An Economic Feasibility Assessment for Adoption of Autonomous Field Machinery in Row Crop Production

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Abstract. *A multi-faceted whole farm planning model was developed to compare conventional and autonomous machinery for grain crop production. Results suggested that autonomous machinery could be an economically viable alternative to conventional manned machinery if the establishment of intelligent controls was cost effective. An increase in net returns of 22% over operating with conventional machinery was found. This study also identified the break-even investment price for intelligent controls for the safe and reliable commercialization of autonomous machinery. Results indicated that the break-even investment price was highly variable depending on the financial benefits resulting from the deployment of autonomous machinery and farm size. The maximum break-even investment price for intelligent, autonomous controls was nearly U.S. $500,000.*

Keywords. *Economics, mathematical programming, machinery selection*

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Introduction

Over the years, the dominant trend in agricultural machinery has been toward the use of larger sizes of conventional equipment in crop production. One of the primary reasons farmers desire larger equipment is to benefit from economies of size. Specifically, farmers can become more economically competitive by substituting capital for labor, thereby reducing per hectare labor costs. 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 the declining and seasonal availability of a skilled agricultural workforce or producers' desire for more leisure time are also possible explanations for the trend to larger machines. However, as the size of agricultural machines continues to increase, consequences that are detrimental to both the operator and environment arise. For the operator, controlling large implements on irregular terrain and moving equipment between fields along narrow public thoroughfares is problematic at best. Furthermore, soil compaction seems to be largely ignored as ballasted mass increases in direct proportion to engine size. Moreover, larger equipment leads to input metering and application errors with overlap and velocity variations across the implement width when turning. Some researchers are concerned that producers may not be capable of achieving uniform application with increasing equipment size (Luck et al., 2011). Autonomous machinery may offer the potential to reverse the deleterious trends of larger equipment while preserving the timeliness advantage.

The replacement of large manned machines with smaller autonomous machinery represents a paradigm shift that may lead to significant changes in the structure of agriculture. The implications of autonomous machinery could be profound and will most certainly encompass a variety of disciplines. At the macroeconomic level, replacing human operators with advanced technology will undoubtedly influence labor markets. Alternately, at the microeconomic level, issues pertaining to economies of size and scope, capital labor substitution, environmental quality, and rural development may be influenced by adopting autonomous machinery. Aside from economics, the implementation of autonomous machinery could create new sociological dynamics by allowing more leisure and family time for the once constrained farm operators. Furthermore, by removing the operator from the tractor, farm safety (i.e., exposure to chemicals and machinery related accidents such as tractor overturn) could improve. Autonomous machinery could also entice a technologically savvy younger generation (e.g. Generation Y) to farming as an occupation. However, none of the above issues are of concern if autonomous machinery is not profitable for producers.

The potential economic benefits from utilizing autonomous machines are numerous. Replacing a human operator with automated controls could reduce average labor requirements and associated costs. Furthermore, autonomous agricultural field operations could occur 24 hours per day and seven days a week during times of favorable field conditions thereby mitigating some of the risk associated with untimely field operations. By utilizing smaller machines with intelligent controls, the metering and distribution of inputs can be improved thereby eliminating off-target and off-rate application errors which increases use-efficiency, reduces costs, and improves crop quality. With the reduction in machine size and inherent weight advantage comes a reduced potential for soil compaction. Coupled with the ability to improve chemical use efficiency, the environmental impacts of autonomous machinery could be significant. Hence, the utilization of autonomous machinery could develop into a more profitable approach to production agriculture.

The opportunity rarely presents itself in which economics can influence the initial development of a technology. A thorough economic evaluation of autonomous machinery systems can provide engineers with valuable information regarding the costs and benefits required for autonomous machinery to compete with conventional machinery. One of the largest challenges facing the machinery industry/engineers is how much to invest in the development of intelligent controls necessary for the implementation of autonomous machinery. A key decision tool for manufacturers is the *break-even investment price*. This represents the maximum price that manufacturers can charge for a technology, (in this case intelligent controls) at which a producer is indifferent between operating with conventional versus autonomous machinery. However, other important factors are embedded within the product price such as the profit to the firms, additional implementation costs (e.g. insurance, legal, product support, and subscription costs), and opportunity costs from switching from conventional to autonomous machinery (e.g. learning curve cost). Therefore, the price which manufacturers could charge producers will likely be some fraction of the break-even investment price.

The goal of this project was to assess the economic viability of performing agricultural field operations autonomously by completing the following objectives: (1) develop a whole farm planning model for grain production that allows comparison between conventional and autonomous machinery systems, (2) determine the optimal conventional machinery complement necessary to perform agricultural field operations common in grain production, (3) determine the optimal complement of autonomous machines necessary to perform the same field operations, (4) determine the break-even investment price for intelligent, autonomous controls, (5) demonstrate the ability of the model to incorporate additional anticipated economic benefits that will accrue to autonomous machinery and the impact on net returns and break-even investment price, and (6) determine the impact of farm size on the above objectives.

