The economics of US row crop production with large-scale autonomous machines

by Strine, J., Fiechter, C. and Lowenberg-DeBoer, J.

Copyright, publisher and additional information: Publishers' version distributed under the terms of the Creative Commons Attribution License

DOI link to the version of record on the publisher's site

Strine, J., Fiechter, C. and Lowenberg-DeBoer, J. (2025) 'The Economics of US Row Crop Production with Large-Scale Autonomous Machines', *Smart Agricultural Technology,* 12, article number 101599.

Smart Agricultural Technology 12 (2025) 101599

Contents lists available at ScienceDirect

Smart Agricultural Technology

journal homepage: www.journals.elsevier.com/smart-agricultural-technology

The economics of US row crop production with large-scale autonomous machines ☆

Joshua Strine [a], Chad Fiechter [a,*], James Lowenberg-DeBoer [b]

[a] Department of Agricultural Economics, Purdue University, West Lafayette, Krannert Bldg, 403 Mitch Daniels Blvd, West Lafayette, IN 47907, United States of America
[b] Harper Adams University, Newport, Shropshire, TF10 8NB, UK

ARTICLE INFO

Keywords:
Economic feasibility
Autonomous machine
Farm management
Linear program
Maize
Soybean

ABSTRACT

Labor challenges are underpinning large multinational farm machine manufacturers' development of autonomy solutions for their large-scale machine offerings. This study simulates a linear optimization model to examine the economics of large-scale autonomous machines for a rotational maize and soybean farm in the Midwest US. Results support the hypothesis that autonomous machines can be economically viable for farms facing severe labor shortages. However, under current technology and pricing structures, conventional mechanization remains the most profitable option for farms with reliable labor. Critical factors shaping the competitiveness of autonomy include subscription fees, field efficiency, and human supervision requirements. As these factors evolve, farm expansion is likely to emerge as an early pathway where large-scale autonomous machines deliver economic advantages.

1. Introduction

Robots and automation will play an important role in the future of production agriculture, reducing soil compaction, chemical pest control, and the economic challenge of small, irregular-shaped fields [18]. However, the potential to maximize farm labor productivity seems to be driving innovation related to large-scale autonomous farm machines from large multinational machine manufacturers (i.e. [14,29,26]). Previous research shows that the economics of autonomous machinery depend on the cropping system, field size, field shape, machinery size, machinery cost, and human supervision requirements [1,35,45]. This study examines the economics of large-scale autonomous machines for a rotational maize and soybean farm in the Midwest US.

This study applies linear programming, a standard arable farm planning and optimization tool (see [4,12]), to evaluate how large-scale autonomous machines affect farm financial returns. Recent studies have used this method to analyze the economics of autonomous machinery in various contexts [2,1,34,35,37], but it has not yet been applied to large-scale autonomous farm machines. Our model parameters reflect a rotational maize–soybean farm in Indiana, a state with large, rectangular fields and high levels of mechanization. Because these conditions are typical of much of the Midwest US and comparable to other agricultural production regions globally, we expect our findings to be relevant for farmers and machinery manufacturers beyond our specific setting.

Much of the existing literature examines small robots performing field operations such as seeding, weeding, or harvesting. When deployed collectively, these are often described as robot swarms. Engineers emphasize their appeal: multiple small machines can reduce soil compaction, lower the risk of total machinery failure, and enhance safety compared to relying on a few large machines [9,18]. However, in the Midwest US, where large, regularly shaped fields dominate, farmers typically use high-capacity tractors, combines, and sprayers to exploit economies of scale [19]. In this study, we define large-scale machines as those of at least 74 kW (100 hp).

Economic modeling in Switzerland, the US, the UK, Greece, and Brazil demonstrates that robot swarms can compete with conventional machinery by reducing labor requirements and total machinery investment [3,25,35,45,49]. These studies suggest that autonomy alters economies of size, allowing small and medium-sized farms to achieve production costs historically limited to large farms. However, regional regulations aimed at minimizing the risk associated with autonomous farm machine failure or malfunction, particularly in geographies with dense populations, reduce some of the economic benefits [8,44]. Additionally, as the frequency and complexity of human supervision of autonomous farm machines increases, the economic benefits are re-

☆ **Funding:** This research did not receive any specific grant from funding agencies in the public commercial or not-for-profit sectors.

* Corresponding author.
E-mail addresses: jstrine@purdue.edu (J. Strine), cfiechte@purdue.edu (C. Fiechter), JLowenberg-DeBoer@harper-adams.ac.uk (J. Lowenberg-DeBoer).

https://doi.org/10.1016/j.atech.2025.101599
Received 17 April 2025; Received in revised form 3 November 2025; Accepted 4 November 2025

Available online 7 November 2025
2772-3755/© 2025 The Author(s). Published by Elsevier B.V. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

duced [37,38], particularly in the case of US maize and soybean production [44]. However, the concept of swarm robotics may solve challenges related to irregularly shaped fields [2], integrated crop production strategies, like strip and mixed cropping [1], and herbicide-resistant weeds [54].

Entrepreneurs have also found the concept of swarm robotics attractive. Most of the roughly 350 startup companies worldwide developing crop robots focus on relatively small machines [48]. All of the robots in the Future Farming crop robot catalog are smaller machines [24]. In contrast, multinational farm machine manufacturers are introducing autonomy primarily for large-scale farm machines [6,14,26,29].

Although autonomy may change economies of size for farms, it is unlikely to make mechanization completely size-neutral. The hardware and software cost of current autonomy technology is very similar regardless of machine size. Consequently, the up-front autonomy cost per unit area of field operation is lower for large-scale machines, especially in areas where fields are large and roughly rectangular. Thus, some economies of machine size continue. There is growing evidence of economies of field size for autonomy [2,46]. Evidence suggests that the time required to move robots from field to field and robot set-up/take-down time favors farmers with large fields because movement, set-up, and take-down are minimized with large fields.

Other factors that affect the machine size decision include safety and insurability. So far, safety concerns have not been a motivating factor for sizing autonomous farm machines in North America. While no country allows autonomous farm machines on public roads, governments in most regions with large-scale farming and sparsely populated rural areas have not been concerned about the safety of autonomous machines operating within farm fields, regardless of size. So far, liability and property insurance for autonomous machines are not contingent on machine size.

Another factor impacting the economic situation of autonomous farm machines is the various commercialization approaches. Many European crop robot companies maintain the traditional farm machine purchase model, which involves a one-time payment at purchase (which may or may not be financed), after which farmers can use the machine as they like. Some companies favor offering "farming-as-a-service" options for hiring autonomous machines (e.g. [16]). Farming-as-a-service assumes that, in a time of rapid technological change, farmers will be reluctant to invest in machines that may be quickly obsolete. Some North American-based farm machine manufacturers prefer a subscription model that involves an up-front purchase price and per unit area payments for use [21]. The subscription approach may reduce the up-front expenditure needed to acquire a given technology but entails continuing payments. It may also commit the manufacturer more fully to upgrading the technology as innovation is commercialized. The commercialization approach is important to contextualize financial returns. For example, Lowenberg-DeBoer et al. [35] and Vahdanjoo et al. [50] show that swarm robotics could reduce the overall farm investment in machines, but this finding is contingent on a one-time purchase business model. Economic feasibility may be quite different if access to autonomy entails a per-unit-area subscription or a farming-as-a-service hiring fee.

Farmers and the farm machine suppliers are increasingly being faced with decisions concerning machine autonomy (e.g., purchase, lease, or hire autonomous machines, how to structure farm businesses, and whether to install infrastructure with eventual conversion to autonomy in mind). However, the research on the economics of large-scale autonomous farm machines is limited. In one of the few publicly available studies of large-scale autonomy in crop production, the Herron [28] thesis shows that small-scale farm machinery platforms have lower costs than large-scale autonomy in grain production. To continue closing that research gap, the objective of this study is to compare the economics of a rotational maize and soybean farm using large-scale conventional farm machines and large-scale autonomous farm machines in the Midwest US. The hypothesis is that large-scale autonomous machines are a viable economic option for farms that face severe labor availability challenges.

