicals applied on the field, only herbicide price fluctuations were investigated by varying their respective original price plus and minus ten and twenty percent, ceteris paribus. Other inputs required in production would only result in a uniform change in net returns, therefore were not investigated. The percent increase in profitability due to the adoption of automatic section control was determined based on the various input price scenarios (Table 3.9). It was determined that as herbicide prices increased, automatic section control with and without lightbar became more profitable. As input prices decreased, all scenarios investigated still exhibited increased profits. However, if herbicide price decreased by 20%, the profitability of automatic section control without lightbar almost was almost zero.

Conclusion

Three base scenarios with initial sprayer overlaps of 5%, 16.5%, and 25.5% are investigated to determine possible economic, risk, and production practice impacts of automatic section control with and without lightbar. The economic results indicate that regardless of risk level or overlap scenario, automatic section control with and without lightbar are profitable. However, the addition of lightbar to automatic section control is only justified for medium and high overlap scenarios. The greatest increase in expected net returns under risk neutrality is 2.44% ($8.43/acre) which corresponds to utilizing automatic section control with lightbar on the largest overlapped area in this investigation. In addition, the average decrease in expected variable costs across all overlap scenarios is 2.29%. This is considerably lower than the 11% that previous studies required to justify the adoption of automatic section control.

The break-even acreage level, percent overlap, payback period, and return on investment for the adoption of automatic section control with and without lightbar under all three overlap scenarios are also determined. Break-even acreages vary from 1893 to 279 acres based on the percentage of overlap and whether or not lightbar is present on the sprayer. In addition, automatic section control has a payback period of no more than five years. The return on investment varies greatly from 10.18% for a low overlap field to 137.00% for a high overlap field. Even though the returns on investment and payback periods favor automatic section control without lightbar for overlaps less than 14%, the returns on investment with lightbar are still above the opportunity cost of capital. In addition, the payback periods never differ more than one year. Greater net returns and lower coefficients of variation for automatic section control with lightbar are preferred for scenarios exhibiting 14% overlap or greater with the self-propelled sprayer.

The results also indicate that the coefficient of variation decreases when compared to each base scenario and risk aversion level. This is due to the adoption of automatic section control with and without lightbar. Automatic section control with lightbar reduces the coefficient of variation the greatest for both medium and high overlap scenarios. Thus, when coupled with increases in net returns, automatic section control with and without lightbar can be used to manage production risk.

In addition, the adoption of automatic section control alone has no impact on optimal production practices. Similarly, results indicate that operating a sprayer with automatic section control and lightbar has the same optimal production practices as the low overlap base scenario. Conversely, automatic section control with lightbar provides the sprayer with an enhanced performance rate for medium and high base scenarios. This allows additional acres to be produced on previously bound production practices. Hence, the adoption of automatic section control with lightbar influences the optimal production practices.

Sensitivity analyses indicate the break-even overlap that justifies the adoption of automatic section control with or without lightbar is 4% or more for a 2600 acre farm. Furthermore, an initial overlap of 14% or more is needed to justify the addition of lightbar to automatic section control. Sensitivity analyses also indicate that automatic section control with and without lightbar become more profitable when herbicide price increases.

Table 3.1.1. Outline of production practices employed within this study for corn.

Planting Date:	March 25, April 1, April 8, April15, April 22, April 29, May 6, May 13, May 20
Maturity Group (GDD):	2600-2650, 2650-2700, 2700-2750
Plant Population[1]:	24,000, 28,000, 32,000
Row Spacing:	30”
Plant Depth:	1.5”
Nitrogen Rate[2]:	100, 150, 175, 200, 225

[1]Plant population values correspond to the amount of plants per acre.

[2]Nitrogen rate values correspond to the actual pounds of nitrogen per acre.

Table 3.1.2. Outline of production practices employed within this study for soybeans.

Planting Date:	April 22, April 29, May 6, May 13, May 20, May 27, June 3, June 10, June 17
Maturity Group:	MG2, MG3, MG4
Plant Population[1]:	111,000, 139,000, 167,000
Row Spacing:	15”, 30”
Plant Depth:	1.25”

[1]Plant population values correspond to the amount of plants per acre.

Table 3.2. Input cost savings ($ per acre) due to the adoption of automatic section control based on overlap and inputs applied on corn and/or soybeans.

	Overlap		
	Low	Medium	High
Herbicide on Soybeans	1.23	4.55	7.10
Herbicide on Corn	1.82	6.58	10.25
Insecticide on Soybeans	0.30	1.08	1.68

Table 3.3. Economics of various base overlap scenarios under a range of risk aversion levels.

	Risk Aversion Level			
	Neutral	Low	Medium	High
Low Overlap				
Expected Net Returns	$1,025,652	$1,013,187	$984,861	$918,937
C.V. (%)	17.72	15.58	13.72	11.00
Minimum Net Returns	$664,244	$672,117	$685,930	$706,787
Maximum Net Returns	$1,369,805	$1,346,354	$1,281,474	$1,142,083
Medium Overlap				
Expected Net Returns	$1,014,088	$1,001,662	$974,450	$907,235
C.V. (%)	17.90	15.76	13.95	11.13
Minimum Net Returns	$653,061	$660,614	$678,119	$695,071
Maximum Net Returns	$1,357,912	$1,334,786	$1,273,399	$1,129,705
High Overlap				
Expected Net Returns	$1,005,182	$992,796	$966,570	$898,198
C.V. (%)	18.04	15.90	14.13	11.23
Minimum Net Returns	$644,536	$651,769	$673,020	$686,055
Maximum Net Returns	$1,348,677	$1,325,876	$1,267,245	$1,119,988

[1] Low, Medium and High risk aversion levels correspond to 60%, 70%, and 85% respectively.
[2] Low, Medium and High overlap correspond to 5%, 16.5%, and 25.5% respectively for a 90 ft. self-propelled agricultural sprayer.

Table 3.4. Economics of automatic section control with and without lightbar for a range of risk aversion levels.

Section 1: Economics of automatic section control without lightbar for various overlap scenarios and risk aversion levels.

	Risk Aversion Level			
	Neutral	Low	Medium	High
Low Overlap				
Expected Net Returns	$1,027,268	$1,014,804	$986,478	$920,544
Percent of Base	100.16%	100.16%	100.16%	100.17%
C.V. (%)	17.69	15.56	13.70	10.98
Minimum Net Returns	$665,861	$673,734	$687,547	$708,403
Maximum Net Returns	$1,371,422	$1,347,971	$1,283,086	$1,143,701
Medium Overlap				
Expected Net Returns	$1,026,710	$1,014,284	$987,071	$919,857
Percent of Base	101.24%	101.26%	101.30%	101.39%
C.V. (%)	17.68	15.56	13.77	10.98
Minimum Net Returns	$665,683	$673,236	$690,749	$707,694
Maximum Net Returns	$1,370,533	$1,347,408	$1,286,017	$1,142,326
High Overlap				
Expected Net Returns	$1,026,270	$1,013,883	$987,657	$919,286
Percent of Base	102.10%	102.12%	102.18%	102.35%
C.V. (%)	17.67	15.57	13.83	10.98
Minimum Net Returns	$665,623	$672,857	$694,107	$707,092
Maximum Net Returns	$1,369,765	$1,346,964	$1,288,332	$1,141,076

Section 2: Economics of automatic section control with lightbar for various risk aversion levels.

	Risk Aversion Level			
	Neutral	Low	Medium	High
Expected Net Returns	$1,026,817	$1,014,352	$986,026	$920,103
Percent Optimal				
Low Overlap	100.11	100.11	100.12	100.13
Medium Overlap	101.26	101.27	101.19	101.42
High Overlap	102.15	102.17	102.01	102.44
C.V. (%)	17.70	15.56	13.70	10.98
Minimum Net Returns	$665,410	$673,283	$687,096	$707,952
Maximum Net Returns	$1,370,971	$1,347,519	$1,282,639	$1,143,249

Table 3.5. Optimal production practices and corresponding land area for low overlap with the self-propelled sprayer without automatic section control for various risk scenarios.

Section 1. Corn Management Practices					Risk Aversion Levels			
Planting Date	Maturity Group	Plant Pop	Nitrogen Rate		Neutral	Low	Medium	High
March 25	2600	28000	150		0	0	333	485
March 25	2650	28000	150		0	362	0	0
March 25	2650	32000	150		362	0	0	0
March 25	2700	24000	100		0	0	0	148
March 25	2700	24000	150		0	0	413	0
March 25	2700	28000	175		0	293	0	0
March 25	2700	32000	175		722	272	0	0
April 1	2700	24000	100		0	0	0	183
April 1	2700	28000	100		0	0	0	30
April 1	2700	28000	150		0	0	142	0
April 1	2700	32000	150		0	157	65	0
April 8	2600	24000	100		0	0	0	238
April 8	2700	28000	150		0	0	103	0
April 15	2700	28000	225		216	0	0	0
April 22	2650	28000	150		0	216	244	216
				Yields[1]	163	159	153	147

Section 2. Soybean Management Practices[2]			Risk Aversion Levels			
Planting Date	Maturity Group		Neutral	Low	Medium	High
April 22	MG3		0	0	731	0
April 22	MG4		1290	0	0	0
April 29	MG2		0	0	0	804
April 29	MG3		0	0	0	91
April 29	MG4		10	616	0	0
May 6	MG4		0	684	50	0
May 13	MG4		0	0	519	0
June 17	MG4		0	0	0	405
		Yields	62	62	61	57

[1]Yields for both corn and soybeans are in bushels per acre.
[2]110,000 plants per acre and 15 inch row spacing where determined optimal production practices for all risk scenarios.

Table 3.6. Optimal production practices and corresponding land area for medium overlap with the self-propelled sprayer without automatic section control for various risk scenarios.

Section 1. Corn Management Practices					Risk Aversion Levels			
Planting Date	Maturity Group	Plant Pop	Nitrogen Rate		Neutral	Low	Medium	High
March 25	2600	28000	150		0	0	340	482
March 25	2650	28000	150		0	362	0	0
March 25	2650	32000	150		362	0	0	0
March 25	2700	24000	100		0	0	0	147
March 25	2700	24000	150		0	0	423	0
March 25	2700	28000	175		0	294	0	0
March 25	2700	32000	175		722	272	0	0
April 1	2700	24000	100		0	0	0	184
April 1	2700	28000	100		0	0	0	29
April 1	2700	28000	150		0	0	97	0
April 1	2700	32000	150		0	156	102	0
April 8	2600	24000	100		0	0	0	242
April 8	2700	28000	150		0	0	100	0
April 15	2700	28000	225		216	0	0	0
April 22	2650	28000	150		0	216	238	216
				Yields[1]	163	159	153	147

Section 2. Soybean Management Practices[2]			Risk Aversion Levels			
Planting Date	Maturity Group		Neutral	Low	Medium	High
April 22	MG3		0	0	724	0
April 22	MG4		1241	0	0	0
April 29	MG2		0	0	0	804
April 29	MG3		0	0	0	85
April 29	MG4		59	608	0	0
May 6	MG4		0	692	230	0
May 13	MG4		0	0	346	0
June 17	MG4		0	0	0	411
		Yields	62	62	61	57

[1]Yields for both corn and soybeans are in bushels per acre.
[2]110,000 plants per acre and 15 inch row spacing where determined optimal production practices for all risk scenarios.

Table 3.7. Optimal production practices and corresponding land area for high overlap with the self-propelled sprayer without automatic section control for various risk scenarios.

Section 1. Corn Management Practices					Risk Aversion Levels			
Planting Date	Maturity Group	Plant Pop	Nitrogen Rate		Neutral	Low	Medium	High
March 25	2600	28000	150		0	0	349	479
March 25	2650	28000	150		0	362	0	0
March 25	2650	32000	150		362	0	0	0
March 25	2700	24000	100		0	0	0	147
March 25	2700	24000	150		0	0	434	0
March 25	2700	28000	175		0	295	0	0
March 25	2700	32000	175		722	272	0	0
April 1	2700	24000	100		0	0	0	184
April 1	2700	28000	100		0	0	0	30
April 1	2700	28000	150		0	0	51	0
April 1	2700	32000	150		0	155	139	0
April 8	2600	24000	100		0	0	0	245
April 8	2700	28000	150		0	0	98	0
April 15	2700	28000	225		216	0	0	0
April 22	2650	28000	150		0	216	228	216
				Yields[1]	163	159	153	147
Section 2. Soybean Management Practices[2]					Risk Aversion Levels			
Planting Date	Maturity Group				Neutral	Low	Medium	High
April 22	MG3				0	0	719	0
April 22	MG4				1192	0	0	0
April 29	MG2				0	0	0	804
April 29	MG3				0	0	0	79
April 29	MG4				108	600	0	0
May 6	MG4				0	700	402	0
May 13	MG4				0	0	170	0
June 10	MG4				0	0	9	0
June 17	MG4				0	0	0	417
				Yields	62	62	61	57

[1]Yields for both corn and soybeans are in bushels per acre.
[2]110,000 plants per acre and 15 inch row spacing where determined optimal production practices for all risk scenarios.