Autonomous Research Development

Introducing smaller, light-weight machinery that can perform agricultural field operations may prove to be a realistic option for producers in the future. These machines will likely operate in fleets and utilize intelligent controls to perform production operations like seeding, spraying, fertilizing, and harvesting. Recently, researchers and engineers have developed various prototype vehicles capable of autonomous operation. These prototypes have the ability to accommodate various attachments such as tillage tools, seeders, and sprayers, much like an operator driven tractor. Several studies have investigated the development, design, and implementation of autonomous machinery (Blackmore et al., 2004; Blackmore and Blackmore, 2007; Vaugioukas, 2007; Vaugioukas, 2009). Further research has been conducted to analyze the accuracy, steering, and performance of various autonomous prototypes (van Henten et al., 2009; Marchant, 1997; Bak and Jakobsen, 2004). Other studies have concentrated specifically on autonomous weed detection and management (Gottschalk et al., 2009; Ruckelshausen et al., 2009; Pedersen et al., 2007; Pedersen et al., 2006; Astrand and Baerveldt, 2002). Harvesting grain could be very difficult to perform with smaller, light-weight autonomous machinery due to the volume of biomass to be processed and removed from the field. As a result, harvest operations may be the last to the automated.

The most difficult issue facing engineers in the development of autonomous machines is making them safe and reliable. Researchers and engineers have begun to address this problem by equipping the autonomous machine with perception and sensing technologies for obstacle detection; interrupt and error handling routines; and multi-level control architectures to optimize system behavior (Griepentrog et al., 2009; Vougioukas, 2009; Rackelshausen et al., 2009; Pitla et al. 2010a; Pitla et al. 2010b). It is recognized that safety is paramount to the successful commercialization and deployment of autonomous field machinery. However, the solution to achieve satisfactory levels of safety and reliability could be costly. In this context, the break-even investment price will serve as a useful guide for researchers and engineers developing such intelligent controls and control architectures.

Economists have also begun investigating the potential 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. Pedersen 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 sensitive to initial investments and the annual costs for the GPS system. In 2007, Pederson et al. conducted an investigation into autonomous weeding and grass cutting. Partial budgeting was used to compare the cost changes to conventional practices and determine if autonomous machinery was cost-effective. Providing adequate safety measures and control systems could be implemented at a reasonable cost, autonomous weeding and grass cutting could be a viable alternative to conventional systems. Because of the infancy of autonomous field machinery and lack of suitable economic investigations, numerous research opportunities exist that could provide valuable insight into the development and profitability of this technology.

Economic Model

The introduction of autonomous field machinery may produce complex interactions affecting not only machinery management but also changes to labor requirements, timing of field operations, and other cropping practices. To facilitate the analysis, a decision-making framework was established. The model considered the entire farming system and allowed for changes in cropping patterns, machinery complements, and labor requirements. A common decision-making framework in farm management is a whole farm planning model. Whole farm planning models have the ability to capture interactive effects that can occur between elements within the model that most decision-making aids, such as partial budgeting, ignore. Also, the attention to detail and complexities of a whole farm model provide a more accurate depiction of changes that occur at the farm level. Given this, a whole farm planning model was ideal for comparing machinery alternatives.

One of the main objectives of this study was to develop a multi-faceted whole farm planning model to accomplish a comparison for conventional versus autonomous machinery options for grain production. A mixed integer mathematical programming formulation was developed that incorporated three optimization models: machinery selection, resource allocation, and sequencing which followed the framework by Danok et al. (1980). The machinery selection component was the foundation of the whole farm planning model and provided insight into the optimal size of conventional machinery and the optimal number of autonomous vehicles required to perform specific agricultural field operations common in grain crop production. When comparing conventional versus autonomous equipment, machinery costs and performance data differentiated the two analyses and were reflected when optimizing net returns while using the same model formulation. The underlying machinery selection model consisted of the following objective function and constraints:

$$\text{Max } \overline{\mathrm{NR}} \tag{1}$$

Subject to:

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

$$\sum_{E} P_E\, SALES_{E,YR} - \sum_{E} \sum_{P} \sum_{M} \sum_{A} \sum_{WK} OP_M ACT_{E,P,M,A,WK} - \sum_{M} OWN_M * BUY_M - \sum_{E} \sum_{V} \sum_{P} \sum_{S} VC_E PROD_{E,V,P,S} - NR_{YR} = 0 \qquad \forall YR \tag{3}$$

$$\sum_{E} \sum_{V} \sum_{P} \sum_{S} EXPYLD_{C,E,V,P,S,YR} PROD_{E,V,P,S} - SALES_{E,YR} = 0 \qquad \forall C, YR \tag{4}$$

$$\sum_{M} BUY_M = 1 \tag{5}$$

$$BUY_{M=T} - BUY_{I \subseteq \mathrm{M}} \geq 0 \quad \forall I \tag{6}$$

Equation 1 represented the objective function of the model which was to maximize average net return ($\overline{NR}$). Equations 2-6 defined relevant variables and imposed various constraints related to the machinery selection portion of the mixed integer programming model. To determine the maximum average net returns, both net returns and the mean of those net returns must be defined. The mean net returns were defined as the sum of net returns (NR_{YR}) estimated each year (YR) divided by the total number of years (N) considered (Equation 2). The net returns per year equaled the total sales minus the total costs (Equation 3). Total sales equaled the amount of each enterprise (E) sold per year in kilograms ($SALES_{E,YR}$) multiplied by the price per kilogram of each enterprise (P_E). Total costs were determined from machinery operating costs, machinery ownership costs, and all other variable costs of production (e.g. seed cost, chemical cost, fertilizer costs, etc.). Total operating costs per machine equaled the cost per hectare to operate machine M (OP_M) multiplied by the total number of hectares covered when performing the various production activities ($ACT_{E,P,M,A,WK}$) common in grain production. Each production activity (e.g. planting, spraying, fertilizing, and harvesting) was defined by enterprise (E), planting date (P), and the appropriate machine (M) to conduct the activity (A) during the specified week(s) (WK). The specification of planting date to defined production activity is clarified in the forthcoming sequencing discussion. Total machinery operating costs were determined by summing across all machines.

To calculate the ownership cost, a machine must be purchased (BUY_M) before the annual ownership cost of the machine (OWN_M) could be incurred. The sum of all ownership costs of purchased machines determined the total machinery ownership costs of production. Furthermore, the total of all other variable costs of production equaled the variable costs per hectare of production (VC_E) for each enterprise multiplied by how many hectares of each enterprise was produced ($PROD_{E,V,P,S}$) and summed across enterprises. The number of hectares of each enterprise (E) produced was defined by variety (V), planting date (P), and soil type (S). These components combined to identify per year and average net returns.

To calculate per year net returns, total sales (Equation 4) was defined as the estimated yields in kilograms per hectare ($EXPYLD_{E,V,P,S,YR}$) multiplied by how many hectares of each enterprise was produced ($PROD_{E,V,P,S}$). The inclusion of estimated yields based on variety, plant population, and soil type allowed for optimal crop planning by determining the area allotment for each enterprise. More details regarding implementation of estimated yields are provided in the next section.

Purchase constraints were also required within the machinery selection portion of the model (Equations 5 and 6). For the selection of conventional machinery, the model was required to choose one machinery complement. Each complement contained the necessary equipment to complete the agricultural field activities, while the combination of varying equipment sizes differentiated each complement. Equation 5 was only necessary when selecting conventional machinery. On the other hand, the selection of autonomous machinery required a different purchase constraint (Equation 6). Since autonomous machinery is still in the developmental stage, only one machinery complement was contained in the choice set (e.g. an autonomous prototype). Instead of selecting the optimal size of machinery (conventional analysis), the autonomous analysis selected the optimal number of autonomous machines to complete the agricultural field activities. Equation 6 specified that the number of autonomous vehicles must equal or exceed the optimal number of implements for a particular operation. For example, if five planters are optimal, then you must own five or more autonomous tractors.

The mixed integer programming model was also constrained by limitations associated with resource allocation and the competition among scarce resources.

$$\sum_V \sum_P \sum_S PROD_{E,V,P,S} - \left(\frac{1}{YRS}\right) * ACRE \ \leq 0 \ \ \forall E \tag{7}$$

$$\sum_E \sum_P \sum_A FC_{M,A}\, ACT_{E,P,M,A,WK} - TIME_{WK} BUY_M \leq 0 \ \ \forall WK, M \tag{8}$$

$$SOILRATIO_{S_i} PROD_{E,V,P,S_j} - SOILRATIO_{S_j} PROD_{E,V,P,S_i} = 0 \quad \forall S_{i,j,i \neq j}, E, V, P \tag{9}$$

One of the limiting resources in agricultural production is land; therefore, a land constraint was required so that the area (ha) designated to producing each enterprise ($PROD_{E,V,P,S}$) did not exceed the designated amount of available cropland for the study (ACRE). Since crop rotation was common in grain production, there existed a rotation component, in which the land area designated to each enterprise was proportionate to the number years in rotation (YRS). To employ the rotational component within the model, a categorization matrix $ROTATE_E$ was required to identify the enterprises in rotation.