2. Materials and methods

This study uses a farm optimization linear program to examine the economic returns of large-scale autonomous farm machines. The model includes parameters for the amount of human supervision, fixed up-front autonomy hardware cost, autonomy subscription fee per operation per field unit, and hired labor rates. Farm optimization or planning via linear programming is common practice [4] and has been previously used to examine the economics of small to large-scale autonomous farm machines for cereal production in the UK [35]. However, our objective is to compare the economics of a rotational maize and soybean production system using large-scale conventional or autonomous farm machines on a Midwest US farm. As a result of this aim, we fix several farm management dimensions in accordance with our farm setting, and then simulate various farm scenarios to identify the differences between farms operating large-scale conventional and autonomous farm machines.

We adapt the Hands Free Hectare-Linear Program (HFH-LP) from Lowenberg-DeBoer et al. [35] to model a typical rotational maize and soybean farm in Indiana, United States (*for more information on Hands Free Hectare see* [23]). Choosing a specific region is necessary to parameterize the model. By choosing Indiana, the simulated farm is representative of farms in a larger geographic region that share crop production characteristics. Within the US, the United States Department of Agriculture (USDA) considers Indiana to be part of the Heartland production region along with Illinois, Iowa, and parts of Ohio, Kentucky, Missouri, Nebraska, South Dakota, and Minnesota. This region is synonymous with rotational maize and soybean production, responsible for 90% of US maize and 80% of US soybeans produced [5,13]. The farms of this region are typically considered large and productive [30]. The landscape is sparsely populated and contains large, roughly rectangular fields.

The model is mathematically expressed as:

$$\mathrm{GM} = \max_{X_j} \sum_{j=1}^{n} c_j X_j, \tag{1}$$

subject to

$$\sum_{j=1}^{n} a_{ij} X_j \le b_i \quad \text{for} \quad i = 1 \dots m \tag{2}$$

and

$$X_j \ge O \quad \text{for} \quad j = 1 \dots n, \tag{3}$$

where GM is the gross margin (returns over variable costs), X_j is the level of the jth production process or activity, $c_j =$ is the per unit return (gross margin) to fixed resources (b_i's) for the jth activity, $a_{ij} =$ is the amount of the ith resource, $b_i =$ is the amount of the ith resource available.

Our aim is to simulate financial returns of autonomy, and as a result, we chose to report returns to owner labor, land, management, and risk taking, or ROLLMRT. ROLLMRT is calculated by ROLLMRT = GM − FC, where GM is the maximized gross margin from (1) and FC is the fixed costs. Consistent with economic theory, the optimal solution only accounts for variable costs. Fixed costs are subtracted after the maximized solution is identified. Included in the fixed costs are the property repair, facilities repair, fixed utilities, building depreciation, insurance, and interest. ROLLMRT does not take into account the opportunity cost of owned land or the environmental and social costs reflected in the Full-cost Accounting methodology of the Food and Agriculture Organization of the United Nations (FAO). Previous studies on economic returns to autonomy have included an opportunity cost of land (i.e. [2,1,35,37]). We choose to calculate ROLLMRT because some farm businesses in the Midwest US consider land value appreciation to be an important source of financial return. Additionally, for many farming families (regardless of legal structure), family members are compensated out of earnings, not by wages. Hence, ROLLMRT accommodates a wide range of farm business strategies. With respect to environmental and social costs, our analysis is a preliminary step, and as a result, these concepts are beyond the scope. However, future studies could include Full-cost Accounting, like the analysis of autonomous electric tractors in Sweden [31].

Our model features two choice variables: hired labor and the amount of land allocated into maize and soybean production activities. In contrast, HFH-LP selects the set of machines, the mix of crops, and the amount of hired labor that maximizes (1) given a set of constraints. In our model, the set of machines is fixed, either large-scale conventional or autonomous, and the farm follows a crop rotation, allocating 50% of the land to maize and 50% to soybeans. Despite these differences, our model adopts a similar set of constraints as described in Lowenberg-DeBoer et al. [35]. Specifically, these constraints include limiting the land used for production to a parameterized farm size and allocating the parameterized owner's daily labor endowment in addition to hiring labor.

Given the constraints of the model, the solution to (1) is the allocation of operator labor, hired labor, and selected maize and soybean production activities that generate the maximum ROLLMRT. Potential solutions allocate farm resources to crop activities that vary by the timing of planting and harvesting. For example, the activity for maize planted in April and harvested in October has the highest level of production. However, depending on the amount of time a field is suitable for operation and the capacity of the farm's machines, the ROLLMRT maximizing solution may not include all land planted within this optimal activity. One alternative X_j could be maize planted and harvested at optimal times, but soybeans harvested later than optimal. The plausible range of plant and harvest date combinations is considered for both maize and soybean. These various production activities (X_j's) have different per-unit returns (c_j's).

The model has two key simplifying assumptions. First, the selected maize and soybean rotation is repeated indefinitely, or "steady state". This assumption holds for many farm operations in Indiana that plan to produce a maize/soybean rotation into the foreseeable future. The second assumption relates to the time step for the crop production activities. In a manner similar to previous studies, we adopt a monthly time step (i.e. [22,35,37]). The rotational production of maize and soybeans in Indiana is seasonal, with planting occurring in April, May, and June and harvesting taking place in September, October, and November. As a result, our activities are a combination of planting and harvesting months. For example, the production activity set for soybeans includes soybeans planted in April and harvested in September and soybeans planted in April and harvested in November.

Table 1 reports the values of the majority of our model parameters. However, the entire model is provided in the supplemental materials. The selection of maize and soybean production activities is influenced by three important parameters: good field days, maize and soybean yields, and maize and soybean prices. Production activities are limited by an estimate of the number of days during a specified time period (for this study, monthly) when the field conditions would be suitable for production activities. The USDA's National Agricultural Statistics Service (NASS) reports this metric as *good field days*. We collected estimated good field days from USDA NASS and computed the five-year average for Indiana. Additionally, USDA NASS reports average yields and prices received for maize and soybeans in Indiana. We collected these statistics and computed the five-year average for our price and yield parameters.

The production capacity of farm machinery is an important constraint for solutions to (1). For this study, we assume that large-scale conventional farm machinery can be fitted with hardware (e.g., sensors and cameras) and enabled with a subscription-based service to operate autonomously. Hence, the same set of farm machinery could be operated conventionally or autonomously. Table 2 reports the values of parameters related to our set of large-scale conventional and autonomous farm machines. We adapt the machine list of Ward et al. [52] to represent a typical Indiana maize and soybean farm. There are four powered large-scale farm machines for field operations: two 225 kW tractors capable of operating all implements, one 335 kW combine harvester, and one self-propelled sprayer. Under the autonomy scenario, the combine harvester and tractor operating the chaser bin are assumed to operate autonomously during harvest. These assumptions are based on the autonomy solutions provided by several large multinational farm equipment manufacturers (e.g. [26,29]).

Initial machinery costs are included in fixed costs, but as long as machines have similar field capacity, our results are not sensitive to the choice of machines. We use initial machinery costs for new machines produced by Deere & Company due to simplicity. Deere & Company's website includes a tool to generate the Manufacturer Suggested Retail Price (MSRP) for selected machines. Although MSRP likely does not reflect the actual price paid by farm customers, this feature simplifies our data collection. Our modeling conventions allow the interpretation of results to be applicable to a broader set of machine choices for two reasons. First, although the initial cost of machines is used to calculate farm fixed costs, the optimized set of activities is not affected by assuming a more or less costly set of machines. As a result, a similar set of machines with the same field capacity that are second-hand or purchased from another manufacturer will not change the reported effects of large-scale autonomous farm machines. Second, we intentionally report ROLLMRT per hectare relative to a baseline farm with conventional mechanization. This choice emphasizes that the differences in ROLLMRT are associated with changes in our parameters pertaining to large-scale autonomous farm machines.

We establish the *Baseline* farm's initial 2,610-hectare size using the solution to (1) and the assumed production system and machine set. Subsequently, we solve (1) without a constraint for farm size. The machine set of Table 2 could potentially operate 3,262 hectares. However, given weather uncertainty, we assume that most Midwest US farms have machine capacity 25% greater than required for the farmland they operate, and as a result, set the *Baseline* farm size at 2,610 hectares.