Table 3.8. Optimal production practices and corresponding land area when utilizing automatic section control with lightbar for various risk scenarios.

Section 1. Corn Management Practices					Risk Aversion Levels			
Planting Date	Maturity Group	Plant Pop	Nitrogen Rate		Neutral	Low	Medium	High
March 25	2600	28000	150		0	0	333	485
March 25	2650	28000	150		0	362	0	0
March 25	2650	32000	150		362	0	0	0
March 25	2700	24000	100		0	0	0	148
March 25	2700	24000	150		0	0	413	0
March 25	2700	28000	175		0	293	0	0
March 25	2700	32000	175		722	272	0	0
April 1	2700	24000	100		0	0	0	183
April 1	2700	28000	100		0	0	0	30
April 1	2700	28000	150		0	0	142	0
April 1	2700	32000	150		0	157	65	0
April 8	2600	24000	100		0	0	0	238
April 8	2700	28000	150		0	0	103	0
April 15	2700	28000	225		216	0	0	0
April 22	2650	28000	150		0	216	244	216
				Yields[1]	163	159	153	147

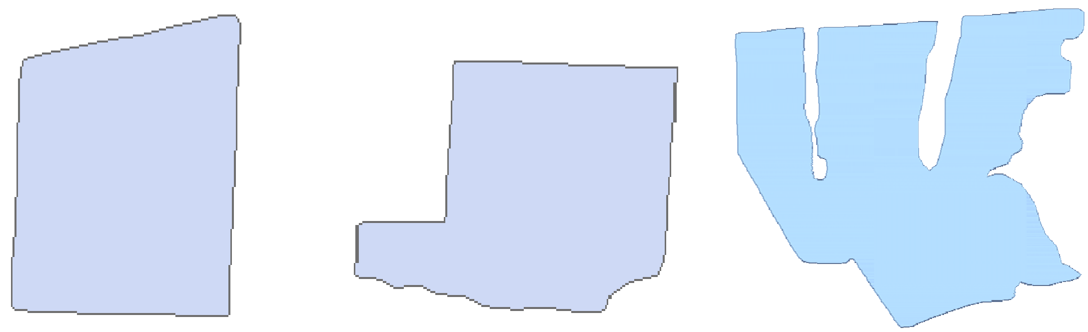
Section 2. Soybean Management Practices[2]			Risk Aversion Levels			
Planting Date	Maturity Group		Neutral	Low	Medium	High
April 22	MG3		0	0	731	0
April 22	MG4		1290	0	0	0
April 29	MG2		0	0	0	804
April 29	MG3		0	0	0	91
April 29	MG4		10	616	0	0
May 6	MG4		0	684	50	0
May 13	MG4		0	0	519	0
June 17	MG4		0	0	0	405
		Yields	62	62	60	57

[1]Yields for both corn and soybeans are in bushels per acre.
[2]110,000 plants per acre and 15 inch row spacing where determined optimal production practices for all risk scenarios.

Table 3.9. The percentage increase in net returns above the base overlap scenarios due to the adoption of automatic section control with and without lightbar as herbicide prices fluctuate.

	Overlap w/o Lightbar[1]			Overlap with Lightbar		
% Change in Price	Low	Medium	High	Low	Medium	High
20%	0.24	1.54	2.58	0.19	1.56	2.63
10%	0.20	1.39	2.33	0.15	1.40	2.39
0%	0.16	1.24	2.10	0.11	1.26	2.15
-10%	0.12	1.10	1.87	0.08	1.11	1.92
-20%	0.08	0.95	1.64	0.04	0.96	1.69

[1] Low, Medium, and High overlap corresponds to 5%, 16.5%, and 25% respectively for a 90 ft. self-propelled agricultural sprayer.



Low Overlap = 5% Medium Overlap = 16.5% High Overlap = 25.5%

Figure 3.1. Three different field shapes representing the base overlap scenarios used to investigate the economic potential of automatic section control.
Source: Stombaugh et al. (2009)

CHAPTER FOUR

DEVELOPMENT OF AN ECONOMIC OPTIMIZATION MODEL TO GUIDE THE ADVANCEMENT OF AUTONOMOUS MACHINERY BY IDENTIFYING DOMINATE EQUIPMENT CHARACTERISTICS

Over the years, there has been a trend in agricultural machinery where equipment size has increased to meet farmer demands. One of the primary reasons farmers' desire larger equipment is to benefit from economies of size. Specifically, farmers can become more financially competitive by substituting capital for labor, thereby reducing average labor requirements. Additionally, larger equipment can mitigate the risks associated with untimely operations due to unfavorable weather conditions. Other factors such as the need to compensate for a declining agricultural workforce or a producer's desire for more leisure time are also possible explanations for acquiring larger machines. However, as the size of agricultural machines continues to increase, consequences that are detrimental to both the operator and environment will arise. For the operator, controlling large implements on irregular soils and navigating narrow country roads becomes problematic. Furthermore, environmental degradation from soil compaction which reduces productivity is only magnified with larger machines. Moreover, larger equipment can lead to excess chemical application on undesired areas due to operator errors and increases in overlaps. The opportunity exists to reverse this trend in agriculture by introducing autonomous machinery to production systems.

The replacement of large manned machines with small autonomous robots will be a paradigm shift in agricultural production to a small scale precision farming approach. Introduction of small, light-weight robots that can perform agricultural tasks autonomously may prove to be a realistic option for farmers in the future. These robots will likely operate in fleets and utilize intelligent controls to cooperate with each other to perform tasks such as scouting for weeds and diseases, yield and field mapping, and plant specific operations like sowing and fertilizing. Numerous benefits potentially exist from utilizing autonomous machines. It is possible that autonomous machines can sense and manipulate the crop and its environment in a site-specific manner with the potential of increasing the efficiency, effectiveness, and quality of crop production. They can potentially have the ability to work in fleets 24 hours per day, year around, and be virtually weather independent. Due to their inherent weight advantage over conventional machines, a reduction in soil compaction is possible. Coupled with the ability to potentially reduce chemical application and lower current energy consumption, the environmental impacts of agricultural production can potentially diminish. It is expected that autonomous machinery will have a smaller initial investment and lower labor costs than conventional systems.

Recently, engineers have developed various autonomous machines capable of agricultural production. Several studies have investigated the mechanization and the design of autonomous robots (Blackmore, et al., 2004; Blackmore and Blackmore, 2007; Vaugioukas, 2007; Vaugioukas, 2009). The majority of studies have focused on the advancement of autonomous platforms with regard to accuracy, steering, and performance (van Henten 2009; Marchant 1997; and Bak 2004). These platforms have the potential to attach various implements such as cultivators, seeders, and sprayers, for agricultural operations. Other studies have concentrated on autonomous weed detection and management (Griepentrog, et al., 2009; Gottschalk et al., 2009; Astrand and Baerveldt, 2002; Penderson, et al., 2006; Penderson, et al., 2007). Rackelshausen, et al. (2009) investigated an autonomous robot prototype that had the ability to perform individual plant phenotyping by detecting plant parameters such as crop density, plant height, stem thickness, biomass, and growth that could benefit plant breeders and farmers when developing agricultural field trials.

Economists have begun investigating the potential benefits of autonomous vehicles for agricultural operations. Goense (2005) analyzed an autonomous row crop cultivator to determine the effect of the size of autonomous implements on mechanization costs. Pederson, et al. (2006) compared the costs and potential benefits of an autonomous machine that was capable of field scouting cereal crops. Partial budgeting was used to determine that autonomous field scouting reduced the costs by 20%, but profitability was susceptible to initial investments and the annual costs for the GPS system. In 2007, Pederson, et al. conducted another investigation into autonomous weeding and grass cutting. Partial budgeting was used to compare the cost changes to conventional practices and determined that the utilization of autonomous machinery could be possible if adequate safety controls and regulatory systems were imposed at reasonable costs. Due to its infancy and lack of economic investigations, numerous research opportunities exist that could provide valuable insight into the advancement of autonomous machinery.

The opportunity rarely presents itself in which economics can influence the development of a technology. Specifically, economic evaluation can provide engineers with valuable information regarding the equipment characteristics required for autonomous machinery to be profitable. Additionally, economics can determine the most influential autonomous machine in a whole farm setting. Furthermore, advanced agricultural machinery, such as autonomous vehicles, are often perceived as only viable when operating on larger farms and/or high value crops. Therefore, providing insights into whether autonomous machinery can flourish on a grain farm operation can also be accomplished through economic studies.

The introduction of autonomous machines can have complex consequences to the farm by affecting not only machinery management but also related issues such as labor and cropping practices. To provide such information, a multi-faceted machinery management model is required. The model must consider the entire farming system and allow for changes in cropping patterns and labor requirements. Therefore, this investigation aims to address the above issues through the following objectives: (1) develop a mixed integer programming model which portrays a typical Western Kentucky grain farm, (2) determine the optimal conventional machines necessary to perform agricultural tasks common for a Western Kentucky grain producer, (3) determine the optimal number of autonomous machines and implements necessary to perform the same agricultural tasks in which profits exceed the use of conventional machinery, (4) determine the appropriate autonomous machinery specifications as well as benefits necessary for autonomous machines to be more profitable than the conventional machinery, and (5) analyze the impact farm size has on objectives 2-4.

Analytical Procedure

The analytical framework of this study consists of the underlying production environment as well as the development of the economic model. This is presented in detail in the following sections.

The Production Environment

To properly assess a Kentucky grain farmers' optimal machinery selection decision, whether conventional or autonomous, the underlying production environment must first be established. This investigation was modeled after a typical western Kentucky corn and soybean producer who operated under no-till farming conditions for various farm sizes. Specific machinery operations occurred during the production of corn and soybeans. For corn production, the following machinery operations must be completed: burn down treatment, planting, pre-emergence application of herbicide, post-emergence application of herbicide, and a nitrogen application. Soybean production required: burn down treatment, planting, post-emergence herbicide application, and an insecticide treatment. These production scenarios were consistent with University of Kentucky Cooperative Extension Service Recommendations (2008). In addition, The University of Kentucky Cooperative Extension Service Recommendations (2008) provided various input application rates and the time for performing each specific operation. These recommendations provided the basis for determining the appropriate levels to employ within the model. Other production operations, such as the application of phosphorous, potassium, and lime, as well as harvest were required and assumed to be custom hired at costs determined from Halich's (2008) Cooperative Extension Report.

To complete the above production activities, appropriate machinery was required. Due to the infancy of autonomous machinery and the lack of appropriate data for comparison, options other than purchasing the equipment (short-term rental, leasing, and custom hiring) were excluded for this study. Therefore, a conventional machinery complement required the purchase of a tractor, planter, sprayer, and fertilizer applicator. The planter, sprayer, and fertilizer applicator were assumed implements, hence attached to the tractor. The conventional machinery choice set assumed for a Kentucky grain producer was listed in Table 4.1. The machinery choice set was developed to represent the breadth of options facing a Kentucky grain producer. All data for conventional machinery was compiled from the Mississippi State Budget Generator (Laughlin and Spurlock, 2007), which complied with ASABE Standards. Specifically, operating costs (fuel, repair and maintenance, and labor), annual costs of ownership, and the performance rates of the implements differentiated each piece of equipment and were utilized in the machinery selection decision.

Data required for modeling a machinery selection decision in which autonomous machines performed the agricultural operation is difficult since they are still in the developmental stage. On the other hand, this poses an opportunity to provide engineers with valuable information regarding the specifications and benefits of an autonomous system that can potentially be favored over conventional machinery for a Kentucky grain producer. For this investigation, it was assumed that small, lightweight autonomous vehicles would perform agricultural tasks. In addition, the implements would be interchangeable on a platform; therefore, one platform could potentially perform multiple tasks throughout the growing season.[19] Various autonomous specifications and benefits were determined based on literature pertaining to autonomous prototypes and presented in Table 4.2 (e.g. Pedersen, et al., 2006; Blackmore, et al., 2004; Rackelshausen, et al., 2009; van Henten, et al., 2009).