Another limiting resource in agricultural production is time; therefore, a suitable field time constraint was required (Equation 8). This constraint ensured that the machinery operating time (h) for each production activity, designated by the field capacity of the machine ($FC_{M,A}$) in ha h^{-1} for each production activity multiplied by the total area (ha) of each production activity, did not exceed the amount of suitable field hours available each week ($TIME_{WK}$). However, the complete complement must be purchased to operate during those suitable field hours. Therefore, the total amount of time to complete each activity must be less than the available suitable field hours.

Since the model incorporated yield data that was estimated on various soil types (S), a soil balance constraint was required (Equation 9). This constraint ensured that the optimal area (ha) of each enterprise produced was proportionate to the ratio of soils in the study area ($SOILRATIO_S$). For example, if the study area consisted of two soil types and the ratio was 4:1, this constraint ensured that the estimated yields on the two soil types reflected this ratio when determining total yields for the study area.

Finally, grain crops are produced through a process involving multiple field activities (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. Therefore a sequential component was incorporated into the mixed integer programming model (Equation 10).

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

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 enterprise. Each production activity must occur during an ideal time frame ($ALLOW_{E,P,A,WK}$) for the study area. This equation guaranteed all production activities were completed in the correct sequence, as well as during the appropriate week. Equations 1-10 comprised the mixed integer mathematical programming formulation that was employed for evaluating conventional versus autonomous machinery.

Combining the three elements above formed a unique and complex whole farm planning model that was capable of joint selection including machinery and crop planning. The focus of this study was solely on the machinery selection to provide valuable information to engineers and researchers with regard to autonomous machinery cost structure and implementation.

Case Analysis Framework

To properly assess a grain farmers' optimal machinery selection decision as required for the second and third study objectives, the underlying production environment must be established. This investigation was modeled after a typical western Kentucky farm producing corn and soybeans in a two year rotation. Both enterprises were produced under no-till conditions for an 850 ha farm. This farm size depicted the upper one third in management as represented by net farm income of grain producers in the Ohio Valley region of Kentucky enrolled in the Kentucky Farm Business Management Program (Pierce, 2009). The yields estimated for this case study used the Decision Support System for Agrotechnology Transfer (DSSAT), a biophysical simulation model (Jones, 2003). Utilizing soil surveys from the National Resources and Conservation Service, four predominant soil types were identified in western Kentucky: deep silt loam, shallow silt loam, deep silt clay, and shallow silt clay. The soil ratios were 60%, 15%, 20%, and 5%, respectively. Validations were performed and the resulting simulated yields were thought representative of a Western Kentucky grain farm. For this investigation, a subset of the yield data from Shockley et al. (2011) was employed

Specific sequences of field operations must occur for the production of corn and soybeans. For corn, the sequence of operations is pre-plant fertilizer/lime application, burn down herbicide treatment, planting, pre-emergence herbicide application, post-emergence herbicide application, nitrogen application, and harvest. Soybean production required pre-plant fertilizer/lime application, burn down herbicide treatment, planting, post-emergence herbicide application, insecticide treatment, and harvest. These production practices for both corn and soybeans were consistent with University of Kentucky Cooperative Extension Service Bulletins (2008). In addition, this bulletin provided input application rates and timing for performing specific operations which, in turn were applied to the whole farm planning model. Harvest and the application of phosphorous, potassium and lime were assumed to be custom hired.

To complete these production activities, the appropriate conventional and autonomous machinery complements were selected. A conventional machinery complement consisted of a tractor, planter, sprayer, and fertilizer applicator. The machinery choice set represented typical options available to a grain producer (Table 1). All data for conventional machinery were compiled from the Mississippi State Budget Generator (Laughlin and Spurlock, 2007), which complied with ASABE Standards D497.7 and EP496.3, and reflected 2010 costs. Specifically, operating costs (fuel, repair and maintenance, and labor), annual costs of ownership, and the performance rates of the implements were utilized in the machinery selection decision. In addition, the Mississippi State Budget Generator was used to estimate all other variable costs based on costs paid by Kentucky producers in 2010.

Table 1. Conventional options to compose machinery complements for development of the choice set under the case study.

Tractor: 105 hp, 130 hp, 190 hp, 300 hp, 400 hp
Sprayer (Broadcast): 8.2 m, 12.2 m, 15.2 m, 18.3 m, 27.4 m, 36.6 m
No-Till Split-Row Planter: 4-row, 6-row, 8-row, 12-row, 16-row, 24-row
Liquid Fertilizer Applicator: 6-row, 8-row, 12-row

Note: All potential solutions followed appropriate draft and equipment matching requirements.