2.1. Simulation parameters

We specify seven key autonomy-related parameters that define the scenarios under which a ROLLMRT-maximizing farm manager operates. These parameters are not regionally specific but pertain to autonomous machines in a broader farm management context. We are interested in the effect of autonomy on ROLLMRT, and as a result, simulate ROLLMRT for 72,026 alternative Midwest US farm management scenarios. Each scenario is a combination of specific values for these seven parameters. The parameters and their potential values are reported in Table 3 and are described as follows:

- *Autonomous Intervention Time:* We assume that an autonomous machine will demand some amount of human intervention time beyond the normal logistics or repair of conventional machines. These interventions could be as small as bypassing an alert on a mobile phone or as intensive as traveling to the machine and helping it navigate an obstacle. We suggest that this intervention time could vary, on average, from six minutes of every hour to 54 minutes of every hour, in 6-minute increments.

  Maritan et al.'s [37] HFH-LP model assumes that there is constant or full-time intervention/supervision. The lower the autonomous intervention time, the more advantageous autonomy becomes. In Lowenberg-DeBoer et al.'s [35] model, the farm operator spends 10% of the available time intervening in autonomous farm machines.
- *Autonomous Efficiency:* Anecdotes suggest that the current large-scale autonomous farm machines are not as efficient at field tasks

Table 1
Variable List.

Variable	Level	Source
Field size	54 hectares	Ward et al. [52]
Distance between fields	2.01 kilometer	Ward et al. [52]
Initial cash	0	
Loan interest	5.84%	5 yr average Federal Reserve Bank of Chicago [41]
Savings interest	4.25%	high yield savings accounts
Corn yield	4.79 t per hectare	5 yr average USDA NASS [42]
Soybean yield	1.57 t per hectare	5 yr average USDA NASS [42]
Corn price	$202.75 per t	5 yr average USDA NASS [42]
Soybean price	$444.60 per t	5 yr average USDA NASS [42]
Good Field Work Days		5 yr average USDA NASS [42]
Jan	1.8	
Feb	0	
Mar	1.6	
Apr	13.1	
May	17.2	
Jun	21.42	
Jul	23.02	
Aug	25.58	
Sep	25.5	
Oct	23.94	
Nov	21.1	
Dec	0	
Production Costs		Purdue University Cost of Production University of Illinois Cost of Production
Corn Seed	$252.04 per hectare	Langemeier et al. [32]
Soybean Seed	$182.85 per hectare	Langemeier et al. [32]
Soybean Herbicide	$54.36 per hectare	Langemeier et al. [32]
Corn Herbicide	$86.49 per hectare	Langemeier et al. [32]
Dryer Fuel	$0.29 per bushel	Langemeier et al. [32]
Nitrogen Fertilizer	$259.46 per hectare	Langemeier et al. [32]
Corn Fertilizer	$222.39 per hectare	Langemeier et al. [32]
Soybean Fertilizer	$192.73 per hectare	Langemeier et al. [32]
Fertilizer Application	$1.28 per hectare	Langemeier et al. [32]
Fertilizer Application	$1.33 per hectare	Langemeier et al. [32]
Corn Insurance	$130.96 per hectare	Langemeier et al. [32]
Soybean Insurance	$106.25 per hectare	Langemeier et al. [32]
Repair (Facilities)	$18.53 per hectare	Paulson and Schnitkey [39]
Fixed Utilities	$21.00 per hectare	Paulson and Schnitkey [39]
Facilities Depreciation	$38.30 per hectare	Paulson and Schnitkey [39]
Misc	$32.13 per hectare	Paulson and Schnitkey [39]
Insurance	$88.96 per hectare	Paulson and Schnitkey [39]

Table 2
Machinery List.

Machine	Width (m)	Initial Cost (USD)	Source	Total Annual Cost (USD)
Planter (2)	12.2	531,948	deere.com	125,198
Disk Ripper	5.2	174,602	deere.com	33,611
Field Cultivator	13.7	142,053	deere.com	27,345
Sprayer	36.6	506,828	deere.com	97,564
Combine (335 kW)		818,273	deere.com	198,723
Soybean Header	15.2	202,972	deere.com	39,072
Corn Header	9.1	173,000	deere.com	33,303
Tractor (225 kW) (2)		1,093,814	deere.com	218,763
Transport Lorry		191,900	tractorhouse.com	46,056
Chaser Bin		101,900	tractorhouse.com	19,616
Nitrogen Applicator	12.2	45,900	tractorhouse.com	8,836

Notes: Assumes a lifespan of 7 years for planters and combine, a lifespan of 10 years for all other machines, opportunity cost of capital at 5% annually, and straight-line depreciation.
The annual insurance cost, annual repair cost, and fuel/lubricants vary by machine type.
For more information, refer to the Supplementary Materials.

as if they were driven by a human. To capture this feature, we allow the efficiency of the autonomous machines to vary from 50% as efficient as human operation to 100%, in 10% intervals.

- *Autonomous Hardware Cost:* Within the model, we assume that there are costs related to the hardware components of autonomy. These costs are associated with each tractor, self-propelled sprayer, and combine harvester, or the "power units". There are four power units in our machine set. Inherent in this assumption is the fact that a conventional set of large-scale farm machines can be made to operate autonomously with this additional hardware. For example, we assume that the farmer pays an additional cost above the price of a conventional farm tractor to enable autonomy.

Table 3
Parameter List.

Parameter	Levels	Description
Autonomous Intervention Time	[10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90%]	of a machine hour
Autonomous Efficiency	[50%, 60%, 70%, 80%, 90%, 100%]	of field efficiency
Autonomous Hardware Cost	[$30,000, $40,000, $50,000, $60,000]	per power unit
Autonomous Subscription Fee	[$0, $2.47, $4.94, $7.41, $9.88, $12.36, $14.83, $17.30, $19.77, $22.24]	per operation per hectare
Hired Labor	[$19, $25, $30]	per hour
Machine hours	[12, 15, 18, 21]	per day
Availability of Labor	[0, 1]	

Table 4
Simulated return to operator labor, land, management, and risk taking (ROLLMRT) and farm size for eight scenarios.

Model	Labor	Int.	Auto	Mach	Autonomous Cost		Δ ROLLMRT	Farm
	hrs	Time	Eff.	Hrs	Hardware	Subscription	/ha	Size (ha)
Baseline	1,536	100%	–	12	–	–	–	2,610
Auto 1A	67	10%	100%	21	$30,000	$2.47	-$7.70	2,610
Auto 2A	131	10%	80%	18	$40,000	$7.41	-$63.41	2,610
Auto 1B	67	10%	100%	21	$30,000	–	+$15.02	2,610
Auto 2B	131	10%	80%	18	$40,000	–	+$4.68	2,610
No Available Labor								
Conv C	0	100%	–	12	–	–	-$1,631.20	1,084
Auto 1C	0	10%	100%	21	$30,000	$2.47	-$15.47	2,610
Auto 2C	0	10%	80%	18	$40,000	$7.41	-$81.60	2,610

Notes: The Autonomous Cost: Hardware are assessed per power unit (i.e. tractor, self-propelled sprayer, combine harvester). The Autonomous Cost: Subscription are assessed to each field operation per hectare. ROLLMRT is return to operator labor, land, management, and risk taking.
Δ ROLLMRT per hectare is compared against the *Baseline* scenario.

- *Autonomous Subscription Cost:* In addition to the up-front hardware costs, the new autonomy technology may be sold with a software-as-a-service framework. As such, the model includes a subscription fee associated with the use of the autonomy software. These costs are assessed for every hectare on which the power unit is used autonomously for each field operation. For example, a per-hectare fee would be associated with the tractor used in the planting operation, and an additional per-hectare fee would be associated with the same hectare during the fall tillage operation.
- *Hired labor costs:* Hired labor costs are motivating the discussion on the potential economic benefits of autonomous farm machines. Therefore, we have included a range of three alternative hourly wages for hired labor between $19 and $30 per hour. As hourly wages increase, the per-hectare cost of labor also increases, which raises the relative profitability of autonomy if prices are constant.
- *Machine hours per day:* A key benefit of autonomy highlighted by Shockley et al. [45], Lowenberg-DeBoer et al. [35], and Maritan et al. [37] is the ability of autonomous machines to operate more hours in a day than conventional machines. In production with conventional machines, machine operations are limited to daytime hours due to labor constraints. Rural US labor markets are constrained [53], and taken together with the documented safety concerns with long work hours in agriculture [20], we assume that a typical Indiana farm operates 12 machine hours per day. This assumption allows additional time, beyond the machine hours, to fuel and service the machines. However, an important caveat is that in the case of soybean harvesting—whether conventional or autonomous—machine hours per day are limited to 10 due to climatic limitations.
- *Availability of labor:* In addition to labor cost, there is concern related to labor availability. We model this parameter by removing the potential for hired labor with a binary variable.