Economic and engineering specifications were included which consisted of the purchase price and performance rates of the platform and implements, as well as operating hours per day. The purchase prices of the platform and implements were determined from the study conducted by Pedersen, et al. (2006). An autonomous micro-sprayer was developed for weed control on sugar beets. The platform's capital outlay was roughly $53,000 with an additional $40,000 for a four row micro-sprayer. A majority of the implement purchase price would come from the electrical components, which would be common to all three implements investigated. Thus, all three implement purchase prices were varied over the same range. The purchase prices of both platform and implement were annualized to include depreciation and the opportunity cost of capital invested. Depreciation was calculated using the straight-line method with an assumed 3 year useful life and salvage value of 50% of the purchase price for both

[19] For this investigation, a platform was defined as a device with locomotion and controls as well as a system for guiding the device.

platform and implement.[20] The opportunity cost of capital investment was calculated using an 8% interest rate.

Engineering specifications were also necessary for this analysis and included the performance rates of the implements as well as the machine operating hours per day. Various factors were taken into consideration when determining the performance rates of the implements. Since it was assumed that small, lightweight autonomous vehicles were utilized, the power supply of these vehicles would range from 10-30 hp (Blackmore, et al., 2004). Hence, implement width would be 2-4 rows with speeds ranging from 1-5 miles per hour (Rackelshausen, et al., 2009; van Henten, et al., 2009). As a result, performance rates for each implement varied from one to three acres per hour. In addition, early studies suggested operating 24 hours per day would be feasible with autonomous machinery. On the other hand, additional time would be required to carry out tasks such as traveling from field to field and performing repairs, which would limit actual field operating time. Therefore, 21-23 hours per day were chosen for this study.

Several potential benefits could occur with the utilization of autonomous vehicles, but for this study the quantitative benefits were limited to input cost and compaction reduction. The reduction in input cost was considered one of the primary benefits of utilizing autonomous machinery. Previous studies have reported up to a 90% reduction in herbicide cost alone for an autonomous micro-sprayer (Pedersen, et al., 2007). Other inputs such as fertilizer and seed were not expected to experience such a dramatic reduction in costs[21]. Therefore, the possible percent reductions of each input were weighted by their respective portion of total input costs to provide a range of 10% to 30% reduction in total input costs. In addition, large, heavy farm machinery used today damages the soil structure resulting in a reduction in yields. The University of Minnesota Extension (2001) services reported a reduction in corn yield of 7.5% due to soil

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[20] The annual costs for owning a autonomous machinery was calculated as follows using the straight-line depreciation method: [((Total Investment – Salvage Value)/(Useful Life)) + ((Total Investment + Salvage Value)*Interest Rate)/2].

[21] The range for reduced input costs were formed from pertinent literature and conversations with professionals. For the high end of the range estimated herein, herbicide costs decreased by 90% and fertilizer and seed costs decreased by 50%. On the low end of the range estimated herein, herbicide costs decreased by 50% and fertilizer and seed costs decreased by 10%. Using the weights of 15%, 40%, and 45% for herbicide, seed, and fertilizer costs, respectively, the range for total input cost reduction was formed.

compaction. Due to the lightweight configuration of the autonomous vehicles, soil compaction should be reduced resulting in increased yield potential. Therefore, possible yield increases of 2.5 and 7.5 percent were modeled for this study. In addition, operating labor typical with conventional machinery was removed from the autonomous investigation. There was anticipated incidental labor costs associated with refilling seed, chemical, and fertilizer, as well as transporting the machines to different locations, but not addressed in this study. In addition, there was an anticipated opportunity cost associated with the implementation of a new paradigm machinery operation, which was not included in this investigation. The overall machinery selection model was consistent with both options of machines, with the above technical data differentiating the two analyses.

The Economic Model

One of the main objectives of this study was to develop a multi-faceted machinery management model to compare operating with conventional and autonomous machinery for a typical Kentucky row crop operation. To accomplish this, a mixed integer mathematical programming formulation was developed that incorporated three optimization models: machinery selection, resource allocation, and sequencing. The machinery selection model was the foundation for the development of the mixed integer programming model. Machinery selection was first published by Wiengartner (1963) as an integer programming model. Numerous researchers within the agricultural sector have utilized machinery selection models to gain insight into purchasing farming equipment (e.g. Camarena, et al., 2004; Sogaard and Sorensen, 2004; Danok, et al. 1980). Even though these studies provided information on agricultural machinery investment, none had the necessary complexity to address no-till grain production in Kentucky or to model autonomous machinery. Audsley (1981) developed a linear programming model to evaluate new machines applicable to arable farms and estimated whether farmers would purchase the hypothetical machines. The overall goal of Audsley's study parallels the goal of this study, but model formulation and application separated both investigations.

In addition to machinery selection, resource allocation and sequencing models were incorporated within the mixed integer programming formulation. The resource allocation model has been widely used in agriculture when products compete for scarce resources such as land, labor, and capital. Also in agriculture, crops are produced through a process involving multiple stages, especially grain crop production (e.g. spraying, planting, fertilizing, and harvesting). Each process is not only competing for resources, but typically involves a sequence in which one process must be completed before the next begins. In this study, sequencing within a variable was incorporated into the model to establish the grain crop production process of a typical Kentucky farmer. More details of all three of the above models were presented in McCarl and Spreen (2004). Combining elements from these three models provided a unique and complex model that was capable of joint selection including machinery and crop planning. The focus of this study was solely on machinery selection which could provide valuable information to engineers and researchers with regard to autonomous machinery specification and operation.

The developed mixed integer programming model contained elements of three different optimization models. The model provided insight into the optimal number and size of machines required to perform specific agricultural tasks. In addition, the model had the ability to select the optimal production practices of corn and soybeans with their respective acreage allotment. The underlying machinery selection model consisted of the objective function and various constraints.

(1) Max $\overline{\mathrm{NR}}$

Subject to:

(2) $\sum_{YR} \frac{1}{N} NR_{YR} - \overline{NR} = 0$

(3) $\sum_{C} P_C \, SALES_{C,YR} - \sum_E \sum_P \sum_M \sum_A \sum_{WK} MC_M ACT_{E,P,M,A,WK} - \sum_M AC_M * MACH_M - \sum_E \sum_V \sum_P \sum_S VC_E PROD_{E,V,P,S} - NR_{YR} = 0 \qquad \forall YR$

(4) $\sum_E \sum_V \sum_P \sum_S EXPYLD_{C,E,V,P,S,YR} PROD_{E,V,P,S} - SALES_{C,YR} = 0 \qquad \forall C, YR$

(5) $\sum_E \sum_P \sum_M \sum_A \sum_{WK} ACT_{E,P,M,A,WK} - \sum_M BIGM * MACH_M \leq 0$

Equation 1 represented the objective function of the model which was to maximize average net return ($\overline{NR}$). Equations 2-4 represented constraints related to the machinery selection portion of the mixed integer programming model. Equation 2 was the expected net returns balance which defined the average net returns as the sum of net returns (NR) estimated each year (YR) divided by the number of years considered (N). Equation 3 was the net returns balance by year. Each year, net returns equaled the total sales of crops produced which included the price of crop C (P_C) multiplied by the amount of crop sold each year ($SALES_{C,YR}$). Total costs were then subtracted from the sales which included: machinery operating costs per acre for each machine M[22] (MC_M) to performing the various production processes ($ACT_{E,P,M,A,WK}$) for activity A, on enterprise E, planted on P with machine M on week WK. The annual cost of owning the machines (AC_M), and all other variable costs (VC_E) in producing ($PROD_{E,V,P,S}$) enterprise E with variety V, on planting date P on soil type S were also subtracted from the total sales. A sales balance equation by crop and year was required so that total sales did not exceed the amount produced, resulting in equation 3. Since the model had the ability for selecting optimal cropping practices, yields were defined by the yield in bushels per acre ($EXPYLD_{C,E,V,P,S,YR}$). Specifically, the yields were estimated using the Decision Support System for Agrotechnology Transfer (DSSAT), a biophysical simulation model (Hoogenboom, 2004). Validations were performed and the simulated yields were thought representative of a Western Kentucky grain producer. For this investigation, a subset of the yield data from the Shockley, et al. (2009) study was employed[23]. Equation 5 was the constraint in which machine M must be purchased ($MACH_M$) before performing the various production processes ($ACT_{E,P,M,A,WK}$). The variable $MACH_M$ represented the integer aspect of this model. In addition, the Big M method, a mathematical programming technique, was utilized to guarantee the correct machine was purchased to perform the specific activities.

The mixed integer programming model was also constrained by limitations associated with resource allocation.

(6) $\sum_E \sum_V \sum_S \sum_S ROTATE_{G,E}\, PROD_{E,V,P,S}\, \frac{1}{2} * ACRE \qquad \forall G$

[22] The machines defined within this model were in two categories, conventional and autonomous. The conventional machinery included a tractor with the implements: sprayer, fertilizer, and planter. The autonomous machinery consisted of a platform, which operates like a tractor in the conventional setting. Additionally, the autonomous implements included: sprayer, fertilizer, and planter. The implements operating autonomously were not the same as the implements operating under the conventional setting.
[23] For both corn and soybeans, five planting dates, three maturity groups, one row spacing, one plant population and one nitrogen rate were used. Therefore, this investigation had the ability to choose the optimal planting date and maturity group combination that maximized net returns.

(7) $SOILRATIO_{S_i}PROD_{E,V,P,S_j} - SOILRATIO_{S_j}PROD_{E,V,P,S_i} =$

$0 \qquad \forall S_{i,j,i\neq j}, E, V, P$

(8) $\sum_E \sum_P \sum_{M_I} \sum_A PR_{M_I} ACT_{E,P,M,A,WK} - FLDDAY_{WK} MACH_{M_T} \leq 0 \qquad \forall WK, M_T$

(9) $\sum_E \sum_P \sum_{M_T} \sum_A PR_{M_I} ACT_{E,P,M,A,WK} - FLDDAY_{WK} MACH_{M_I} \leq 0 \qquad \forall WK, M_I$

Equation 6 represented the typical land constraint for which the cropland produced ($PROD_{E,V,P,S}$) for enterprise E with variety V, on planting date P on soil type S should not exceed the total amount of available cropland acres assumed for the study (ACRE). Also, there existed a rotation component that was common of a Kentucky grain farmer, in which 50% of the land area was designated to soybeans and the other 50% to corn. To employ the rotational component within the model, a rotation categorization matrix $ROTATE_{G,E}$ by enterprise E was utilized to include corn if G=1 and soybeans if G=2. In addition, various soil types (S_i) were incorporated into the production data for which a soil balance constraint was required. Equation 7 ensured that the optimal production practices chosen were consistently proportioned across all soil types S ($SOILRATIO_S$). It also guaranteed that variable rate by soil type did not occur. Furthermore, equation 8 and 9 represented the available machinery operating time, which was limited to the number of suitable field days each week[24] ($FLDDAY_{WK}$). The total amount of time to complete various production activities were calculated based on the performance rate of the machine (PR_M) and the total acres of each activity to be completed ($ACT_{E,P,M,A,WK}$). Both tractor and/or platform (M_T) and the implements (M_I) in question must be purchased ($MACH_M$) to have the suitable field days available. Therefore, the total amount of time to complete each activity must be less than the available suitable field hours.

Finally, the sequential aspect of the mixed integer programming model was incorporated.

(10) $\sum_E \sum_V \sum_S PROD_{E,V,P,S} - \sum_E \sum_M \sum_A \sum_{WK} ALLOW_{E,P,A,WK} \; ACT_{E,P,M,A,WK} < 0 \qquad \forall P$

When determining the sequence of events, a reference point was designated. For this model, all activities were performed either before or after planting (P) a specific crop.

[24] Suitable field days were calculated based on the 30 years of historical climatological data and estimated based on the probability of it not raining 0.15 inches or more per day over a period of a month. Each week in a month had the same number of suitable field days.

The optimal number of acres chosen to be planted on week S ($PROD_{E,V,P,S}$) corresponded to the acres ($ACT_{E,P,M,A,WK}$) of various activities (A), for enterprise E, planted on P with machine M on week WK. Each activity (A), for enterprise E, planted on P, was assigned particular week(s) (WK) in which the activities could be performed based on the matrix $ALLOW_{E,P,A,WK}$. This equation guaranteed that all production activities were completed in the correct sequence, as well as in the appropriate week typically performed by Kentucky grain farmers. Equations 1-10 made-up the developed mixed integer mathematical programming formulation that was employed for evaluating conventional versus autonomous machinery.

Results and Discussion

The use of both conventional and autonomous machinery for grain crop production in Kentucky was analyzed. First, the optimal conventional machines were determined for various farm sizes. Then, the combination of the profit maximizing number of autonomous machines and their economically superior set of machinery specifications and benefits were determined such that the expected net returns were greater than operating conventional machinery on the same acreage allotment.