Economic modeling of autonomous machinery is scarce because of the lack of necessary data, especially when considering machinery selection decisions. Fortunately, faculty members in the University of Kentucky Department of Biosystems and Agricultural Engineering have developed autonomous tractor prototypes. This study used actual costs and performance data based on one of these prototypes (Table 2). The base autonomous prototype machine was designed to be fitted with interchangeable implements (planter, sprayer, and fertilizer applicator), similar to a conventional tractor. The ownership costs of the autonomous tractor and implements were annualized to include depreciation and the opportunity cost of capital invested. Since optimal intelligent, autonomous controls have yet to be established, the cost of such controls was excluded from those presented in Table 2.

Therefore, this study determined a break-even investment price (Objective 4) to guide the development of intelligent, autonomous controls. Options other than purchasing the equipment (i.e. short-term rental, leasing, and custom hiring) were excluded from this study because of the lack of appropriate data. Depreciation was calculated using the straight-line method with an assumed three year useful life and salvage value of 50% of the cost for the autonomous vehicle (without controls) and implements.[1] The opportunity cost of capital investment was calculated using an 8% interest rate. In addition, labor equivalent to that required with conventional machinery was removed from the autonomous investigation. There were anticipated incidental labor costs associated with refilling seed, chemical, and fertilizer, as well as transporting the

[1] The annual costs for owning an autonomous machinery was calculated as follows using straight-line depreciation plus opportunity cost of the capital investment: [((Total Investment – Salvage Value)/(Useful Life)) + ((Total Investment + Salvage Value)*Interest Rate)/2].

machines to different locations, but these were not addressed in this study. In addition, there was an anticipated opportunity cost associated with the implementation of the new machinery paradigm, which was not included in this investigation.

Table 2. Cost and performance data related to the autonomous prototype developed by the University of Kentucky and estimates of implement specifications utilized for the case analysis.

	Tractor[2]	Planter[3]	Sprayer[4]	Fertilizer Applicator[5]
Total Ownership Cost (U.S.$)[1]	24,543	6,000	7,500	13,000
Implement Specifications				
Speed (mph)		5	8	8
Width (m)		3.0	6.1	7.6
Efficiency (%)		70	80	75
Field Capacity (ha h^{-1})		1.7	6.3	7.4
Repair and Maintenance (%)	50	50	50	50
Useful Life (years)	3	3	3	3
Annual Usage (hours)	600	200	150	150

[1]Total ownership costs exclude the costs of intelligent controls for automation.

[2]The tractor was a 46 hp KAT II in which costs composed of a U.S.$3,600 engine, U.S.$2,760 wheel motors, U.S.$900 pumps, U.S.$1,800 hydraulics, U.S.$720 wheels/tires, U.S.$750 electronics, and U.S.$14,013 for the structure. In addition, the tractor had fuel use rate of 2.7 gal h^{-1} and fuel efficiency of 17.04 hp·h gal^{-1}

[3]A row seeder attachment was estimated at U.S.$1,500 per row.

[4]The sprayer was equipped with a 1514 l (400 gal) tank.

[5]The fertilizer applicator consisted of a spinner and apron chain mechanism with a 1814 kg spreader box.

Additional data required included determining suitable field time ($TIME_{WK}$) for both conventional and autonomous analyses. The total available hours per week was dependent on the number of probable suitable field days and the hours worked per day. The number of probable suitable field days per week for the study area was based on historical data from Crop Progress and Condition Reports for Kentucky (USDA-NASS, 2010). The conventional analysis was limited by the human operator; therefore, only 13 hours per day was assumed (Shockley et al., 2011). On the other hand, autonomous machinery can operate 24 hours per day, which was assumed for this study (Pedersen et al., 2006; Blackmore et al., 2004). The overall machinery selection model was consistent across both types of machines with respect to the tasks performed, with the technical data differentiating the two analyses.

Results

Conventional versus Autonomous Machinery Results: Base Comparison

Given the framework above, the models selected the optimal conventional machinery complement from the inventory of available equipment, and also selected the optimal number of autonomous machines to perform the same sequence of field operations for an 850 hectare grain farm (Table 3). The model suggested that two autonomous tractors and planter were necessary, but only one of all other implements. This was attributed to the field capacity of the planter and the area to be planted.

When comparing autonomous and conventional machinery (Table 3), the net returns were U.S.$15,196 (2%) greater when operating with autonomous machinery. The majority of additional returns were attributed to a reduction in machinery ownership and operating costs. There was a