Based upon the parameters and values described above, and for the benefit of the readers' understanding, the list below details an example scenario. Specifically, this is the scenario that the authors believe to be a likely short-term reality for large-scale autonomous farm machines.

- *Autonomous Intervention Time:* 10% or 6 minutes of each hour
- *Autonomous Efficiency:* 80% as efficient as human operation
- *Autonomous Hardware Cost:* $40,000 per power unit
- *Autonomous Subscription Fee:* $7.41 per hectare per field operation
- *Hired labor cost:* $30 per hour
- *Machine hours per day:* 18 hours per day
- *Availability of labor:* Yes - hired labor is available

Solutions to (1) are solved in Julia [11] using the JuMP 1.0 package [36] and GLPK package [51]. We generate solutions to 72,026 farm scenarios defined by varying the parameters above. The generated solutions are compared to the *Baseline* farm to examine the effects of large-scale autonomous farm machines on farm ROLLMRT.

3. Results

Table 4 reports the parameters, the simulated ROLLMRT, and the size of the farm for eight scenarios of interest. As mentioned previously, these scenarios are a subset of our total simulations (72,026) and are chosen to simplify and focus our discussion. The interested reader can find plots visualizing the ROLLMRT from all simulated scenarios in Appendix B of the supplemental materials. The top panel of Table 4 reports the effect of large-scale autonomous farm machines on farm ROLLMRT for a 2,610-hectare farm with unlimited access to hired labor. The bottom panel (No Available Labor) reports the effect for a 2,610-hectare farm *without* access to labor. The statistics reported in the column labeled *ROLLMRT* are relative to the *Baseline* scenario in the top panel.

Table 5

Simulated return to operator labor, land, management, and risk taking (ROLLMRT) and farm size for 12 scenarios.

Model	Labor hrs	Int. Time	Auto Eff.	Mach Hrs	Autonomous Cost: Hardware	Autonomous Cost: Subscription	Δ ROLLMRT /ha	Farm Size (ha)
2 Transport Trucks								
Conv D	1,536	100%	–	12	–	–	-$17.64	2,610
Auto 1D	286	10%	100%	21	$30,000	$2.47	-$3.68	2,610
Auto 2D	240	10%	80%	18	$40,000	$7.41	-$66.50	2,610
2 Transport Trucks, 2 Combines, and 2 Chaser Bins								
Conv E	1,601	100%	–	12	–	–	-$88.61	2,610
Auto 1E	286	10%	100%	21	$30,000	$2.47	-$87.33	2,610
Auto 2E	403	10%	80%	18	$40,000	$7.41	-$137.50	2610
81 Hectare Fields								
Conv F	1,522	100%	–	12	–	–	+$0.57	2,610
Auto 1F	65	10%	100%	21	$30,000	$2.47	-$7.53	2,610
Auto 2F	124	10%	80%	18	$40,000	$7.41	-$63.23	2,610
No Fall Tillage								
Conv H	1,199	100%	–	12	–	–	+$16.63	2,610
Auto 1H	63	10%	100%	21	$30,000	$2.47	+$7.55	2,610
Auto 2H	119	10%	80%	18	$40,000	$7.41	-$43.08	2,610

Notes: The Autonomous Cost: Hardware are assessed per power unit (i.e. tractor, self-propelled sprayer, combine harvester). The Autonomous Cost: Subscription Costs are assessed to each field operation per hectare. ROLLMRT is return to operator labor, land, management, and risk taking. Δ ROLLMRT per hectare is compared against the *Baseline* scenario in Table 4.

For example, the scenario labeled *Auto 2C* in the bottom panel generates $81.60 per hectare less ROLLMRT than the *Baseline* scenario in the top panel.

Additionally, we use three modeling conventions to report the results of Table 4. First, each scenario with hired labor is assumed to pay $30 per hour. Although we simulate labor rates of $19, $25, and $30, we believe the results using $30 per hour are more similar to the anecdotes driving the discussion of large-scale autonomous farm machines beneficially replacing farm labor in the Midwest US. Second, the scenarios with the prefix *Auto 1* represent the optimal scenario for large-scale autonomous farm machines. Third, the scenarios with the prefix *Auto 2* represent the authors' most likely short-term scenario for large-scale autonomous farm machines. The exact parameter assumptions for each scenario are presented in Table 4.

3.1. Autonomous production with available labor

The simulation results of the top panel of Table 4 suggest that Midwest US, rotational maize and soybean farms, with access to labor, are better off with large-scale conventional farm machines than large-scale autonomous farm machines. Under the optimal scenario for large-scale autonomous farm machines (*Auto 1A*), the farm hires only 67 hours of labor, and farm ROLLMRT decreases by $7 per hectare relative to the *Baseline*. Under the authors' most likely short-term scenario for large-scale autonomous farm machines (*Auto 2A*), the farm hires 131 hours of labor, and the farm ROLLMRT decreases by $63.41 per hectare. However, in the scenario where there are no subscription fees, the optimal autonomy scenario (*Auto 1B*) increases ROLLMRT by $15.02 per hectare, and the most likely autonomy scenario (*Auto 2B*) increases ROLLMRT by $4.68 per hectare. For a fuller contextualization of how the linear program allocates land, labor, and machinery to maximize the gross margins of the three scenarios and the costs associated with the model's constraints, interested readers can refer to Appendix C and D, respectively.

3.2. Autonomous production without available labor

The simulation results in the bottom panel of Table 4 (No Available Labor) suggest that farms without access to labor are better off adopting large-scale autonomous farm machines for maize and soybean production than being forced to fallow a portion of their crop land. The scenario labeled *Conv C* only differs from the *Baseline* scenario in the access to hired labor. The lack of hired labor decreases the amount of crop land operated (1,084 out of 2,610 hectares) and generates $1,631.20 less ROLLMRT per hectare. The significant decrease in ROLLMRT is largely due to the fact that fixed costs are unchanged despite operating less land. The scenario labeled *Auto 1C* represents the optimal large-scale autonomous farm machine scenario and generates $15.47 less ROLLMRT than the *Baseline* scenario. The scenario labeled *Auto 2C* represents the most likely short-term scenario for large-scale autonomous farm machines and generates $81.60 less ROLLMRT per hectare than the *Baseline*. When labor is not available, the autonomous scenarios are better off than the farmer operating 42% of the hectarage with conventional machines by $1,615.73 per hectare (optimal autonomous) and $1,549.60 per hectare (most likely autonomous).

4. Model sensitivity tests

In this section, we examine how modeling assumptions influence our results. We simulate the model for a conventional mechanization scenario, an optimal autonomy scenario, and a most likely short-term autonomy scenario for large-scale farm machines under six alternative assumption sets. First, we include additional harvest machines. Second, the field size is increased from 54 hectares to 81 hectares. Third, the distance between fields is increased from 2.01 kilometers (following Ward et al. [52]) to 4.83 kilometers. Fourth, we jointly increase the field size to 81 hectares and increase the distance between fields to 4.83 kilometers. Fifth, the tillage machine set is modified, and a fall tillage pass is removed. Sixth, we examine the potential of farm expansion.

The results for the first, second, and fifth sensitivity analysis are reported in Table 5, and the simulated ROLLMRT is reported as relative to the *Baseline* farm of Table 4. The second, third, and fourth alternative assumption sets all adjust the relative travel time between fields and yield consistent results. Therefore, we have included results and a discussion of the latter assumption sets in Appendix D. The results for farm expansion are reported in Table 6, and instead of ROLLMRT per hectare, we use whole farm ROLLMRT. We report whole farm ROLLMRT to capture

Table 6
Simulated return to operator labor, land, management, and risk taking (ROLLMRT) and farm size for seven scenarios.