The optimal conventional machinery chosen for various acreage levels were ascertained, which also included their expected net returns and machinery costs from production (Table 4.3). It was determined that the same combination of tractor size and certain implements were optimal up to 2000 acres. Specifically, a tractor with 150-hp was optimal for operating a 60-ft sprayer and an 8 row planter. A 10 row fertilizer applicator was optimal for 500 acres but as the acreage level increased, a 12 row fertilizer applicator was required. To plant 3000 acres, a larger planter was required, hence the increased tractor size. The above results indicated the optimal machinery set for completing the agricultural tasks given the assumptions of this investigation. Ultimately, the estimated suitable field days were the most influential factor with regards to optimal machinery selection. In reality, most farmers have some degree of risk aversion towards expected suitable field days, which would lead to investing in larger equipment than indicated. However, suitable field day risk was beyond the scope of this study. The main purpose of analyzing conventional machinery was to collect the maximum net returns and compare those to various scenarios with autonomous machinery.

General information with regard to the autonomous analyses and the optimal number of machines required to perform the necessary agricultural tasks were also presented in Table 4.3.[25] For each acreage level analyzed, an individual investigation was conducted for every combination of specifications and benefits in this study to determine their respective net returns. As a result, 20,250[26] autonomous investigations were conducted for each acreage level. The estimated net returns for every scenario were then compared to those for conventional machinery. If the net returns of autonomous machinery were greater than conventional, the specifications and benefits were recorded. When averaged across all acreage levels examined, results indicated that 0.9% (188) of the autonomous investigations were economically superior than operating with conventional machinery. The largest number of observations in which autonomous machinery was preferred occurred under the lowest acreage level examined. Additionally, the lowest acreage level provided the second largest potential increase in net returns over operating conventional machinery. Contrary to popular belief, this indicated that advanced agricultural machinery could potentially flourish even when operating on small grain farms. Unlike many new technologies, these results provided evidence of the economic potential for autonomous machinery for farms less than 1000 acres in size. This result was directly attributed to the reduced opportunity for improvement afforded to larger farms because of economies of size. Specifically, new opportunities were afforded to small farms through autonomous machinery, while larger farms had already captured economies of size benefits under optimal conventional machinery. In addition, farm machinery was considered an asset that cannot be acquired in small increments but must be obtained in large, discrete units. Therefore, smaller farms had more opportunities to exploit the cost reducing potential enabled by autonomous machinery. Moreover, a farm size of 1000 acres experienced the largest possible increase in net returns of 10.6% over operating with conventional machinery.

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[25] In addition to the optimal number of autonomous machines required, their frequency of occurrence based on the total number of observations preferred to conventional machinery were also presented in Table 4.3.
[26] These experiments were conducted for every combination of specifications and benefits, which included: three platform purchase prices, 3 implement purchase prices, five performance rates, three operating times, three input cost reductions, and two increases in yield.

To experience such increases in expected net returns, a wide range of autonomous machines were required.

The optimal number of autonomous machines necessary to perform the agricultural tasks and had greater net returns than conventional machinery was also determined. As the acreage levels increased, more platforms and implements were required to produce corn and soybeans. The optimal number of autonomous machines varied from only needing one of each for 500 acres, to five platforms and as many as three sprayers and three planters for 3000 acres. However, operating with only one of each implement, the autonomous system could still manage to complete every agricultural task required for up to 2000 acres given certain characteristics. The optimal number of machines were determined exclusively by both the specifications and benefits evaluated in this study.

Values for the specifications and benefits of autonomous machinery were varied to determine which would provide net returns greater than conventional machinery. Four specifications were the focus of this investigation: platform purchase price, implement purchase price, implement performance rate, and suitable field hours of operation per day. If a particular specification was observed in which autonomous machinery provided greater net returns than conventional machinery, it was recorded. The frequency of a particular specification being observed was then determined. These frequencies were then presented as a percentage of the total number of observations in which autonomous machinery was favored (Table 4.4). Of the specifications examined, the purchase price of the platform had a relatively minor influence on determining whether autonomous machinery could be more profitable than conventional machinery. For each platform price investigated, autonomous was favored in at least one investigation. However, of the three purchase prices investigated, the lowest purchase price of $40,000 was most often preferred.

Similarly, low implement purchase price was important. Compared to the average platform cost per acre, the implement cost per acre was larger. This was attributed to the potential to utilize one platform for all production operations, therefore accruing a lower cost per acre. Without a smaller implement investment, few scenarios occurred where the net returns were greater in the autonomous setting. For all investigations and acreage levels analyzed, observations favored autonomous machinery when the implement purchase price was less than $40,000. One way a higher initial investment could be optimal would be providing the implements with a longer useful life.[27] The useful lives of the implements were not investigated but increasing the life would reduce annual costs, therefore providing a better chance that higher initial investments could be preferred.

When considering the performance rates of the implements, the sprayer was the most crucial machine in a whole farm setting, especially as acreage levels increased. This was due to the number of trips across the field required for the sprayer compared to the other implements (i.e. three trips for corn and soybeans compared to one trip for both planting and fertilizing). Under no acreage level was a performance rate less than two acres per hour for the sprayer economically superior to conventional machinery. Conversely, the planter and fertilizer applicator could operate at lower performance rates only if the sprayer was operating at the highest specified performance rate investigated. This was attributed to the ability of the model to choose multiple planting dates instead of investing in additional machinery to complete planting. By choosing multiple planting dates, sprayer activities often occurred during the same weeks as planting and fertilizing. If the performance rate of the sprayer was high, more hours would be available during weeks in which multiple activities were conducted. Therefore, the other implement performance rates could be more flexible since more hours were available for accomplishing the required tasks. For the planter, operating below two acres per hour rarely occurred as an observation in which autonomous was favored. In addition, the fertilizer applicator was the only implement able to operate at the lowest performance rate evaluated because of its exclusive operation on corn acres.

Suitable field hours of operation per day were the last of the specifications analyzed. The available field hours evaluated for this study did not have a considerable impact on determining whether autonomous machinery could be more profitable than conventional machinery. For example, every combination of specifications and benefits that was economically superior to conventional machinery for 21 suitable field hours was

[27] Due to the technical components that would be involved for each implement, a useful life of 3 years (similar to a computer) was employed in this investigation.

economically superior for both 22 and 23 hours for 500 acres. On the other hand, as acreage levels increased, suitable field hours did become more pertinent.

The benefits that could occur from utilizing autonomous machinery were also influential characteristics in determining the economic viability of autonomous machinery. In particular, input cost reductions and yield increases due to reduced compaction were investigated (Table 4.5). An overwhelming frequency of 76%-87% of the observations, depending on farm size, required an input savings of 30%. If an input savings of 30% was achieved, there would be more flexibility when it came to the machinery specifications. Since input costs were reduced, additional machines could be purchased, therefore a lower performance rate was permissible. Also, a reduction of only 10% in input costs rarely occurred as an optimal choice. Most importantly, a yield increase of 7.5% should occur for autonomous to be favored. For all acreage levels analyzed, an observation that included only a 2.5% increase in yields rarely resulted in net returns greater than conventional machinery.

Conclusions

A mixed integer programming formulation that integrates three optimization models is developed to compare conventional and autonomous machinery for various acreage levels. Specifically, a machinery selection model provides the foundation for the formulation while both resource allocation and sequencing models are embedded within. The multifaceted economic model is utilized to conduct numerous investigations to address issues that can aid in the advancement of autonomous machinery.

The optimal conventional machinery and the expected net returns are determined to compare with autonomous machinery. Results indicate that the same combination of tractor size and implements, besides the fertilizer applicator, are optimal for up to 2000 acres. To compare to each acreage level in this study, an individual investigation is conducted for every combination of specification and benefit to determine their respective net returns. The largest number of observations in which autonomous machinery is preferred occurs under the lowest acreage level. In addition, acreage levels under 1000 acres exhibit the greatest potential to increase profits. Therefore, this study concludes that advanced agricultural machinery can potentially flourish when operating on smaller grain farms.

Results also indicate that several key factors shall exist if autonomous machinery becomes commercially viable. First, a smaller implement investment is required for autonomous to be favored over conventional machinery. Additionally, the sprayer is the most important of all the implements due to the operating time required for grain production. As long as the sprayer is operating at a high performance rate, the other implement performance rates are more flexible. Ultimately, for autonomous machinery to economically dominate conventional machinery, an input savings of at least 20% is required. In fact, 30% input savings is required in most cases. Finally, yield increases in excess of 2.5% are required for autonomous to become commercially viable. These results provide valuable information to guide engineers in the development of autonomous machinery by identifying critical characteristics and isolating the most influential operating machine.

This study analyzes the most crucial specifications of autonomous machinery as well as their most likely benefits. Results of this study are understated since only a few benefits are incorporated within the model. Once additional benefits (e.g. energy savings and yield increases due to plant phenotyping) are quantified, or a refined range of current benefits are analyzed, a more thorough analysis can be conducted. Furthermore, future investigation into suitable field day risk will provide a more comprehensive examination into the potential for autonomous machinery in grain crop production.

Table 4.1. Conventional machinery choice set for a Kentucky grain producer.

Tractor[1]: 150hp, 200hp, 300hp, 400hp
Sprayer (Broadcast): 27’, 40’, 50’, 60’
No-Till Split-Row Planter[2]: 8R, 12R, 16R
Liquid Fertilizer Applicator[3]: 6R, 8R, 10R, 12R

[1]The 150 and 200 hp tractors were mechanical front wheel drive (MFWD) while the 300 and 400 hp tractors were four wheel drive (4WD).
[2]Due to the draft parameter necessary to pull various planters, certain tractor sizes were required. Specifically, the 150hp tractor could not pull the 12 row planter and neither the 150hp nor the 200hp tractor could pull the 16 row planter.
[3]The liquid fertilizer applicators were utilized only in corn production and were all for designed for 30 inch row spacing.

Table 4.2. Autonomous machinery specification and benefit ranges modeled.

Specifications
Platform Price ($): 40,000; 50,000; 60,000
Implement Price[1] ($): 30,000; 40,000; 50,000
Performance Rate (acres/hr): 1, 1.5, 2, 2.5, 3
Operating Time (hours/day: 21, 22, 23
Benefits
Input Cost Reduction (%): 10, 20, 30
Increase in Yields due to Reduced Compaction (%): 2.5, 7.5

[1]The implement prices listed above apply to each sprayer, planter, and fertilizer applicator.

Table 4.3. Optimal conventional and autonomous machinery results for various acreage levels required to perform the same agricultural tasks.

	Acres			
	500	1000	2000	3000
Conventional				
Expected Net Returns	$155,336	$333,774	$688,768	$1,039,892
Total Ownership Cost	$22,990	$23,177	$23,177	$28,487
Total Operating Cost	$5,530	$10,480	$20,960	$30,420
Optimal Machinery Complement:				
Tractor	150hp	150hp	150hp	200hp
Sprayer	60'	60'	60'	50'
Planter	8R	8R	8R	12R
Fertilizer	10R	12R	12R	12R
Autonomous				
Number of Economically Superior Cases[1]	305 (1.5%)	211 (1.0%)	105 (0.5%)	132 (0.7%)
Maximum Expected Net Returns[2]	$170,795 (10.0%)	$369,213 (10.6%)	$745,226 (8.2%)	$1,124,086 (8.1%)
Optimal Number of Machines:[3]				
Platform	1 - 100%	1 - 80% 2 - 20%	2 - 64% 3 - 36%	3 - 52% 4 - 48% 5 - ~1%
Sprayer	1 - 100%	1 - 100%	1 - 10% 2 - 90%	2 - 68% 3 - 32%
Planter	1 - 100%	1 - 100%	1 - 45% 2 - 55%	1 - 2% 2 - 87% 3 - 11%
Fertilizer	1 - 100%	1 - 100%	1 - 92% 2 - 8%	1 - 68% 2 - 32%

[1] The numbers in parentheses represented the percentage of the total number of investigations (20,250) that were economically superior to conventional machinery.
[2] The dollar amount represented the maximum net returns that occurred for the total number of investigations (20,250). The numbers in parentheses represented the percent increase in expected net returns compared to conventional machinery.
[3] The percentages represented the fraction of economically superior cases for which each number of machines occurred. Example: For 1000 acres, 80% of the 211 economically superior cases required 1 platform.

Table 4.4. The percentage of each autonomous specification that occurs in the total number of observations preferred to the conventional setting for various acreage levels and model specifications.