24% reduction in machinery ownership costs and a 17% reduction in machinery operating costs. In addition, a slight yield increase in corn contributed to greater net returns because of the ability to plant more of the area to corn within the optimal planting period using autonomous versus conventional machinery. Since the investment costs of modeled autonomous machinery did not include the cost of intelligent controls, the difference in net returns (U.S.$15,196) represented a "maximum annual willingness to pay" by producers for intelligent, autonomous controls. Specifically, this investment price reflected what a manufacturer may be able to charge for intelligent controls in addition to the explicitly modeled U.S.$24,543 per autonomous tractor for which a producer would be indifferent between operating with conventional versus autonomous machinery, ceteris paribus. This value considered the investment price impacts on both ownership (depreciation and interest) and operating costs (repairs and maintenance). For this scenario, the break-even investment price for intelligent controls was U.S.$33,327. When broken down, an investment price of U.S.$33,327 led to a depreciation cost of U.S.$11,108, interest cost of U.S.$3,999, and repairs and maintenance cost of U.S.$89 which totaled U.S.$15,196. Recall that this represents the maximum a manufacturer can charge for intelligent controls as discussed in the introduction; therefore, the actual charge will likely be some fraction of this price. It is important to note that these results are representative of this particular case study and autonomous prototype examined.

Table 3. Machinery selection and corresponding economic results for both conventional and autonomous machinery scenarios for an 850 hectare grain farm.

	Conventional	Autonomous
Tractor(s)	130 hp	2 – 46 hp
Planter(s)	8 row	2 – 4 row
Fertilizer App.	8 row	1 – 7.6 m
Sprayer	18.3 m	1 – 6.1 m
Avg. Net Returns (U.S.$)	751,358	766,554
Min. Net Returns (U.S.$)	471,517	468,695
Max. Net Returns (U.S.$)	962,506	1,026,745
Std. Dev Net Returns (U.S.$)	145,086	148,265
Coef. of Var. Net Returns (%)	19.31	19.34
Ownership Costs (U.S.$)	24,191	18,493
Operating Costs (U.S.$)	26,187	21,811
Production Input Costs (U.S.$)	348,512	348,512
Corn Yield (kg ha^{-1})	10,168	10,231
Soybean Yield (kg ha^{-1})	4,169	4,169

Inclusion of Additional Anticipated Economic Benefits

Beyond the results for the base comparison, this study focused on two of the most anticipated additional quantitative benefits that could accrue through utilization of autonomous machinery: reduced selected input costs and increased yields from reduced compaction. The estimates used for demonstrating the ability of the model to incorporate such benefits were determined from literature pertaining to various autonomous prototypes (e.g. Pedersen et al., 2006; Blackmore et al., 2004; Rackelshausen et al., 2009; van Henten et al., 2009).

The reduction in selected input costs was considered one of the primary benefits of utilizing autonomous machinery. For this study, the input costs impacted by autonomous machinery included herbicide, insecticide, seed, and nitrogen costs. Previous studies have reported up to a 90% reduction in herbicide cost alone for an autonomous micro-sprayer because of its ability to recognize individual weeds and target herbicide application (Pedersen et al., 2007). Other inputs such as fertilizer and seed were not expected to experience such a dramatic reduction in costs but could be reduced by eliminating overlap application of inputs. Therefore, a conservative estimate of a 10% reduction in the total cost for selected inputs was applied to autonomous machinery. In addition, large, heavy farm machinery often contributes to soil compaction resulting in a reduction in yields. The University of Kentucky Extension Services reported a reduction in corn and soybean yields of 7% due to soil compaction (Murdock and James, 2008). As a result of the lightweight configuration of the autonomous vehicles, soil compaction should be reduced resulting in increased yield potential; therefore, a yield increase of 7% percent was used for this study.

Given the inclusion of the anticipated quantitative benefits from autonomous machinery, new selection and economic results were determined (Table 4). Four different scenarios were represented: base comparison (Scenario 1), the inclusion of only a selected input cost reduction (Scenario 2), the inclusion of only a yield increase (Scenario 3), and the inclusion of all anticipated benefits (Scenario 4). Scenario 4 combines the benefits accrued under the base comparison with a selected input cost reduction and yield increase. Under Scenarios 2-4, the optimal number of autonomous machines remained the same as the base comparison; hence, there was no change in machinery operating and ownership costs.

Table 4. Autonomous machinery selection and economic results for the inclusion of various input cost reductions and yield increases due to reduced compaction for an 850 hectare grain farm.

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Selected Input Cost Reduction	0%	10%	0%	10%
Yield Increase	0%	0%	7%	7%
Avg. Net Returns (U.S.$)	766,554	801,406	862,364	897,215
Min. Net Returns (U.S.$)	468,695	503,547	543,655	578,506
Max. Net Returns (U.S.$)	1,026,745	1,061,597	1,140,768	1,175,619
Std. Dev. Net Returns (U.S.$)	148,265	148,265	158,643	158,643
Coef. of Var. Net Returns (%)	19.34	18.50	18.40	17.68
Production Input Costs (U.S.$)	348,512	313,661	348,512	313,661
B-E Investment Price (U.S.$)[1]	33,327	109,755	243,436	319,864
Avg. Corn Yield (kg ha^{-1})	10,231	10,231	10,984	10,984
Avg. Soybean Yield (kg ha^{-1})	4,169	4,169	4,438	4,438

[1]B-E refers to break-even.