Model	Labor hrs	Intervention Time	Autonomous Efficiency	Machine Work Hours	ROLLMRT	Farm Size (ha)
Farm Expansion						
Conv J	2,224	100%	–	12	$1,538,387.49	3,262
Auto 1J	253	10%	100%	21	$2,696,338.74	4,699
Auto 2J	178	10%	80%	18	$1,645,659.84	3,528
Auto 1K	0	10%	100%	21	$1,898,304.82	3,618
Farm Expansion with Scaled Machinery Fixed Cost						
Conv L	2,224	100%	–	12	$1,326,509.58	3,262
Auto 1L	253	10%	100%	21	$2,008,330.99	4,699
Auto 2L	178	10%	80%	18	$1,241,930.22	3,528

Notes: The Autonomous Cost: Hardware are assessed per power unit (i.e. tractor, self-propelled sprayer, combine harvester). The Autonomous Cost: Subscription are assessed to each field operation per hectare. ROLLMRT is return to operator labor, land, management, and risk taking.

the added financial returns to farming more hectares that may be obscured by ROLLMRT per hectare. This convention is necessary because the farm size in the analysis reported by Table 6 varies.

4.1. Additional machinery

The machinery set is described in Table 2, and as previously stated, we assume that the representative Midwest US farm has machines capable of 25% more capacity. However, there is potential that maize and soybean farmers in the Midwest US prioritize an even greater degree of machine capacity. In the presence of adequate labor, having additional machines increases overhead costs but allows the farm to produce more crops within optimal time windows and mitigate the effects of fewer good field days. We examine the role of binding machine constraints by adding additional machinery. We add harvest machinery because its capacity is binding in the initial models. First, we add an additional transport truck. The results in the first panel of Table 5 compare the ROLLMRT under three new scenarios.

When an additional transport truck is included in the model, the farm generates less ROLLMRT. The scenario with conventional machines (*Conv D*) decreases ROLLMRT by $17.64 per hectare relative to the *Baseline*. The optimal large-scale farm machine autonomy scenario (*Auto 1D*) and most likely short-term scenario for large-scale autonomous farm machines (*Auto 2D*) also decrease ROLLMRT relative to the *Baseline*. The additional transport truck allows for the reallocation of crop production into more optimal activities. As a result, all of the production is within the highest producing activity for the optimal autonomy scenario. The most likely autonomy scenario shifts all maize to the optimal activity and partially shifts soybeans to the optimal activity. Both autonomy scenarios require additional hired labor as the additional machinery shifts farming practices into months when the owner-operator is already constrained. Since the transport truck is not the only binding constraint in the conventional scenario, the scenario's production schedule did not change. However, the additional transport truck does increase fixed costs in the conventional scenario (*Conv D*), resulting in a ROLLMRT decrease.

Following the inclusion of the second transport truck, the next binding equipment constraints are the combine, tractor, and chaser bin. These three machines bind in the conventional and most likely autonomy scenarios. Since the optimized autonomy scenario allocates all crop production to the ideal activities, there are no longer binding machine constraints. To see how further expansion of machinery affects relative return, an additional combine and chaser bin are added to the previous machine set. The results are shown in the second panel of Table 5.

The inclusion of additional harvesting machinery shifts production allocation in the conventional scenario (*Conv E*) and the most likely short-term autonomy scenario (*Auto 2E*) to more optimal activities. However, additional costs associated with the additional machinery are greater than the benefits, and the resulting ROLLMRT is lower for each scenario. It is important to reiterate that while the returns over variable costs increase with the inclusion of additional machines, the returns over fixed costs are lower for each scenario compared to the *Baseline* with the initial machinery set. Therefore, the additional fixed machine cost outweighs the productivity gains from more efficient activity allocation.

4.2. Larger field size

The simulated farm's field size is assumed to be 54 hectares in the initial model, following the assumption of [52]. The field size assumption affects the ratios of labor and machinery hours spent during field operation as opposed to travel. With 54-hectare fields, a 2,610-hectare farm will consist of 48 fields. Therefore, machinery must be transported between fields 47 times, which we assume to be a completely manually operated process. Increasing the assumed field size requires fewer fields to aggregate to the 2,610 hectares. Thus, less machinery transport is required. Since machinery transport is a process that employs labor hours and machinery hours, adjusting the number of field transfers is expected to alter the farm's activity allocation. As a result, the relative ROLLMRT of the autonomous and conventional mechanized farms may be altered. We change this assumption and simulate three scenarios. The new results under the altered assumption sets are shown in the third panel of Table 5.

The relative return to large-scale autonomous farm machines is consistent with a 50% increase in field size. Under the conventional machinery set (*Conv F*), the simulated ROLLMRT is $0.57 per hectare greater than the *Baseline*. Additionally, the optimal scenario for large-scale autonomous farm machines (*Auto 1F*) and most likely short-term scenario (*Auto 2F*) have very similar ROLLMRT (less than $0.20 per hectare difference) as the corresponding scenarios reported in the top panel of Table 4. While the relative ROLLMRT is constant, all three scenarios employ fewer labor hours, shift crop production to higher-returning activities, and generate greater returns per hectare, as expected.

4.3. Elimination of fall tillage pass

Production practices are assumed to be the same across all hectares. Specifically, there are two tillage passes, two pesticide passes, one fertilizer pass unique to maize, one planting pass, and one harvest pass (combine harvester and tractor operating the chaser bin). Adjustments are made to the tillage assumptions to test the robustness of our results against alternative production plans. First, the fall tillage pass is removed from all production plans. Additionally, the field cultivator and disk ripper are removed from the machine set and replaced with a single disc tillage tool. The new tillage plan consists of a single conservation tillage pass with a disc tillage tool in the same month as planting.

By decreasing machine cost and field passes, the conventional machinery scenario generates $16.63 per hectare more ROLLMRT than the *Baseline*. The relative ROLLMRT of the optimal scenario for large-scale autonomous farm machines (*Auto 1H*) increases by $7.55 per hectare under the alternative set of tillage assumptions. In contrast, the relative returns of the most likely short-term scenario for large-scale autonomous farm machines (*Auto 2H*) decreased by $43.08 per hectare under the alternative set of tillage assumptions. All three scenarios employ less labor than the two-tillage pass scenarios. However, the relative adjustment from similar scenarios in Table 4 suggests that the reduced tillage passes are more beneficial for the most likely autonomous scenario (*Auto 2H*) due to the elevated autonomy subscription fee ($4.94 greater per hectare in *Auto 2H* than in *Auto 1H*).

Under this alternative assumption set, only the conventionally operated scenario (*Conv H*) has a reallocation of the cropping activities. This result is explained by the machinery limitations in the initial model. The *Baseline* has a binding tractor constraint during harvest and fall tillage. Removing the tillage pass relaxes the constraint and allows for the reallocation of crop production to more productive activities. The increased activity optimization and labor savings in *Conv H* outweighed the autonomy cost savings in *Auto 1H*, but are not enough to overcome the additional savings of *Auto 2H*.

4.4. Farm expansion

Table 6 reports the simulated whole farm ROLLMRT for seven scenarios where farm size is allowed to vary. We report whole farm ROLLMRT because these scenarios are of varying farm size, and whole farm ROLLMRT captures the potential fixed cost efficiency of farming more land. The results in the top panel suggest that large-scale autonomous machines may allow farms to expand profitability, a finding that is more pronounced as autonomous farm machines achieve greater performance. The scenario labeled *Conv J* differs from the assumptions of the *Baseline* by allowing the farm to expand to the maximum possible hectares given the capacity of the conventional machines. *Conv J* generates $1,538,387 of whole farm ROLLMRT. Relative to the *Baseline*, the activities are shifted away from optimal times to accommodate operating more land. Under the most favorable scenario for autonomy with hired labor (*Auto 1J*) and without hired labor (*Auto 1K*), the whole farm ROLLMRT increases by $1,157,951 and $354,917, respectively. Hence, there may be an incentive to pursue the adoption of large-scale autonomous machines when the farm has the potential to expand. Even in the most likely short-term scenario for large-scale autonomous farm machines, *Auto 2J*, the whole farm ROLLMRT is increased by $107,272, relative to the conventionally operated farm *Conv J*.