	Acres			
	500	1000	2000	3000
Platform Price ($/unit)				
$40,000	60	55	59	60
$50,000	29	29	28	30
$60,000	11	16	13	10
Implement Price ($/unit)				
$30,000	98	88	92	92
$40,000	2	12	8	8
$50,000	-	-	-	-
Suitable Field Hours (hr/day)				
21	33	25	30	27
22	33	35	29	32
23	33	40	42	41
Performance Rates (Ac/hr)				
Sprayer				
3.0	60	78	68	76
2.5	32	21	30	24
2.0	8	1	2	-
1.5	-	-	-	-
1.0	-	-	-	-
Planter				
3.0	40	57	63	50
2.5	31	30	25	33
2.0	21	9	9	14
1.5	8	4	3	3
1.0	-	-	-	-
Fertilizer				
3.0	30	37	43	42
2.5	27	29	30	30
2.0	21	22	17	19
1.5	16	8	9	9
1.0	6	4	1	-

Table 4.5. The percentage of each autonomous benefit that occurs in the total number of observations preferred to the conventional setting.

	Acres			
	500	1000	2000	3000
Input Reduction				
30%	80	76	87	87
20%	20	22	13	13
10%	-	2	-	-
Yield Increase				
2.5%	-	2	-	-
7.5%	100	98	100	100

CHAPTER FIVE

SUMMARY AND CONCLUSIONS

The three investigations that are presented herein complement one another while covering an assortment of specific objectives that address the overall goal of this dissertation. The overall objective of this dissertation is to investigate farm management concerns faced by Kentucky grain producers due to the addition, replacement, and selection of various precision agriculture technologies. The specific farm management elements for this dissertation include machinery management, production management, and risk management. The technologies that are evaluated in the three manuscripts include auto-steer navigation, automatic section control, and autonomous machinery. This research provides a wide array of economic insight and valuable information for researchers and developers to aid in the advancement of precision agriculture technologies.

The first manuscript in this dissertation investigates machinery, production, and risk management implications of the addition of sub-meter auto-steer and/or RTK auto-steer systems on specific farm machinery. The enhancement of a previous whole farm risk model is required to appropriately reflect the production system of a Kentucky grain producer as well as to evaluate auto-steer technology. Specifically, the model is adjusted to include additional production practices, harvest requirements, land types, and the benefits and costs associated with auto-steer. In addition, four farmer risk attitudes are considered for this analysis.

Machinery management issues are addressed by evaluating various economic aspects of auto-steer navigation. Results indicate that each auto-steer system increases net returns over the base case without any navigational aid on average by $4.05/acre, $7.36/acre, and $11.30/acre for sub-meter, RTK, and both auto-steer systems, respectively. The addition of both auto-steer systems proves to be the soundest economical investment. This is due to higher increases in net returns ($11.30/acre), a low payback period (1.18 years), and a high return on investment (74.93%). On the other hand, RTK auto-steer alone requires the most acres to break-even on the investment, the largest number of years to payback, and the lowest return on investment. In general, auto-steer requires less than 525 acres to breakeven, no more than 1.5 years for farms with 2600 acres to see a payback on the investment, and all returns on investment are greater than the opportunity cost of capital (8%). Therefore, all auto-steer scenarios investigated in this manuscript are a sound economical investment.

Production management issues are undertaken by incorporating alternative production practices, along with their representative simulated yields, within the whole farm model. This allows for the substitution of inputs due to the benefits that incur by adopting auto-steer navigation. This manuscript provides strong evidence that the adoption of auto-steer navigation alters optimal production practices. These changes in production practices can be found in all three auto-steer scenarios analyzed. For example, the addition of sub-meter auto-steer influences the production strategies of soybeans, but not corn. With the ability to spray more efficiently with sub-meter auto-steer, more suitable field hours are available during competing production operations. Furthermore, RTK auto-steer reduces overlap which results in an overall decrease in the total amount of fertilizer applied to the field and an increase in the application rate that the corn plant actually receives. In addition, the increase in efficiency results in a higher plant population, which also corresponds to greater nitrogen rates. Therefore, this manuscript demonstrates the importance of a whole farm analysis and the need for a producer to adjust production practices to take full advantage of auto-steer.

Risk management issues are addressed by utilizing a mean-variance formulation and incorporating four farmer risk aversion levels: risk neutral, low risk aversion, medium risk aversion, and high risk aversion. By employing this framework throughout this manuscript, the potential for auto-steer navigation to manage production risk can be investigated. For each risk aversion level, if the adoption of an auto-steer decreases the coefficient of variation as well as increases expected net returns, when compared to the base scenario, it can be inferred that the technology can be used to manage production risk. All three auto-steer scenarios have the potential to manage production risk. This is attributed to the enhanced performance rate provided by auto-steer and the ability of the model to alter production practices. The greatest potential for managing production risk is exhibited when operating with both auto-steer systems. This is attributed to greater reductions in the coefficients of variations and larger increases in net returns when compared to the other auto-steer scenarios. Therefore, this manuscript addresses the risk reduction potential of auto-steer navigation, and contributes to the meager research in this area.

The second manuscript in this dissertation investigates machinery, production, and risk management implications due to the replacement of conventional controls on a self-propelled sprayer with automatic section control, while navigating with and without lightbar. Including both technologies in a whole farm setting together is a novel approach of this manuscript. The enhancement of a previous whole farm risk model is necessary to appropriately reflect the production system, as well as to evaluate automatic section control. The model is adjusted to include additional production practices, harvest requirements, land types, and the benefits and costs associated with automatic section control. Similar to the first manuscript, four farmer risk attitudes are considered for this analysis. In addition, the unique approach of including various field shapes, hence overlaps, are analyzed to determine their impact on the farm management elements due to automatic section control. Specifically, three different field shapes are assessed that represent low (5%), medium (16.5%), and high (25.5%) overlap scenarios.

Machinery management concerns are assessed by determining various economic implications of adopting automatic section control. Utilizing automatic section control with and without lightbar navigation is profitable on all three field shapes. However, the addition of lightbar with automatic section control is only justified for the medium and high overlap scenarios. The average increase in net returns, over the base case, for all three field shapes is $8.43/acre and $3.40/acre for automatic section control with and without lightbar, respectively. As the overlapped area increases, the profitability of automatic section control also increases. It is also important to note that, as the overlapped area increases, the benefit of input savings that occur with automatic section control increasingly dominates the ownership cost of the technology. As a result, there is a wide range of returns on investments (14% - 137%). In addition, an overlap of 4% or more is required to justify the adoption of automatic section control with or without lightbar navigation. Furthermore, an overlap of 14% or more is necessary to justify the addition of lightbar to automatic section control. For all scenarios in this study, automatic section control has a payback period of no more than five years. Also, all returns on investment are greater than the opportunity cost of capital (8%). Therefore, automatic section control is deemed a sound economical investment for the scenarios in this manuscript; however, profitability is highly influenced by the shape of the field.

Production management issues are addressed by incorporating alternative production practices, along with their representative simulated yields, within the whole farm model. This allows for the substitution of inputs due to the benefits that incur by adopting automatic section control. Similar to auto-steer, operating a sprayer equipped with automatic section control with the aid of lightbar can improve the performance rate of the sprayer and, in turn, impact the optimal production strategies. Evidence from this manuscript suggests that only automatic section control with lightbar will impact production decisions. This is evident in the change in the production of soybeans that occurs, especially as the overlapped area increases. This is due to the competition for suitable field hours with other production practices. However, there is no change in the production practices if automatic section control with lightbar is operating on fields with little overlap. Therefore, the additional cost of attaining lightbar is not justified for this scenario. This demonstrates the importance of a whole farm analysis and the incorporation of both field shape and alternative production practices to capture the interactive effects that occur between automatic section control and lightbar.

Risk management issues are ascertained through a mean-variance formulation and incorporating four farmer risk aversion levels: risk neutral, low risk aversion, medium risk aversion, and high risk aversion. By employing this framework throughout this manuscript, the ability for automatic section control to manage production risk can be investigated. For each risk aversion level, if the adoption of automatic section control decreases the coefficient of variation as well as increases expected net returns when compared to the base scenario, it clearly can be inferred that the technology can be used to manage production risk. The results of this manuscript demonstrate that automatic section control without lightbar can be utilized to manage production risk for all three field shapes. Additionally, automatic section control with lightbar reduces the coefficient of variation the greatest for two of the three field shapes (medium and high overlap). This is due to greater reductions in the coefficients of variations and larger increases in net returns when compared to automatic section control without lightbar. Therefore, this manuscript addresses the risk reduction potential of automatic section control, and contributes to the meager research in this area.

The third manuscript in this dissertation incorporates machinery and production management elements to analyze the economic feasibility of operating autonomous machinery on a Kentucky grain farm. Although production strategies are incorporated into the model, the impact of autonomous machinery on production decisions are ignored due to the breadth of the objectives already undertaken. This area of study is very unique, since autonomous machinery is not commercially available today. Therefore, determining the circumstances for which autonomous machinery will be favored over conventional machinery is examined. In addition, the opportunity rarely presents itself in which economics can influence the development of a technology.

To analyze various machinery management issues pertaining to autonomous machinery, a multifaceted economic model is developed. Three economic optimization models are incorporated together for the analyses and include machinery selection, resource allocation, and sequencing. Since autonomous machinery is not commercially available today, determining the circumstances for which autonomous machinery will be favored over conventional machinery is examined. General results from this investigation suggest autonomous machinery can be profitable for a Kentucky grain producer if the machinery has certain characteristics. In addition, advanced agricultural machinery, such as autonomous vehicles, can potentially flourish when operating on smaller grain farms. This is apparent when the largest number of observations in which autonomous machinery is preferred occurs under the lowest acreage level (1.5% of the total observations). Additionally, the lowest acreage level provides the second largest potential increase in net returns over operating conventional machinery (10%). This is attributed to more opportunities to exploit the cost reducing potential enabled by autonomous machines because of economies of size experienced with conventional machinery by large farms. Furthermore, the optimal number of autonomous machines necessary to perform agricultural tasks varies from only needing one of each machine for 500 acres, to five platforms and as many as three sprayers and three planters for 3000 acres.

In addition to the general conclusions of this manuscript, several key factors are needed if autonomous machinery becomes commercially viable. The results indicate that a smaller implement investment is required for autonomous machinery to be preferred to conventional machinery. When considering the performance rates of the implements, the sprayer is the most crucial machine in a whole farm setting, especially as acreage levels increase. This is due to the number of trips across the field required for the sprayer compared to the other implements. When examining the potential benefits that can occur with autonomous machinery, two factors are necessary in order for autonomous to become commercially viable. First, an input savings of at least 20% are essential. Second, yield increases in excess of 2.5% due to reduced compaction are crucial for autonomous machines to favor conventional. By developing an economic optimization model, the deductions from this manuscript provide information to guide engineers in the development of autonomous machinery by identifying critical characteristics and isolating the most influential operating machine.

This dissertation provides a comprehensive investigation into various precision agriculture technologies and their impact on machinery, production, and risk management decisions. However, the potential for further research exists that extends this investigation to include a host of topics which explore various economic aspects of precision agriculture technologies. Due to the infancy of autonomous machinery and the lack of economic investigations, this manuscript has the most potential for expansion in an economic framework. Such opportunities include conducting a more accurate economic analysis once the specifications and benefits of autonomous machinery are more clearly defined. For instance, if any additional benefits (e.g. energy savings and yield increases due to plant phenotyping) are quantified or a finer range of current benefits are analyzed, a more thorough analysis can be conducted. Additionally, the model specification of the autonomous analysis can be expanded to include suitable field day risk and its impact on the economic feasibility of the technology.

Possibilities also exist for expanding both auto-steer and automatic section control analyses. When considering the investigation into auto-steer navigation, exploring how the accuracy of GPS receivers impacts the profitability of auto-steer can be assessed. Furthermore, the concept of automatic section control has expanded to other agricultural machinery operations. Specifically, automatic section control on a planter is currently commercially available. Therefore, a whole farm economic analysis of automatic section control on a planter is a possibility for future research. Finally, the most promising expansion of this manuscript includes evaluating the environmental potential of precision agriculture technologies. In particular, the impact of precision agriculture on the carbon footprint of a Kentucky grain producer can be analyzed.

APPENDIX 1: MATHEMATICAL SPECIFICATION OF THE ECONOMIC DECISION-MAKING MODEL

The economic decision-making model described in the text is depicted mathematically as shown in Figure A1. A description of the activities, constraints, coefficients, and indices, is provided in Figure A2.

