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Economically optimal farmer supervision of crop robots

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ABSTRACT

One of the key issues in regulation of crop robots is the need for human supervision. Economic analysis indicates that autonomous farming potentially reduces agricultural production costs, but such costs may often become higher than conventional when constant on-site human supervision is required by law. However, there are cases where a higher level of crop robot supervision helps maximise profits even if it is not mandated by law, such as when field operations or crop robots inherently require frequent human intervention. The objective of this study is to identify economically optimal levels of farmer supervision of crop robots in the absence of regulation through the HFH-LP optimisation model developed at Harper Adams University, Newport (UK). Four scenarios characterised by different human intervention requirements are developed and compared with two baseline scenarios to identify thresholds at which farm management decisions would change from remote supervision of crop robots to on-site supervision. The findings of this analysis show that the economically optimal farmer supervision of crop robots falls within a range which is substantially lower than the 100% level mandated by jurisdictions such as the EU and California. More specifically, the economically optimal supervision of crop robots falls between 13% and 85% of machine field time across scenarios depending on: (i) the required number of human interventions in a given field operation; (ii) the supervisor's location; and (iii) the number of crop robots being used in that operation. The economic effects of these three factors reveal crucial implications for health and safety regulators and draw attention to crop robot reliability as a priority for researchers, entrepreneurs, and crop robot manufacturers.

1. Introduction

One of the key issues in regulation of highly automated and autonomous agricultural equipment (HAAAE), also known as crop robots, is the need for human supervision (Lowenberg-DeBoer *et al.*, 2021a) [1]. Economic analysis indicates that HAAAE may potentially reduce agricultural production costs [1]. However, if a human supervisor must be in the field 100% of the time HAAAE is in operation, most economic advantages are lost, and in many cases farmers may as well utilise conventional equipment (Lowenberg-DeBoer *et al.*, 2021a; 2021b) [1,2]. Nevertheless, there are cases in which a high level of machine supervision is economically optimal without regulatory obligation, such as when field operations require frequent human intervention. This study uses a linear programming model to identify factors that determine economically optimal farmer supervision of crop robots for autonomous grains and oilseeds production in the absence of regulation. The presented results show the need for balancing health and safety concerns with financial gain for those regulators imposing constant crop robot supervision, and help researchers, entrepreneurs, and crop robot manufacturers understand how equipment reliability is a prerequisite for the profitability of autonomous farming.

Owing to the potential for incidents and related tort claims from use of crop robots, some jurisdictions have imposed constant human supervision to reduce on-farm health and safety risk (Lowenberg-DeBoer *et al.*, 2021a; Martin, 2021) [1,3]. In the EU, the use of agricultural machinery, including tractors, trailers, and interchangeable equipment, is currently governed by Directive 2006/42/EC [4], commonly referred to as Machinery Directive, and Regulation (EU) No 167/2013 [5], also known as Tractor Regulation. As these pieces of legislation do not explicitly regulate crop robot use, several EU Member Nations and private manufacturers have been independently filling this void. Examples include the Digital Agricultural Strategy in Hungary and national rules following the EU Machinery Directive in Denmark, with most Member State jurisdictions always requiring a human supervisor when a crop robot is in operation [1]. Some cases also exist where private manufacturers commercialised HAAAE that is self-certified as per

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international standards such as the ISO 18497:2018 in France or the ISO 3691-4:2020 in Germany [1,6,7]. For instance, Danish manufacturer FarmDroid availed of the ISO 3691-4:2020 in Germany by classifying their crop robots as driverless industrial trucks, whose use must abide with certain safety measures such as a speed limit of 800 m/h and a restriction to non-public zones [1,7].

Another regulatory example is the State of California, where constant on-site supervision of crop robots is mandated by the Occupational Safety and Health Association (Cal/OSHA) (California Code of Regulations, Title 8, Section 3441(b), 2016) [8]. When controlling HAAAE remotely, an operator is expected to always be watching the machine and nearby workers, thus making it impossible for such an operator to focus on other tasks [2,8]. This rule leads to increased farm-level capital investment, potentially hindering many of the economic advantages of agricultural automation (Lowenberg-DeBoer *et al.*, 2021b; Shockley *et al.*, 2021) [2,9]. For this reason, in 2018, the American Association of Equipment Manufactures (AEM) filed a petition to remove the requirement of constant supervision of crop robots in California (California Department of Industrial Relations, 2019a) [10]. Although AEM's petition was denied on the basis that human injury data and other historic information on HAAAE were not available at the time (California Department of Industrial Relations, 2019b) [11], the agency has shown itself willing to consider the trade-off between health and safety risk and benefits from crop robot use. For example, they have granted some waivers for pesticide application robots on the argument that it is safer for the human operator not to be in the field when the pesticides are applied. If accumulated data shows a low risk to humans from crop robots and an economic analysis reveals economically optimal supervision levels could manage that risk appropriately, perhaps Cal/OSHA and similar jurisdictions would reconsider the constant supervision rules.

To foster regulation of crop robots that better balances benefits and risks, some jurisdictions are developing voluntary codes of practice for agricultural robots. In Australia, a code of practice on the use of crop robots was recently developed by Grain Producers Australia, the Tractor and Machinery Association, and the Society of Precision Agriculture Australia, with the hope that the code would lay the foundation for upcoming state and national laws [2]. The Australian Code of Practice recognises that some supervision is a fundamental safety precaution with HAAAE use, and that effective supervision helps, among others, to monitor the workplace and to report and record machine performance issues (GPA-TMA-SPAA, 2021) [12]. However, it also acknowledges that autonomous farm equipment may be operated in tele-remote mode [12]. In the UK, a similar initiative was launched by Harper Adams University to advise on the development of a code of practice for autonomous farming by the British Standards Institution (BSI) [2]. To make the most of the regulatory flexibility granted by the departure of the UK from the EU, a group of researchers and industry leaders have gathered at Harper Adams University over the past three years to discuss regulatory and economic aspects of crop robotics [2]. This led to an initiative by BSI to develop a crop robot code of practice specifically for UK conditions.