4.4.1. Scaled machinery fixed cost

The final alternative assumption set analyzes the effect of the relative ROLLMRT when the farm can expand, but the machinery fixed costs are increased to reflect a potential decrease in salvage value. In the top panel of Table 6, machinery and autonomy fixed costs are calculated by taking the difference between the upfront cost and the salvage value, divided over seven or ten years. Therefore, the annualized fixed machinery costs are the same in the 2,610-hectare farm of Table 4 and Table 5 or the expanded farm. This assumption does not take into account the additional use of the machine as a result of operating more land. However, additional use has been shown to decrease the market value or potential salvage value of farm machines [17], and as a result, the calculated relative ROLLMRT reported in the top panel of Table 6 are likely an upper bound with respect to fixed machinery costs.

We allow the annualized fixed cost of farm machinery to be directly related to the farm size, increasing the costs by the additional use. The alternative calculation implements a machinery fixed cost scaled by farm expansion. For example, if the farm size doubles, the machinery fixed cost doubles. The results for the three alternative scenarios are reported in the bottom panel of Table 6. The expanded farm operating conventional farm machines, *Conv L*, generates $1,326,510 whole farm ROLLMRT. This scenario results in $211,878 less than *Conv J*. However, the whole farm ROLLMRT in the favorable autonomy scenario (*Auto 1L*) increases by $496,640, relative to *Conv J* and $681,821, relative to *Conv L*. Hence, as mentioned above, there may be an incentive to pursue the adoption of large-scale autonomous machines when the farm has the potential to expand. This result is contingent on large-scale autonomous machines attaining a higher level of performance. The results of the most likely autonomy scenario suggest an $84,579 decrease in whole farm ROLLMRT, relative to *Conv L*.

The whole farm ROLLMRT reported in the scenarios of the top and bottom panels of Table 6 are likely upper and lower bounds for returns of large-scale autonomous farm machines under farm expansion. As mentioned in the motivation of the **Scaled Machinery Fixed Costs** section, the top panel of Table 6 likely omits costs related to machinery usage and could be considered an upper bound. Intuitively, all three scenarios in the bottom panel are lower than their corresponding scenarios in the top panel. However, the effect of autonomous capabilities on machine salvage value is unknown. Farm machinery updating may be influenced by the need to update technology to benefit an operator. If this motivation is reduced because the operator is no longer necessary for constant operation, salvage values may be greater. Hence, the results in the lower panel of Table 6 may be overstated. Given the unknowns, the realistic fixed cost of machinery likely falls somewhere between the assumptions of the scenarios reported in the top and bottom panels of Table 6.

5. Discussion

Our results suggest that highly mechanized farms with large, regularly shaped fields and simple traditional crop rotations will only benefit from adopting large-scale autonomous farm machines when they face severe labor availability challenges. Further, in a broad range of less extreme labor situations, the current economic returns to large-scale autonomous farm machines are not positive. However, this section will discuss the developments that would make large-scale autonomous farm machinery more economically viable in the Midwest US.

Changes in the procurement and subscription costs for large-scale autonomous machines will drive the degree to which farms with reliable labor will experience positive economic returns. In this analysis, autonomy costs are composed of the initial hardware and software costs and the per-hectare per-operation subscription fee. Estimating the cost of new technology is always difficult, but the $30,000 lower end of the autonomy initial investment per power unit range in this analysis is probably close to the cost of the components. The bare bones component retrofit cost for small machines is estimated at over $40,000 for one small tractor and one small combine [1]. Large machines would probably need more sensors and safety equipment than assumed for the smaller machines and, consequently, be somewhat more costly to retrofit. There is probably more flexibility in the per-hectare per-operation subscription fees. While common in consumer electronics and other industries, widespread use of subscription fees for farm machines is relatively new, and some companies use the absence of technology subscription fees as a marketing tool. This analysis shows that without a subscription fee, autonomy increases profitability, and even the lowest subscription fee level ($2.47 per hectare) pushes the return into negative territory. Based on our current assumptions, the level of subscription fee is a key driver of economic viability in our context.

Additionally, as the relative field efficiency of large-scale autonomous machines improves, the financial returns will improve. Robotic engineers have long hoped that autonomous machines would be able to achieve higher levels of efficiency closer to theoretical efficiency [18,50]. The hope for higher autonomous efficiency is based on optimizing machine speed, better path planning, no breaks or fatigue, and higher operation accuracy. Recently, Bahmutsky et al. [7] used a case study approach for evaluating the field and fuel efficiency of the *OMNiPOWER* autonomous platform for small grain production in Canada.

They find that relative field efficiency is dependent on field operation, but that the autonomous machinery performed similar to conventional counterparts. For our analysis, autonomous efficiency levels would have to exceed 100% to push autonomy profits into positive ranges for farmers with labor available.

Another key determinant of returns to large-scale autonomous farm machines is the time required for human supervision and intervention. The previous literature has made various assumptions about this parameter, from a lack of supervision in Shockley et al. [45], to 10% in Lowenberg-DeBoer et al. [35], to full supervision in Maritan et al. [37]. Our results suggest that farm returns are sensitive to this assumption. Specifically, in this analysis, all of the economic scenarios that come close to profitability assumed human intervention for 10% of autonomous field time. Higher levels of human supervision of robots favor conventional mechanization solutions. Currently, this discussion is driven by the assumed needs of the machines, but, as discussed in Maritan et al. [37], the emergence of regulation on human supervision requirements would reduce the potential economic gains.

Beyond financial returns, there are several reasons why farmers may choose to adopt large-scale autonomous farm machines. A farmer may choose to adopt large-scale autonomous farm machines to improve their quality of life. Our results suggest that a farm operator could potentially operate a 2,610-hectare farm with no additional labor under the most likely short-term scenario for large-scale autonomous farm machines for $213,006.87 (ROLLMRT for *Auto 2C* – $81.60 × 2,610 hectares). In cases where a farm operator owns a large proportion of their land and has minimal debt service, the choice to forgo labor may simplify their operations. An established farm operator may use large-scale autonomous farm machines to maximize their personal utility instead of maximizing farm returns. As discussed in Lowenberg-DeBoer [33], this result is similar to findings related to robotic milking machines. In some scenarios, adoption of milking robots is driven primarily by owner-operators who desire a more flexible schedule and a higher quality of life [10,15,27,47].

An alternative reason for large-scale autonomous farm machine adoption is the reduction in time devoted to managing labor, resulting in greater productivity of operator labor. For example, in an analysis of autonomous weeding in Bavaria, the use of robots shifts the labor burden away from hired workers to the farm operator and/or family labor [43]. Instead of short, intensive periods where crews come to the field for manual weeding, the supervision of the robot by the farm operator and family is done throughout the first half of the growing season. Depending on the farmer, this may or may not be a good thing. For some farmers, supervising the robot is just more work added to an already busy schedule. Other farmers may be glad to find a way to productively substitute family labor for hired labor. Reducing the HR burden of hiring may be one of the greatest benefits of autonomy.

This study has many limitations and consequently opens the door to a range of follow-up studies. This study uses multiple assumptions that have implications for the economics of large-scale autonomous machines that could be tested. We assume a 50/50 maize and soybean rotation, but the economic returns to large-scale autonomous machines may be related to a more profitable crop production system. For example, Al-Amin et al. [1] showed the economic potential for autonomous strip cropping. Specific studies should evaluate alternative crop geometries, like intercropping and patch cropping, or alternative crop mixes, like three or four-year rotations more similar to those in Europe. Further, future studies should examine the degree to which the profitability of large-scale autonomous machines is influenced by machine size. In this study, we focus on one set of machine sizes (building on Ward et al. [52]). However, as highlighted by the prevalence of previous studies on robot swarms, machine size is an important determinant of profitability. Future studies should relax our equipment size assumptions and allow for the optimal selection of machines.

Varying the assumptions of the macro-environment is also an important topic for future studies. This study assumes that the farms use conventional chemical weed control, but the combination of weed herbicide resistance and regulatory changes may motivate more use of targeted herbicides and mechanical weed control. Yu et al. [54] show that weed resistance levels directly impact the optimal weed management strategy with a mechanical weeding robot. As a result, future studies should examine how weed management needs change the profitability of large-scale autonomous farm machines.

As a last point, the assumptions about large-scale farm machinery values are inherently excluding the potential changes in salvage values. For example, previous studies show that usage is directly related to market values [17,40]. However, these results do not take into account the potential that farm machines are updated for the sake of technology upgrade or operator comfort. Autonomy may allow for machinery to retain market value despite higher use. Future studies should examine the degree to which autonomous large-scale farm machines will change the market for and salvage values of farm machinery.