(1) $$\max \ \bar{y} - \Phi \sigma_y^2$$

subject to:

(2) $$\sum_E \sum_V \sum_P \sum_S \sum_N \sum_R \sum_L X_{E,V,P,S,N,R,L,H} \leq 2600$$

(3) $$\sum_E \sum_V \sum_P \sum_S \sum_N \sum_R \sum_L LAB_{WK,V,S,E,H,T} X_{E,V,P,S,N,R,L,H} \leq FLDDAY_{WK,T} \quad \forall WK$$

(4) $$\sum_E \sum_V \sum_P \sum_S \sum_N \sum_R \sum_L EXPYLD_{C,E,V,P,S,N,R,L,YR} X_{E,V,P,S,N,R,L,H} - SALES_{C,YR} = 0 \ \forall C,YR$$

(5) $$\sum_E \sum_V \sum_P \sum_S \sum_N \sum_R \sum_L REQ_{I,P,T} X_{E,V,P,S,N,R,L,H} - PURCH_I = 0 \quad \forall I$$

(6) $$\sum_I IP_I PURCH_I - \sum_C P_C SALES_{C,YR} + Y_{YR} + TECHCOST_T = 0 \quad \forall YR$$

(7) $$\sum_{YR} \frac{1}{K} Y_{YR} - \bar{Y} = 0$$

(8) $$\sum_E \sum_V \sum_P \sum_S \sum_N \sum_R \sum_L ROTATE_{G,E} X_{E,V,P,S,N,R,L,H} \leq 1300$$

(9) $$SOILRATIO_{L_i} X_{E,V,P,S,N,R,L,H_j} - SOILRATIO_{L_j} X_{E,V,P,S,N,R,L,H_i} = 0 \quad \forall L, E$$

Figure A1.1. Mathematical description of the auto-steer and automatic section control whole farm planning model.

Activities include:

$\bar{Y} =$ expected net returns above variable cost (mean across years)

$Y_{YR} =$ net returns above variable cost by year (net returns)

$X_{E,V,P,S,N,R,L,H} =$ production of enterprise E of variety V with plant population P under sowing date S with nitrogen rate N and row spacing R on land type L harvested in period H in acres

$SALES_{C,YR} =$ bushels of crop C, sold by year

$PURCH_{I} =$ purchases of input I

Constraints include:

(1) Objective function

(2) Land resource limitation

(3) Labor resource limitation by week

(4) Sales balance by crop and year

(5) Input purchases by input

(6) Net return balance by year

(7) Expected net return balance

(8) Rotation limitations

(9) Ratio of soil type

Coefficients include:

$\Phi =$ Pratt risk-aversion coefficient

$P_{C} =$ Price of crop C in dollars per bushel

$EXPYLD_{C,E,V,P,S,N,R,L,YR} =$ Expected yield of crop C for enterprise E of variety V planted in population P planted on sowing date S with nitrogen rate N and row spacing R on land type L for year YR in bushels

$REQ_{I,P,T} =$ Requirement of input I for production in row and plant spacing P for auto-steer scenario T in units per acre

$LAB_{E,V,S,WK,H,T} =$ Labor requirements for production of enterprise E planted with variety V on sowing date S in week WK harvested in period H for auto-steer scenario T in hours per acre

$FLDDAY_{WK,T}$ = Available field days per week for auto-steer scenario T at varying probabilities

$TECHCOST_T$ = Cost of auto-steer for scenario T

$ROTATE_{G,E}$ = Rotation categorization matrix by enterprise E to include corn if G=1 and other crops if G=2

$SOILRATIO_L$ = Ratio of total acres allotted for each soil type

Indices include:

C = Crop

E = Enterprise

V = Maturity group

P = Plant population

S = Planting date

N = Nitrogen rate

R = Row spacing

L = Land type

YR = Year

H = Harvest period

I = Input

T = Technology scenario

WK = Week

G = Rotation category

K = Total number of years

Figure A1.2. Explanations of activities, constraints, coefficients, and indices in the auto-steer and automatic section control whole farm planning model.

APPENDIX 2: VALIDATION OF BIOPHYSICAL SIMULATION MODEL

The validation for the biophysical simulation model is presented in Appendix 2. A description of the model is given in the first section and why it was chosen for this study. The second section validates the inputs utilized for both corn and soybeans within the biophysical simulation model. The last section includes the validation of the estimated yield produced by the biophysical simulation model for both corn and soybeans.

Biophysical Simulation Validation

With regards to usefulness for this dissertation, biophysical simulation has been used in the past for whole farm economic modeling. The motive for using The Decision Support System for Agrotechnology Transfer (DSSAT v4) was to estimate the yields of full season corn and soybeans over a 30 year period (Hoogenboom, et al., 2004). DSSAT has been utilized in numerous journals for almost 15 years and have encompassed various geographical locations. Several authors have published articles utilizing DSSAT in journals such as: Agronomy Journal, Transactions of the ASAE, Field Crops Research, Agricultural Systems, Crop Science, European Journal of Agronomy, and Climate Research. DSSAT has also been used for multiple presentations at conferences such as: ASAE Annual International Meeting, Southern Agricultural Economics Association Annual Meetings, International Association of Agricultural Economics, Acta Horticulture (ISHS), and International Symposium of Systems Approaches for Agricultural Development. Finally, the overall objective of this dissertation was to economically evaluate precision agriculture technologies in a whole farm model. DSSAT has been used for precision agriculture research in over 15 journal articles. The majority of these studies have focused on variable rate management (irrigation and fertilizer). It could be argued that DSSAT is a precision agriculture tool itself. It can be used to assist in determining the production decisions best suited to optimize yields.

Input Validation

The minimum data set required to run the crop models in DSSAT included site weather data for the duration of the growing season, site soil data, and definition of production practices. Each of the required data sets are discussed in detail in the follow sections.

Weather Validation

Site weather data were collect from the University of Kentucky Agricultural Weather Center (2008). Daily climatology data were collected which included: minimum temperature, maximum temperature, and rainfall for 30 years in Henderson County, Kentucky. DSSTAT's weather module then calculated solar radiation based on the coordinates of Henderson County, Kentucky. These four elements completed the required weather data set in order to operated DSSAT.

Soil Validation

Soil data were collected for DSSAT from a National Cooperative Soil Survey of Henderson County, Kentucky from the Natural Resources Conservation Service (NRCS). After identifying all soil series located in Henderson County, information on those soil series was gathered using the NRCS's Official Soil Series Description from their website. From the gathered information, soil inputs into DSSAT were determined. First, information was calculated to establish the two most predominant types of general soils. It was determined that the two most common types of soil in Henderson County were silty loam and silty clay soils. These two soil types represented 70% and 20% of all soils in Henderson County respectively. DSSAT comes with various soils preloaded into its model. Of the soils within DSSAT, it was determined that deep silty loam, deep silty clay, shallow silty loam, and shallow silty clay would best represent a hypothetical farm in Henderson County. Further information was then gathered through NRCS's Official Soil Series Description in order to edit the default soils to more accurately represent Henderson County's soils. Specifically, factors that determine the surface information and soil water holding capacity were required

The required surface information included: soil color, drainage, percent slope, and runoff potential. First, all four soil colors were changed to brown which was consistent for almost all soils in the county. Conversely, drainage was kept the same as the default soils. Furthermore, runoff potential was changed for the deep soils from the default. Deep silty loam was changed from a moderately low runoff potential to the lowest. The lowest runoff potential was characterized as deep, rapidly permeable loess soil. The qualification for a loess soil required 60-90% of the soil to be silt. Since the deep silt loam was a deep soil and contained 60% silt, the runoff potential was changed accordingly. Deep silty clay was then changed from moderately high to moderately low runoff potential. The description given for moderately low runoff potential was “deep soils less aggregated than soils in the lowest classification, but as a group have an above average infiltration after thorough wetting” (Hoogenboom, et al., 2004, SBuild).

The final surface characteristic changed was the percent slope of the soils. These were also determined from the web soil survey in which they indicate the slope of the soils in the county. The percent slopes were used to differentiate between deep and shallow soils. The soil survey indicated that about 83% of the soils fall between no slope and 6%. The majority of those soils were in the range of 1-3% slopes. In addition, about 17% of the soils were between 6-50% slopes. A majority of these soils were categorized as having 6-10% slope. Therefore, the percent slopes of one and eight percent were chosen for deep and shallow soils respectively. The last three parameters presented in Table A2.1 included: runoff curve number, albedo and drainage rate were all determined within DSSAT once the surface information above is entered.

Once the soil surface information was attained, variables associated with soil water holding capacity could then be determined. These variables include drained upper, crop lower limit, bulk density, saturation, saturation hydraulic conduct, and root growth factor. All of the variables values were determined within DSSAT and were not altered, except for the drained lower limit. Conversations with Dr. Kenneth Boote (2008), an expert in biophysical simulation and co-creator of DSSAT, were conducted about water stress. It was determined that the simulated water capacity (difference between drained upper limit and crop lower limit) was too low, resulting in the over estimation of water stress. For that reason, he suggested lowering the crop lower limit by .04 in order to accurately depict water stress for soils in Kentucky.

Production Practice Validation

Defining the production practices must be determined in order to complete the minimum requirements to operate DSSAT. Such production practices included: planting date, plant population, row spacing, crop variety, and fertilizer practices. Each of these production practices was ranged in order to investigate the optimal production strategy in a whole farm setting. Providing a range for various production practices to conduct specific research has been utilized in previous studies, which are presented in Table A2.2. These references utilized various production practices in order to simulate corn and soybeans in DSSAT for published journal articles.

Production practices were determined for both full season corn and soybeans through the University of Kentucky Cooperative Extension Service Bulletins (2008). A majority of the corn production practices were determined from the University of Kentucky's Cooperative Extension Service Bulletin, ID-139: A Comprehensive Guide to Corn Management in Kentucky, except for crop variety and nitrogen applications. Since this dissertation was modeling a hypothetical farm in Henderson County, a broad spectrum of GDD varieties of corn were desired, therefore the three corn varieties of 2600-2650, 2650-2700, and 2700-2750 GDD were chosen. According to the University of Kentucky's Cooperative Extension Service Bulletin ID-139, the optimal planting date in Western Kentucky (Henderson County is located in Western Kentucky) usually ranges from April 1 to May 1 at a planting depth of 1.5 to 2-inches and a recommended row width of 30 inches. Given the above recommendations, the expected plant populations ranged from 26,000-30,000 plants/acre. In accordance with the above recommendations, the following management practices were utilized in DSSAT for the simulation of corn: nine planting dates beginning March 25 and ending May 20 (planting every seven days), planting depth of 1.5 inches, row spacing of 30 inches, and three plant populations of 24,200, 28,000 and 32,000 plants/acre. Finally, the University of Kentucky Cooperative Extension Service Bulletin, AGR-1: 2008-2009 Lime and Nutrient Recommendations was utilized in determining the amount of nitrogen applied. AGR-1 recommends a range of 125-200 lb actual N/A for conservation tillage to be applied approximately five weeks after planting. Given this, five nitrogen rates of 100, 150, 175, 200, and 225 actual lbs N/acre applied five weeks after planting were chosen to simulate in order to cover the range suggested.

Management practices for soybean production were collected from the University of Kentucky's Cooperative Extension Service Bulletins (2008), AGR-129: Soybean Production in Kentucky Part II: Seed Selection, Variety Selection and Fertilization and AGR-130: Soybean Production in Kentucky Part III: Planting Practices and Double Cropping. According to the above bulletins, soybean varieties best suited for Kentucky are in maturity Groups III, IV, and V, with the earlier maturing varieties adapting the best to northern portions of Kentucky. Also, optimal planting periods for Kentucky occurs in early May to mid-June at depths of 1-1.5 inches. The Bulletins suggest 5 different row spacing ranging from 7-36 inches in which the expected plant populations were based. In accordance with the above recommendations and to accomplish the goal of a broad spectrum for the simulations, the following management practices were simulated: maturity Groups II, III and IV (II was chosen due to northern location of Henderson County), planting dates beginning April 22 through June 17 (planting every seven days), and planting depth of 1.25 inches. Two row spacings were chosen, 30 inches rows and 15 inch rows to represent the lowest spacing without drilling. With these row spacings, expected plant population ranged from 111,000 plants/acre to 167,000 plants/acre. Therefore, three plant populations of 111,000, 139,000 and 167,000 plants/acre were simulated.