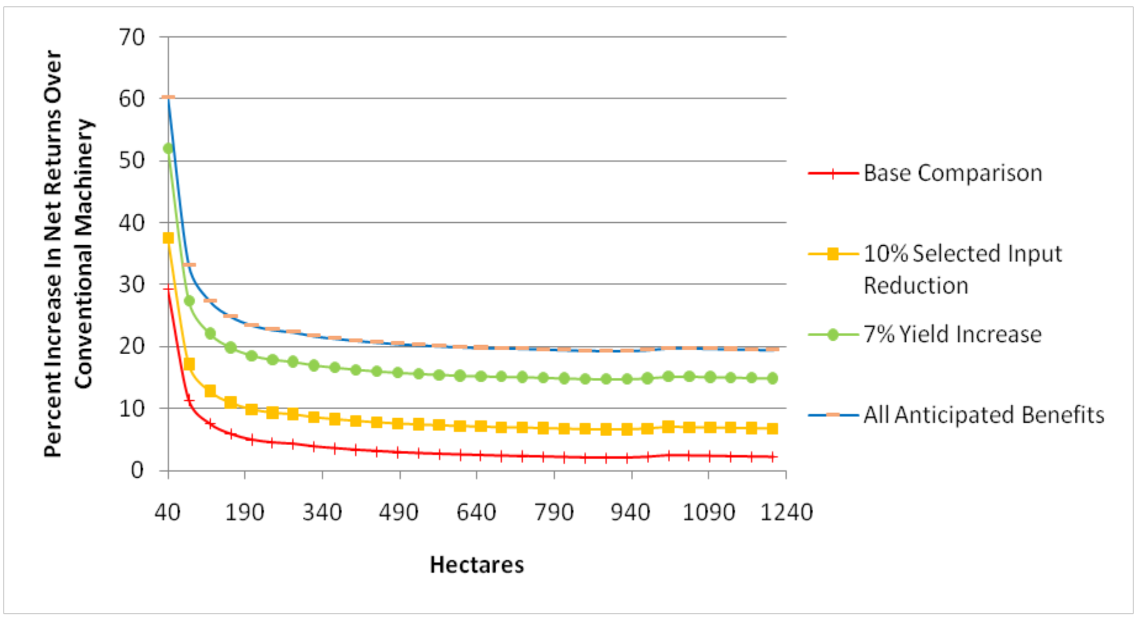
The inclusion of additional anticipated benefits from operating with autonomous machinery increased net returns above those with conventional machinery. Net returns increased by approximately 7%, 15%, and 19% for Scenarios 2-4, respectively. Therefore, if operating with autonomous machines provides such additional benefits, the break-even investment price for intelligent control increases dramatically to almost U.S.$320,000. Consequently, it is important to first understand what additional benefits and to what magnitude they will occur because they will have a substantial impact of what manufacturers could charge for and invest in the development autonomous machinery.

In addition, all scenarios incorporating additional benefits increased the minimum and maximum net returns and illustrated the potential for reducing yield risk as represented by a decrease in the coefficient of variation when compared to operating with conventional machinery. This again illustrated the importance of understanding the potential for additional benefits because it could possibly lead to interesting implications such as risk reduction.