There are two obvious extensions of the current analysis. First, we assume that the farm either operates conventional machines or autonomous machines. This assumption could be relaxed to examine which field operations would generate the greatest return under autonomous operation. For example, some Midwest US farms simultaneously operate multiple machines for tillage. If those machines are operating in the same field, one may be operated by a human who is also supervising an autonomous machine in a leader-follower scenario. Second, this analysis has focused on large-scale autonomous farm machines, but this assumption could be relaxed to examine the economic potential or viability of small- or medium-scale farm machines for our specific setting, Midwest US maize and soybean production.

6. Conclusion

This study uses a farm management optimization model to examine the effect of large-scale autonomous farm machines for Midwest US maize and soybean production on returns to operator labor, land, management, and risk-taking. Using all combinations of seven key parameters, we compute optimal profit-maximizing solutions for 72,026 scenarios. These simulations result in three important findings. First, when a farm has access to labor, conventional large-scale farm machinery generates the greatest return to operator labor, land, management, and risk-taking. Even when large-scale autonomous farm machines are assumed to achieve optimal performance under the lowest parameterized costs (both hardware and subscription fees), we show that a farm would need to have labor expenses of greater than $44 per hour for a return-maximizing farm manager to adopt the machines. Second, if a farm does not have access to labor at any price, they are better off adopting large-scale autonomous machines than being forced to fallow a portion of their land. Without access to large-scale autonomous machines and labor, we show that a 2,610-hectare farmer can only operate roughly 40% of their land. Third, a farm could potentially expand its operations with the same set of large-scale autonomous machines and labor. However, the large-scale autonomous machines will need to achieve near-optimal performance for this expansion to generate greater financial returns.

The results of this study have implications for farm managers and machine manufacturers. First, farm managers will want to carefully evaluate their labor situation and the implied cost of adopting large-scale autonomous farm machines. Specifically, farm managers should understand the relative efficiency of large-scale autonomous farm machines and the amount of supervision or intervention time needed to effectively experience the benefits within their production system. Second, the diversity of crop production systems adds complexity to marketing and pricing autonomous solutions for machine manufacturers. Integrating additional costs of autonomy into commodity production will be limited by the regional costs of replaced labor.

CRediT authorship contribution statement

Joshua Strine: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. **Chad Fiechter:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **James Lowenberg-DeBoer:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used Writefull in order to supplement editing. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.atech.2025.101599.

Data availability

Data and code will be provided in supplementary materials.

References

[1] A.K.M.A. Al-Amin, J. Lowenberg-DeBoer, B.J. Erickson, J.T. Evans, M.R. Langemeier, K. Franklin, K. Behrendt, Economics of strip cropping with autonomous machines, Agron. J. 116 (2) (2024) 572–589, https://doi.org/10.1002/agj2.21536.

[2] A.K.M.A. Al-Amin, J. Lowenberg-DeBoer, K. Franklin, K. Behrendt, Economics of field size and shape for autonomous crop machines, Precis. Agric. 24 (5) (2023) 1738–1765, https://doi.org/10.1007/s11119-023-10016-w.

[3] D. Albiero, A.P. Garcia, C.K. Umezu, R. Leme de Paulo, Swarm robots in mechanized agricultural operations: a review about challenges for research, Comput. Electron. Agric. 193 (2022) 106608, https://doi.org/10.1016/j.compag.2021.106608.

[4] J.E. Annetts, E. Audsley, Multiple objective linear programming for environmental farm planning, J. Oper. Res. Soc. 53 (9) (2002) 933–943, https://doi.org/10.1057/palgrave.jors.2601404.

[5] A.M. Ates, Corn and other feed grains – feed grains sector at a glance, https://www.ers.usda.gov/topics/crops/corn-and-other-feed-grains/feed-grains-sector-at-a-glance, 2025.

[6] Autonomous Solutions Inc. (ASI), Autonomous Solutions Inc. and CNH Industrial unveil concept autonomous tractor, https://asirobots.com/autonomous-solutions-inc-and-cnh-industrial-unveil-concept-autonomous-tractor/, 2023. (Accessed 27 March 2025).

[7] S. Bahmutsky, A. Singh, T.A. Burgers, R. Maki, Autonomous agricultural equipment evaluation for broad-acre crop production, J. ASABE 68 (3) (2025) 437–449, https://doi.org/10.13031/ja.16118.

[8] S. Basu, A. Omotubora, M. Beeson, C. Fox, Legal framework for small autonomous agricultural robots, AI Soc. 35 (1) (2020) 113–134, https://doi.org/10.1007/s00146-018-0846-4.

[9] A. Bechar, C. Vigneault, Agricultural robots for field operations: concepts and components, Biosyst. Eng. 149 (2016) 94–111, https://doi.org/10.1016/j.biosystemseng.2016.06.014.

[10] K. Bergman, E. Rabinowicz, Adoption of the automatic milking system by Swedish milk producers, AgriFoods Economic Center Working Paper 7 (2013) 21.

[11] J. Bezanson, A. Edelman, S. Karpinski, V.B. Shah, Julia: a fresh approach to numerical computing, SIAM Rev. 59 (1) (2017) 65–98, https://doi.org/10.1137/141000671.

[12] J.N. Boles, Linear programming and farm management analysis, Am. J. Agric. Econ. 37 (1) (1955) 1–24, https://doi.org/10.2307/1234071.

[13] M. Bukowski, B. Swearingen, Soybeans and oil crops – oil crops sector at a glance, https://www.ers.usda.gov/topics/crops/soybeans-and-oil-crops/oil-crops-sector-at-a-glance, 2025.

[14] Case New Holland (CNH), New Holland and Bluewhite to bolster autonomous capabilities and offering with strategic partnership, https://media.cnh.com/north-america/new-holland-agriculture/new-holland-and-bluewhite-to-bolster-autonomous-capabilities-and-offering-with-strategic-partnership/s/8dcb485b-2ae1-46c9-8a83-fe2835943a87, 2024. (Accessed 27 March 2025).

[15] Á. Castro, J.M. Pereira, C. Amiama, J. Bueno, Typologies of dairy farms with automatic milking system in northwest Spain and farmers' satisfaction, Ital. J. Anim. Sci. 14 (2) (2015) 3559, https://doi.org/10.4081/ijas.2015.3559.

[16] H. Claver, Trimble invests in autonomous farming-as-a-service company Sabanto, Future Farming (2022), https://www.futurefarming.com/tech-in-focus/autonomous-semi-autosteering-systems/trimble-invests-in-autonomous-farming-as-a-service-company-sabanto/. (Accessed 27 March 2025).

[17] T.L. Cross, G.M. Perry, Depreciation patterns for agricultural machinery, Am. J. Agric. Econ. 77 (1) (1995) 194–204, https://doi.org/10.2307/1243901.

[18] T. Duckett, S. Pearson, S. Blackmore, B. Grieve, W.-H. Chen, G. Cielniak, J. Cleaversmith, J. Dai, S. Davis, C. Fox, et al., Agricultural robotics: the future of robotic agriculture, arXiv preprint, arXiv:1806.06762, 2018.

[19] M. Duffy, Economies of size in production agriculture, J. Hunger Environ. Nutr. 4 (3–4) (2009) 375–392, https://doi.org/10.1080/19320240903321292.

[20] K. Elliott, J.M. Lincoln, M.A. Flynn, J.L. Levin, M. Smidt, J. Dzugan, A.K. Ramos, Working hours, sleep, and fatigue in the agriculture, forestry, and fishing sector: a scoping review, Am. J. Ind. Med. 65 (11) (2022) 898–912, https://doi.org/10.1002/ajim.23418.

[21] B. Flowers, J. White, Focus: deere tapping into apple-like tech model to drive revenue, Reuters, https://www.reuters.com/business/autos-transportation/deere-tapping-into-apple-like-tech-model-drive-revenue-2022-05-26/, 2022. (Accessed 27 March 2025).

[22] C.A. Fontanilla-Díaz, P.V. Preckel, J. Lowenberg-DeBoer, J. Sanders, L.M. Peña-Lévano, Identifying profitable activities on the frontier: the altillanura of Colombia, Agric. Syst. 192 (2021) 103199, https://doi.org/10.1016/j.agsy.2021.103199.