Estimated Yield Validation

Once the above data sets were collected, corn and soybean yields were determined. For each crop, every combination of soil and management practices were simulated across 30 years of weather data resulting in 48,600 observations for corn and 19,440 observation for soybeans. These yields were then weighted by soil type then added together to get one yield for every production practice over 30 years. The weights were determined by the web soil survey conducted for Henderson County. According to the survey, 70% of the soil is composed of silty loam and 20% composed of silty clay. The other 10% was then split between silty loam and silty clay resulting in a weighted measure by soil type of 75% silty loam and 25% silty clay. The weights for depth of soils were determined by their slope and erosion. Soils with a greater slope and those with greater erosion possibilities were categorized as shallow soils. Sixteen percent of Henderson County soils have slopes greater than 16%, as well as 23.7% of the soils with some degree of erosion. Therefore, those percentages were averaged together resulting in the weights for soil depth of 80/20 for deep and shallow soils respectively. Once the weighted yields were calculated, comparisons to previous research were conducted.

Corn Yield Validation

A regression analysis was conducted to compare detrended historical corn yields for Henderson County, Kentucky to estimated corn yields averaged across all management practices. A t-test confirmed that the simulated yield for corn was not statistically different from the actual historical yields, with a significance of 99%. The R^2 calculated from the t-test conducted on corn was 0.22. Figure 2A.1 depicts maps historical yields versus simulated yields. It is apparent that no critical errors occurred in the simulation of corn.

Corn yields were then analyzed by focusing on yield response to planting date. Early planting is not as important in Kentucky as other states to the north. Kentucky's growing season is long enough that late planting still results in relatively high yields. For summary purposes the nine planting dates are categorized by early planting (March 25, April 1 and April 8), intermediate planting (April 15, April 22 and April 29) and late planting (May 6, May 13 and May 20). Yields for these planting dates favor early planting as expected, with an average yield across all management practices for 30 years of 155 bu/acre, compared to 142 bu/acre and 129 bu/acre for intermediate and late planting dates respectively. Also, early planting was favored in 24 of the 30 years simulated. Research has shown a yield loss of 1% per day when planting corn after May 10-15, according to University of Kentucky's Cooperative Extension Service Bulletin, ID-139: A Comprehensive Guide to Corn Management in Kentucky. For this simulation, there was only one date of May 20th that yield loss would occur. After the previous planting date of May 13th, there was a yield loss of 5% when planting seven days later, which is consistent with research at the University of Kentucky. Perez-Bidegain, et al., (2007) on the other hand, analyzed tillage systems by planting date and their effect on corn yields in Iowa. Unlike this study, planting dates were determined by soil temperature and soil water content. None the less, when averaged across the three year study, corn yields were significantly impacted by planting date, in which the earlier planting dates were favored. Early planting was also favored in several other studies (Imholte and Carter, 1987; Lauer, et al., 1999; Nafziger, 1994). However, planting too early or too late resulted in yield reductions due to the potential of frost. Corn's planting date was not the only production practice analyzed to determine the validity of the yield estimates.

Corn yield and plant population were also evaluated. Recent studies at the University of Kentucky have shown that higher plant populations result in higher yields, unless plant populations greatly exceed the recommended optimal range. Then, significant yield decreases could occur (Bitzer and Herbek, 2001). Plant populations of 24,000, 28,000, and 32,000 plants per acre were simulated and when averaged across all production practices and 30 years resulted in yields of 138 bu/acre, 142 bu/acre, and 147 bu/acre. The average yield difference between low and high plant populations was 7 bu/acre. All but one year, 1988, was consistent with research suggesting higher yields at each increasing level of plant populations. The greatest benefit of higher plant populations occurred in 1989 with an average difference in yield of 13 bu/acre between low and high plant populations. A three year study at the University of Kentucky showed an increase in corn yield at each increased level of plant populations (Bitzer and Herbek, 2001). Similar to the simulated results, the difference between low and high plant populations (22,000 plants/acre and 30,000 plants/acre) was 15 bu/acre, a difference of only 3 bu/acre. Further investigations into the validity of corn yields based on the influence of production practices were also conducted.

Furthermore, the maturity groups' effect on corn yields were examined and compared to the study conducted by Bitzer and Herbek (2001). This study suggests that early and medium maturity hybrids yield higher than late maturity hybrids in stress conditions. On both deep soils simulated, the later maturity group performed better than both early and medium maturities. On the other hand, early and medium maturities preformed better than the late maturity group on both shallow soils simulated. These are consistent with Bitzer and Herbek (2001). However, conversations conducted in 2009 with Dr. Chad Lee, an Extension Grain Crop Specialist at the University of Kentucky, revealed that no substantial correlation between maturity groups and expected yields exists. This is due to the complexity involved with the interaction of maturities group with other contributing factors (i.e. planting date, weather, and soil conditions). In turn, predicting a specific maturity group's impact on yields is difficult.

Finally, nitrogen rates effect on corn yields were examined and also compared to previous research. Bitzer and Herbek (2001) report that it is impossible to precisely predict the exact amount of nitrogen to apply in order to maximize yields due to weather variability in Kentucky. For that reason, nitrogen application rates are based on cropping history (intensive vs. conservation), soil management (no-till versus conventional) and soil properties (drainage). Numerous studies have concluded that yield response to increased nitrogen rates operate in a quadratic manner (Blackmer and Sanchez, 1988; Liang, et al., 1996; Miao, et al, 2006; Perez-Bidegain, et al., 2007; Shapiro and Wortmann, 2006). Figure 2A.2 depicts the simulated yield response to actual nitrogen rate averaged across all management practices and over 30 years. As depicted, results indicate a quadratic response to nitrogen rates, consistent with previous studies. Also, when examining nitrogen rates impacts on yield for each year simulated, only three years exhibit a non-quadratic functional form. This indicates that, as Bitzer and Herbek (2001) stated, nitrogen application rates are impacted based on the variability in weather conditions.

Soybean Yield Validation

Soybean yields were also simulated for all management practices and soil types in DSSAT. The same percentages were used, 75-25 silty loam and silty clay, as well as 80-20 deep and shallow, to determine a soybean yield for each management practice over 30 years. First, a regression analysis was conducted comparing detrended historical yields for Henderson County, Kentucky to simulated yields averaged across all management practices. A t-test confirmed that the simulated yield for soybeans was not statistically different from the actual historical yields, with a significance of 99%. The R^2 calculated for the t-test conducted on soybeans was 0.46. Figure 2A.3 depicts historical yields versus simulated yields. It can be seen that simulated yields fit the trend of historical yields but are relatively higher. A good portion of Kentucky soybean production is double-cropped with winter wheat resulting in late planting, hence lowers yields. Therefore simulated yields were higher than historical yields for Henderson County, Kentucky.

Soybean yields were then analyzed for their response to planting dates. Soybeans yield response to planting date can vary from year to year due to fluctuating environmental conditions. On average it is known that soybeans planted later in the year yield less than earlier planting dates for many areas in the United States (De Bruin and Pedersen, 2008; Oplinger and Philbrook, 1992; Perez-Bidegain, et al., 2007). Multiple studies have been conducted on soybean production in Kentucky and the impacts that occur when planting dates vary. Egli, et al., (1987) found planting soybeans late for the majority of Maturity Groups resulted in yield reduction due to incomplete insolation and the reduction of vegetative mass at pod set. Egli and Bruening (1992) found late planting significantly reduce yields 13-36% in a majority of cases. Herbek and Bitzer (1988b) suggest the penalty for planting late (June 10-15) results in a 1.5% per day yield loss. Egli (2008) supports this decline by concluding that states in the Upper South (including Kentucky) exhibit yield loss due to late planting after June 7th at a rate of 1.1% per day on average. Figure 2A.4 depicts average soybean yields response to planting date averaged across all management practices. When yields for all planting dates before June 10th (Julian day 161) are averaged and compared to June 17th (Julian day 168), yield loss of 7% occurs (1% per day). Yield loss is not as dramatic as research suggests, but due to the numerous factors involved in computing the average yields, such as soil type and management practices, these yields are creditable. The shallow soils had an adverse planting date effect on yields with late planting being optimal. This can be explained by Kentucky rainfall patterns. With earlier planting dates, pod fill in soybeans occur on average in August when average rainfall was the lowest of the year. This results in lower yields since the water table was not filled at this critical time in soybean production. Whereas, with later planting dates, pod fill occurred on average in September with greater rainfall. Therefore, the adverse yield response to planting date on shallow soils is not a problem. Further investigations into the validity of soybean yields based on the influence of production practices were also conducted.

Plant populations were also analyzed against previous research. According to Herbek and Bitzer (1988b), soybean populations are not seriously affected by plant population when varied between the optimal ranges. Excessively high or low plant populations (+/- >50%) result in yield losses. However, these extreme ranges were not simulated for this research. Therefore, simulated soybean yields, when averaged across years and management practices holding plant populations constant resulted in a difference of 2 bu/acre between the low and high plant populations. Over all 30 years, the difference between high and low plant populations was never greater than 3 bu/acre. Given this, it is believed that simulated yields based on plant population support the literature.

Soybeans were then analyzed based on their response to row spacing. Herbek and Bitzer (1988b) suggest that research from other states north of Kentucky have indicted yield advantages with narrower row spaces. Oplinger and Philbrook (1992) also concluded that narrower row spacing increased soybean yield. On the other hand, the farther you move south, the tendency for yield advantages due to narrow row spaces decreases, suggesting that Kentucky is in a transitional area and consistent yield responses to row spacing is lacking. Herbek and Bitzer (1988b) also advise that for most varieties of soybeans for most years, row widths less than 15 inches will maximize yields. Across all years and management practices, holding row spacing constant, 15 inch row spacing yield 1 bu/acre higher than 30 inch row spacing. For all 30 years simulated, when averaged across management practices holding row spacing constant, 15 inch row spacing yielded higher than 30 inch row spacing, with the greatest difference being 1 bu/acre. Simulated yield response to row spacing is also supported by Egli and Bruening (1992) where it was determined that row spacing of 8 inches and 15 inches did not constantly produce different yields in Kentucky. Furthermore, a study conducted by Harder, et al., (2007) concluded: (1) soybean yields were greater in high plant population compared with low plant populations in 15 inch rows, (2) soybean yields were greater in moderate plant populations compared with low plant populations in 30 inch rows and (3) within plant populations row spacing of 15 inches always preformed better than 30 inch rows. All three of these conclusions are akin to simulated results when averaged across 30 years.

Finally, cultivar's impacts on soybean yields were examined against previous studies. Herbek and Bitzer (1988a) indicate that for most years full-season varieties will yield the highest, but occasionally early varieties yield higher than full season varieties due to adverse weather conditions. Lee, et al. (2005) study on maturity groups and soil type also indicate that Maturity Group IV typically yields higher than any other Maturity Group's for Kentucky's conditions. Also, Kane, et al. (1997) concluded in a four year study in Lexington, KY that Maturity Group IV maximized yields over Maturity Group II and III. Simulated soybean yields are consistent with the above studies. Maturity Group IV yielding higher than the other Maturity Groups 26 out of the 30 years, with the other four years dominated by Maturity Group II. When averaged across all years and management practices, holding Maturity Group constant, results indicate Maturity Group IV maximizes yields. Lee, et al. (2005) also indicated that Maturity Group II fair well or even better than Maturity Group IV varieties on drought-prone soils (i.e. shallow soils) in Kentucky. Simulated yields directly illustrate this relationship with Maturity Group II attaining the maximum yields on both shallow soils when averaged across years when compared to the other Maturity Groups. For the three year study conducted by Lee, et al. (2005), Maturity Group IV yielded about 10% better than Maturity Group III and 20% better than Maturity Group II averaged across the three years. When averaged across 30 simulated years, Maturity Group IV yielded 5% better than Maturity Group III and 12% better than Maturity Group II. Due to unusual rainfall and weather conditions in Kentucky, the chance is greater over a 30 year period that Maturity Group II or III could maximize yields over Maturity Group IV. This would result in lower yield advantages for the various Maturity Groups, when compared to Lee, et al. (2005) study.

In conclusion, given all that has been validated in this paper, it is believed that both corn and soybean yields are representative of yields produced in Henderson County, Kentucky, therefore should be utilized in the economic model.

Table A2.1. Description of soil parameters entered into DSSAT for simulated Henderson County yields.

Soils	Color	Drainage	Runoff Potential	Slope (%)	Runoff Curve #	Albedo	Drainage Rate
Deep Silty Loam	Brown	Moderately Well	Lowest	1	61	0.13	0.40
Shallow Silty Loam	Brown	Somewhat Poor	Moderately Low	8	80	0.13	0.25
Deep Silty Clay	Brown	Moderately Well	Moderately Low	1	73	0.13	0.40
Shallow Silty Clay	Brown	Somewhat Poor	Moderately High	8	88	0.13	0.25

Table A2.2. A list of references that have utilized DSSAT for conducting research and have incorporated a range for each production practice.