Sensitivity Analysis on Farm Size

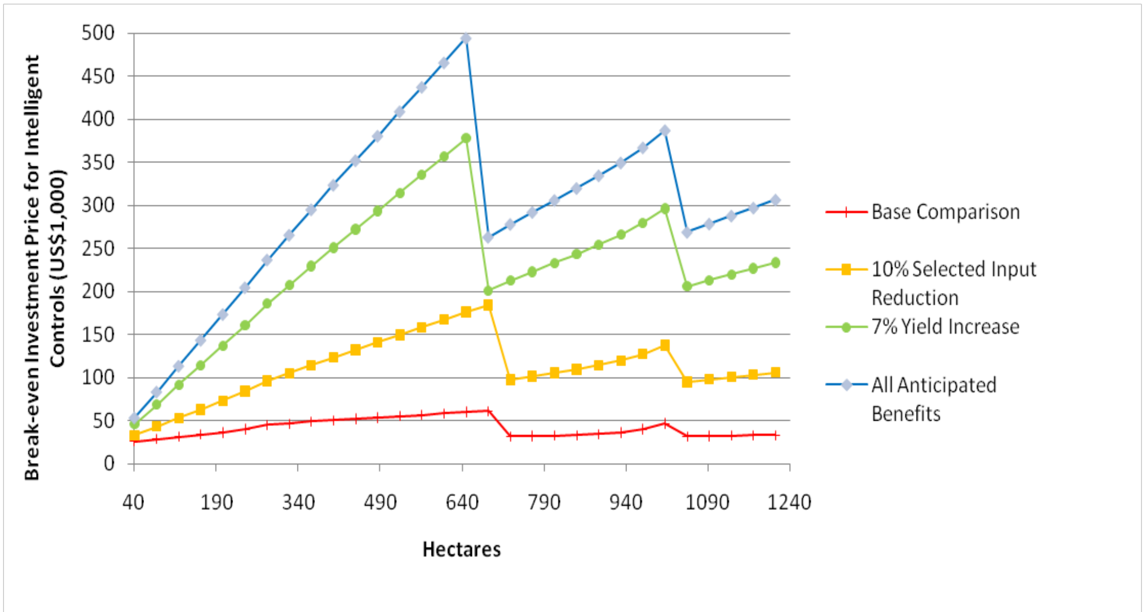
Sensitivity analyses were conducted to determine the effect farm size had on the increase in net returns above operating with conventional machinery, and the break-even investment price for intelligent, autonomous controls under the four scenarios examined in this study. Farm size had little impact on net returns over operating with conventional machinery for each scenario (Figure 1). The average increase in net returns across field size was 4%, 9%, 18%, and 22% for Scenarios 1-4, respectively. The percent increase in net returns did increase dramatically for smaller farm sizes under each scenario. This might be a function of excluding ownership of used machinery in the conventional choice set. Nonetheless, the results do provide evidence of the potential for greater profitability by operating autonomous machinery on smaller farms due to the ability of smaller farms to capture economies of size with autonomous machinery.

Figure 1. The percent increase in net returns above operating with conventional machinery based on farm size for the four scenarios examined.



The impact farm size had on the break-even investment price for intelligent, autonomous controls was interesting. The breaks illustrated in Figure 2 represent when an additional autonomous tractor was required to complete the agricultural tasks and represented the integral nature of machinery acquisition. Under Scenario 1 (base comparison) and Scenario 2 (10% selected input reduction), the number of autonomous tractors required goes from one to two when farm size was 689 ha and from two to three at 1043 ha. Under Scenario 3 (7% yield increase) and Scenario 4 (all anticipated benefits), the additional autonomous tractors occurred at 667 and 1021 ha, respectively. Across farm sizes examined, the break-even investment prices for intelligent, autonomous controls averaged U.S.$41,200, U.S.$110,490, U.S.$225,027, and U.S.$292,272 for each scenario, respectively. In addition, the maximum break-even investment price for intelligent, autonomous controls across farm sizes for each scenario were U.S.$61,017, U.S.$184,313, U.S.$378,088, and U.S.$494,194, respectively. Therefore, farm size must be considered when manufacturers determine how much they will be investing in intelligent, autonomous controls.

Figure 2. The break-even investment price for intelligent, autonomous controls based on farm size for the four scenarios examined.



Conclusion

The replacement of human operators in agricultural production with advanced technology can lead to changes in the entire structure of agriculture and impact society at a multitude of levels. However, if advanced technologies such as autonomous machinery are not profitable for producers, their impacts will never be realized as these technologies will not be adopted. Therefore, a multifaceted whole farm planning model was developed to compare conventional and autonomous machinery options for a grain crop operation. A mixed integer mathematical programming formulation was developed that incorporated three optimization models: machinery selection, resource allocation, and sequencing. The model determined the optimal conventional machinery complement necessary to perform agricultural tasks common for the farm. In addition, the model determined the optimal number of autonomous machines to perform the same agricultural tasks. Given the case study, autonomous machinery was more profitable than conventional machinery for all scenarios investigated. The most costly investment in autonomous machinery is intelligent controls. Therefore, the break-even investment price for intelligent, autonomous controls was determined. If no quantitative benefits were incorporated into the model, the break-even investment price for intelligent, autonomous controls was U.S.$33,327 for the case study. However, when incorporating additional benefits such as selected input cost savings and increased yields, the break-even investment price for intelligent, autonomous controls increased dramatically (up to U.S.$319,864 for an 850 ha farm). There was also evidence to suggest that autonomous machinery could reduce yield risks associated with grain crop production. In addition, sensitivity analyses were conducted to determine the effect farm size had on the increase in net returns above operating with conventional machinery and the break-even investment price for intelligent, autonomous controls. It was concluded that farm size influences the break-even investment price for autonomous controls, and must be considered by researchers and manufacturers.

Given that autonomous field machinery can have a profound impact on the structure of agriculture, a host of research opportunities exist. One apparent area of research concerns the impact on labor markets. By removing operators from agricultural field machinery, opportunities exist to study off-farm income and the impact this will have on rural economic development. Finally, there are numerous managerial concerns to address for the successful implementation of autonomous machinery.

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