[23] K. Franklin, J. Gill, J. Lowenberg-DeBoer, M. Gutteridge, M. Abell, R. Godwin, Hands free hectare: the heuristics of the first arable crop produced by robots, Smart Agric. Technol. (2025), https://doi.org/10.1016/j.atech.2025.101475.

[24] Future Farming, Field and harvest robot catalogue expands to 70 different models, Future Farming (2024), https://www.futurefarming.com/tech-in-focus/field-robots/field-and-harvest-robot-catalogue-expands-to-70-different-models/. (Accessed 27 March 2025).

[25] C.-C. Gaus, L.-M. Urso, T.-F. Minßen, T. de Witte, Economics of mechanical weeding by a swarm of small field robots, in: 57th Annual Conference of the GEWISOLA, German Association of Agricultural Economists, 2017.

[26] A. Gray, Agco to launch OutRun autonomous tractor retrofit kits for mixed-fleets in 2025, Success. Farming (2024), https://www.agriculture.com/agco-to-launch-autonomous-tractors-retrofit-kits-for-mixed-fleets-in-2025-8672374. (Accessed 27 March 2025).

[27] B.G. Hansen, Robotic milking-farmer experiences and adoption rate in Jæren, Norway, J. Rural Stud. 41 (2015) 109–117, https://doi.org/10.1016/j.jrurstud.2015.08.004.

[28] V. Herron, Economics of small vs large scale production platforms in row crop agriculture, Master's thesis, The Ohio State University, 2025.

[29] John Deere, Why do I need autonomy?, https://www.deere.com/en/autonomous/, 2025. (Accessed 27 March 2025).

[30] N. Key, Productivity increases with farm size in the heartland region, Amber Waves: The Economics of Food, Farming, Natural Resources, and Rural America 2018(11), https://www.ers.usda.gov/amber-waves/2018/december/productivity-increases-with-farm-size-in-the-heartland-region, 2018.

[31] O. Lagnelov, G. Larsson, A. Larsolle, P.-A. Hansson, Life cycle assessment of autonomous electric field tractors in Swedish agriculture, Sustainability 13 (20) (2021) 11285, https://doi.org/10.3390/su132011285.

[32] M. Langemeier, S. Casteel, D. Quinn, T. Vyn, B. Johnson, 2024 Purdue crop cost & return guide, https://ag.purdue.edu/commercialag/home/resource/2023/11/2024-crop-cost-and-return-guide/, 2023.

[33] J. Lowenberg-DeBoer, Instant Insights: Economics of Agriculture, Chapter Economics of Agricultural Robotics, Burleigh Dodds Science Publishing, 2025.

[34] J. Lowenberg-DeBoer, K. Behrendt, R. Godwin, K. Franklin, The impact of swarm robotics on arable farm size and structure in the UK, in: 93rd Annual Conference of the Agricultural Economics Society, Agricultural Economics Society, 2019, https://www.researchgate.net/publication/332653186_The_Impact_of_Swarm_Robotics_on_Arable_Farm_Size_and_Structure_in_the_UK.

[35] J. Lowenberg-DeBoer, K. Franklin, K. Behrendt, R. Godwin, Economics of autonomous equipment for arable farms, Precis. Agric. 22 (2021) 1992–2006, https://doi.org/10.1007/s11119-021-09822-x.

[36] M. Lubin, O. Dowson, J.D. Garcia, J. Huchette, B. Legat, J.P. Vielma, Jump 1.0: recent improvements to a modeling language for mathematical optimization, Math. Program. Comput. 15 (3) (2023) 581–589, https://doi.org/10.1007/s12532-023-00239-3.

[37] E. Maritan, J. Lowenberg-DeBoer, K. Behrendt, K. Franklin, Economically optimal farmer supervision of crop robots, Smart Agric. Technol. 3 (2023) 100110, https://doi.org/10.1016/j.atech.2022.100110.

[38] J.E. Ørum, T.W. Tamirat, S.M. Pedersen, A.D.H. Stratton, B. Veldhuisen, H. Hilbrands, Optimal use of agricultural robots in arable crop rotation: a case study

from the Netherlands, Smart Agric. Technol. 5 (2023) 100261, https://doi.org/10.1016/j.atech.2023.100261.

[39] N. Paulson, G. Schnitkey, Revised 2024 crop budgets, Farmdoc daily, https://farmdocdaily.illinois.edu/2024/01/revised-2024-crop-budgets.html, 2024.

[40] G.M. Perry, A. Bayaner, C.J. Nixon, The effect of usage and size on tractor depreciation, Am. J. Agric. Econ. 72 (2) (1990) 317–325, https://doi.org/10.2307/1242335.

[41] AgConditions, Federal Reserve Bank of Chicago, 2024, https://www.chicagofed.org/research/data/ag-conditions/index.

[42] USDA NASS, Quick stats, https://quickstats.nass.usda.gov/, 2024.

[43] A. Rossmadl, M. Gandorfer, S. Kopfinger, A. Busboom, Autonomous robotics in agriculture – a preliminary techno-economic evaluation of a mechanical weeding system, in: ISR Europe 2023; 56th International Symposium on Robotics, 2023, pp. 405–411, VDE, https://www.vde-verlag.de/proceedings-en/456140057.html.

[44] J. Shockley, C. Dillon, J. Lowenberg-DeBoer, T. Mark, How will regulation influence commercial viability of autonomous equipment in us production agriculture?, Appl. Econ. Perspect. Policy 44 (2) (2022) 865–878, https://doi.org/10.1002/aepp.13178.

[45] J.M. Shockley, C.R. Dillon, S.A. Shearer, An economic feasibility assessment of autonomous field machinery in grain crop production, Precis. Agric. 20 (2019) 1068–1085, https://doi.org/10.1007/s11119-019-09638-w.

[46] O. Spykman, M. Gandorfer, J. Lowenberg-DeBoer, Crop robots can defy economies of size and make small-scale agriculture economic – or can they?, in: Precision Agriculture '25, Wageningen Academic, 2025, pp. 1054–1060.

[47] E.P. Stræte, J. Vik, B.G. Hansen, The social robot: a study of the social and political aspects of automatic milking systems, in: Proceedings in System Dynamics and Innovation in Food Networks, 2017, pp. 220–233.

[48] C. Taylor, M. Rose, R. Trice, The expanding 2024 crop robotics landscape, navigating to commercialization. The mixing bowl, https://www.mixingbowlhub.com/landscape/the-expanding-2024-crop-robotics-landscape-navigating-to-commercialization, 2024. (Accessed 27 March 2025).

[49] E. Tziolas, E. Karapatzak, I. Kalathas, A. Karampatea, A. Grigoropoulos, A. Bajoub, T. Pachidis, V. Kaburlasos, Assessing the economic performance of multipurpose collaborative robots toward skillful and sustainable viticultural practices, Sustainability 15 (4) (2023) 3866, https://doi.org/10.3390/su15043866.

[50] M. Vahdanjoo, R. Gislum, C.A.G. Sørensen, Operational, economic, and environmental assessment of an agricultural robot in seeding and weeding operations, AgriEngineering 5 (1) (2023) 299–324, https://doi.org/10.3390/agriengineering5010020.

[51] Various Authours, Glpk.jl: gnu linear programming kit wrapper in Julia, Retrieved from https://github.com/jump-dev/GLPK.jl, 2013.

[52] B. Ward, B.E. Roe, M.T. Batte, Potential profitability of strip intercropping with corn and soybeans, J. ASFMRA (2016) 149–166, https://www.jstor.org/stable/90016046.

[53] M. White, A. Spell, Workforce trends in the midwest's food, agriculture, and forestry industries, Farmdoc daily 14 (76) (2025), https://farmdocdaily.illinois.edu/2024/04/workforce-trends-in-the-midwests-food-agriculture-and-forestry-industries.html.

[54] C. Yu, M. Khanna, S.S. Atallah, S. Kar, M. Bagavathiannan, G. Chowdhary, Herbicide-resistant weed management with robots: a weed ecological-economic model, Zeměd. Ekon. 55 (6) (2024) 943–962, https://doi.org/10.1111/agec.12856.