Planting Date: Egli and Bruening, 1992; Farquharson, et al., 2006; Guerena, et al., 2001; Jagtop, et al., 1999; Jagtop and Abamub, 2003; Mavromatis, et al., 2002; O'Neil, et al., 2002; O'Neil, et al., 2004; Royce, et al., 2001; Walfula, 1995.

Cultivar: Cora, et al., 1999; Egli and Bruening, 1992; Guerena, et al., 2001; Jagtop, et al., 1999; Jagtop, et al., 2003; Mavromatis, et al., 2002; O'Neil, et al., 2004; Paz, et al., 2001; Paz, et al., 2003; Royce, et al., 2001; Walfula 1995.

Row Spacing: Egli, 1992; Mavromatis, et al., 2002; Royce, et al., 2001.

Plant Population: Jagtop, et al., 1999; Jagtop, et al., 2003; Paz, et al., 1999; Paz, et al., 2001; Royce, et al., 2001; Sadler, et al., 2000; Walfula 1995.

Nitrogen (corn): Braga and Jones, 1999; Farquharson, et al., 2006; Hartkamp, et al., 2004; Jagtop, et al., 1999; Jagtop, et al., 2003; O'Neil, et al., 2002; O'Neil, et al., 2004; Paz, et al., 1999; Royce, et al., 2001; Sadler, et al., 2000; Thorp, et al., 2007; Walfula 1995.

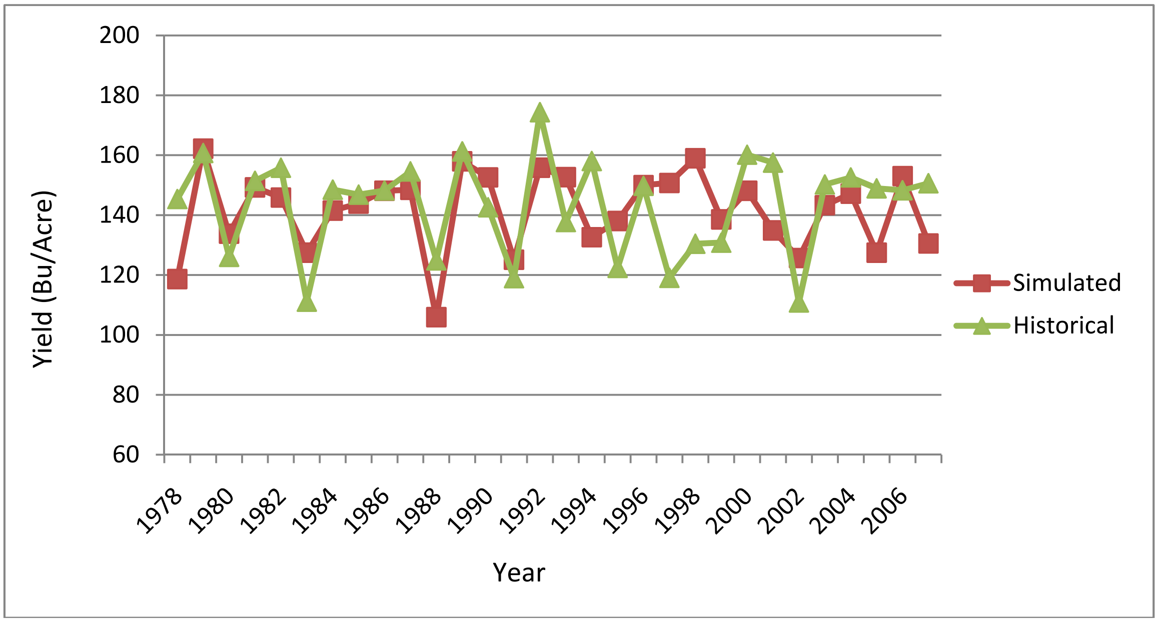

Figure A2.1. Average Corn Yield for Henderson County, Kentucky by Year: Simulated versus Historical Yield (Detrended).

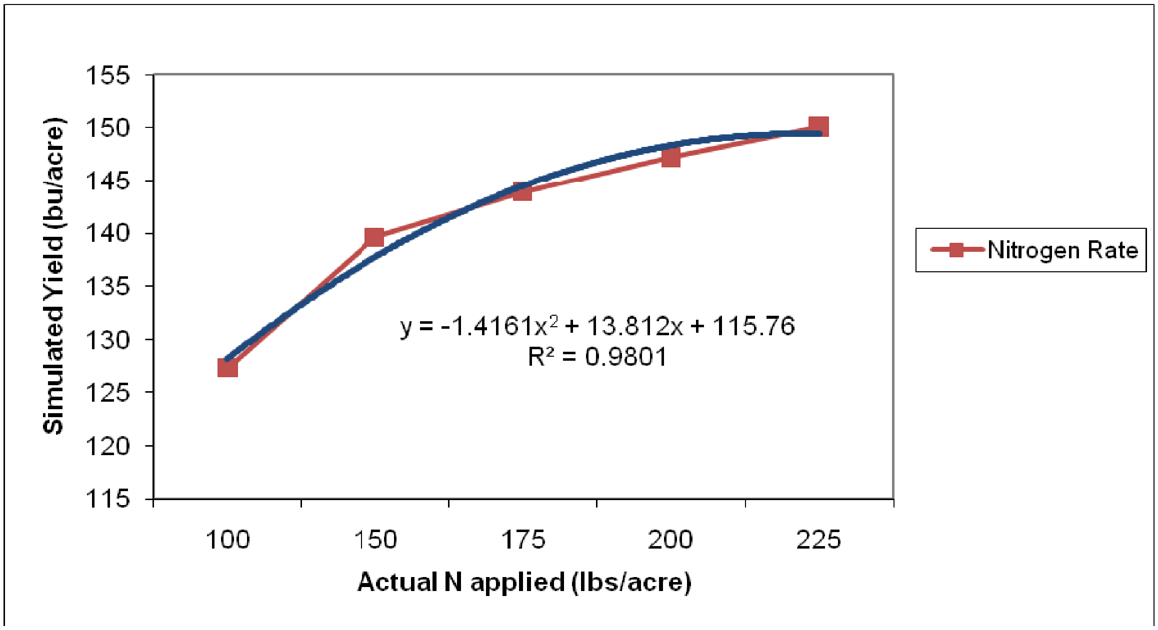

Figure A2.2. Simulated yield response to actual nitrogen applied per acre.

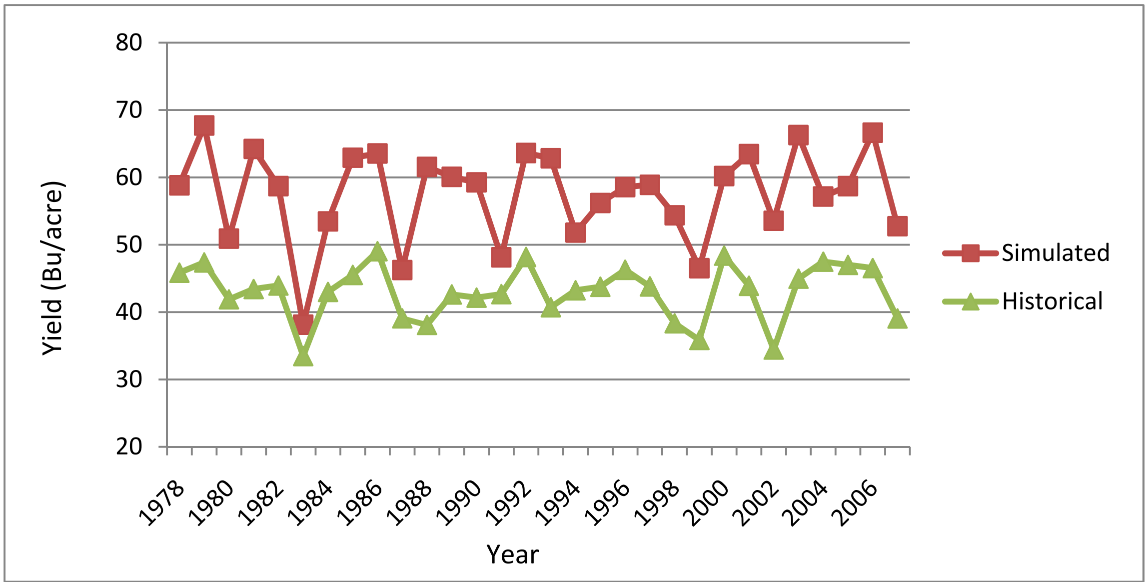

Figure A2.3. Average Soybean Yield for Henderson County, Kentucky by Year: Simulated versus Historical Yield (Detrended)

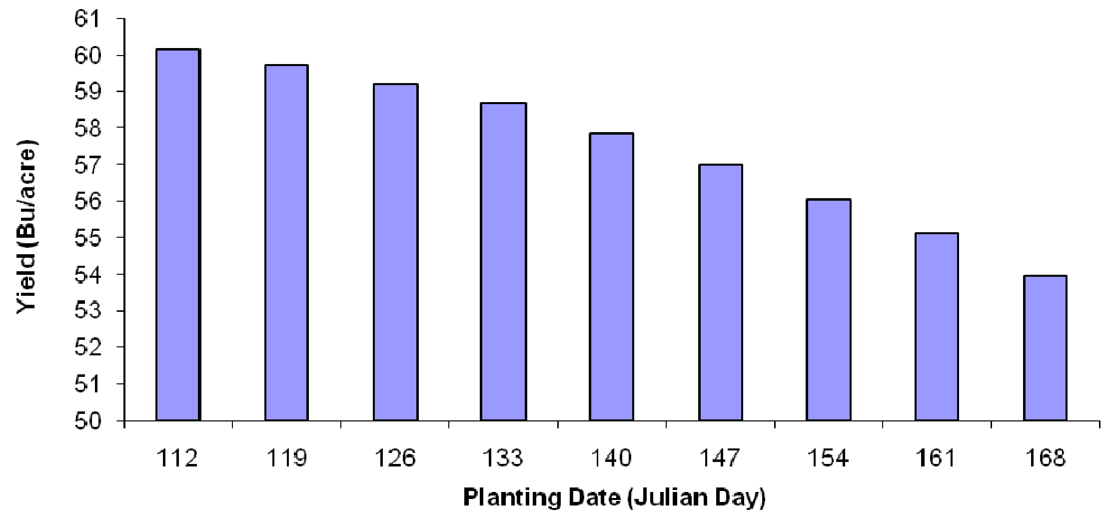

Figure A2.4. Simulated soybean yields response to various planting dates averaged across management practices and years.

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Shockley, J.M., C.R. Dillon, and T. Stombaugh. "Auto-Steer Navigation Profitability and its Influence on Management Practices: A Whole Farm Analysis." In: *Proceedings of the 7th European Conference on Precision Agriculture*. Wageningen, Netherlands. July 6-8, 2009 pp.751-757.

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Dillon, C.R. and **J.M. Shockley.** 2010. "Precision Management for Enhanced Farmer Net Returns with the Conservation Reserve Program." Invited Paper to be presented at the *10th International Conference of Precision Agriculture and Other Precision Resource Managemen*t ASA/SSA/CSSA, Denver, CO.

Balkcom, K., B. Ortiz, **J.M. Shockley**, and J. Fulton. 2010. "Profitability of RTK Auto-Steer Guidance and its Influence of Peanut Production: A Whole Farm Analysis" Selected Paper to be presented at the *10th International Conference of Precision Agriculture and Other Precision Resource Management* ASA/SSA/CSSA, Denver, CO.

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NON-REFEREED EXTENSION PUBLICATIONS:

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DEPARTMENTAL PUBLICATIONS:

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GRANTS AWARDED:

United States Department of Agriculture. CSREES-Special Grant through Hatch Funds. 2009-2012. New Crop Opportunities: Phase X-Specialty Grains. "Whole Farm Analysis of Edamame Production in Kentucky.." C.R. Dillon and **J.M. Shockley**. $49,096.

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GRANT INVOLVEMENT:

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Southern Region Risk Management Education Center. USDA – CSREES RMA. $49,961. Retirement Portfolio Planning for Farmers. C. Dillon and E. Bazen. 2007.

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MANUSCRIPTS IN PROGRESS:

Shockley, J.M., C.R. Dillon, and T. Stombaugh. “A Whole Farm Analysis of the Influence of Auto-steer Navigation on Net Returns, Risk, and Production Practices.” Being revised for second review at *Journal of Agricultural and Applied Economics*.

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Shockley, J.M., C.R. Dillon, and T. Stombaugh. “Development of an Economic Optimization Model to Guide the Advancement of Autonomous Machinery by Identifying Dominant Equipment Characteristics.” Being prepared for submission to either *Biosystems Engineering* or *Journal of Agricultural Engineering Research*.

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