Although constant robot supervision may compromise the profitability of autonomous farming [1,2,9], there are instances where a farmer would choose to supervise HAAAE a high percentage of the machine field time regardless of regulatory impositions, such as when field operations inherently require frequent human intervention or when the farmer proactively scouts out other farm-related problems. For example, autonomous fruit and vegetable harvesting is likely to require 100% of human supervision owing to crop value, machine harvesting errors, and post-harvest handling checks (Ghahremani *et al.*, 2021) [13]. Likewise, problematic field operations such as no-till planting in heavy crop residue, the combining of oilseed crops (e.g., oilseed rape and linseed), or the harvesting of any arable crop under adverse weather conditions, may compel higher machine supervision to achieve economic optimum. Lastly, even in less problematic field operations, a farm manager could choose to proactively monitor farm activities whilst operating crop robots similarly to the way dairy farmers are able to spend more time with their cows after adopting milking robots.

The objective of this study is to analyse some operational and farm management factors that determine the optimal level of farmer supervision of crop robots for autonomous grains and oilseeds production from an economic standpoint. The Hands Free Hectare (HFH) and Hands Free Farm (HFF) team at Harper Adams University (Newport, UK) and other stakeholders in robotic farming have identified three key factors determining economically optimal farmer supervision of crop robots. The hypothesis is that voluntary supervision of crop robots is affected by at least three factors, namely: (i) the required number of human interventions in a given field operation; (ii) the supervisor's location; and (iii) the number of crop robots being used in that operation. It is expected that when a farmer is required to frequently intervene, to travel from a remote location, and to assist multiple crop robots, that farmer would remain on-site for more time to supervise field operations, even in the absence of regulation imposing a certain level of supervision. The focus here is on relatively minor problems that need human intervention (e.g., unexpected obstacles in the field, machine operation impeded by crop residue), so the length of the intervention time is short. Overall, machine downtime which includes some more lengthy interventions is important, but beyond the scope of this study.

2. Materials and methods

The current analysis builds on the HFH and HFF demonstration projects at Harper Adams University (Newport, UK), where a fully autonomous grain-oilseed farm has been operated since 2017 (Lowenberg-DeBoer *et al.*, 2021c) [14]. Among three different approaches to crop robotics (see Gonzalez-de-Santos *et al.,* 2017) [15], the HFH and HFF projects use conventional equipment retrofitted for autonomous production to reduce machine capital investment [14]. Based on the HFH and HFF experiences, Lowenberg-DeBoer and colleagues (2021c) [14] developed a farm-level linear programming (LP) optimisation model, known as the HFH-LP model, to compare autonomous and conventional farming in terms of gross margins, return to operator labour, management and risk taking (ROLMRT), and wheat production costs. The HFH-LP model was coded with the General Algebraic Modelling System (GAMS) software [16]. The present study employs the HFH-LP model to explore the degree to which a farm manager prioritising profit maximisation would supervise crop robots in the absence of regulation. A total of four new scenarios incorporating times to deal with minor operational incidents were constructed and compared with the conventional and autonomous scenarios presented by Lowenberg-DeBoer and colleagues [14]. The comparison was performed based on the results generated by the HFH-LP model, which included human and machine field times, gross margins and ROLMRT, initial equipment investment, and wheat production costs. The cost curve focus is on wheat because it is the most common arable crop in the UK and it is well studied, so that national and international comparisons are facilitated.

The HFH-LP model is mathematically expressed as:

$$Max \prod = \sum_{j=1}^{n} c_j X_j \tag{1}$$

Subject to:

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

$$X_j \geq 0 \text{ for } j = 1 \ldots n \tag{3}$$

Where:

Π = total farm profit

X_j = the level of the jth production process or activity

c_j = the per unit return (gross margin) to fixed resources (b_i's) for the

jth activity

a_{ij} = the amount of the ith resource required per unit of the jth activity

b_i = the amount of the ith resource available.

The objective of the HFH-LP model is to analyse all possible production alternatives under a set of resource constraints (e.g., arable land, available operator time, and good field days) to produce a solution that allocates farmland to either winter wheat, oilseed rape or spring barley in such a way that gross margin is maximised. ROLMRT is then calculated by subtracting fixed costs from the optimal gross margin. Fixed costs include annual machine cost, land rental, farm property and building repairs, professional fees and subscriptions, fixed utilities, building depreciation, and other miscellaneous expenses. Solutions of the HFH-LP model are generated at four different farm sizes (66, 159, 284, and 500 ha) that are operated with any of four different machine types (a 28 kW autonomous tractor, or a 28 kW, 112 kW, or 221 kW conventional tractor) [14].

In Lowenberg-DeBoer *et al.* [14], minimum wheat production costs were achieved by applying a swarm robot strategy using one to three 28 kW autonomous units depending on the farm size [14]. In the conventional machine scenarios, minimum wheat production costs were always higher than in the autonomous scenarios. The lowest conventional wheat production costs were obtained when using one or two 28 kW conventional tractors on the two smallest farms respectively, one 112 kW conventional tractor on the 284 ha farm and one 221 kW conventional tractor on the 500 ha farm [14]. In the present study, these solutions are compared with four additional autonomous scenarios characterised by different human intervention requirements that depend on the three factors under investigation. More information on the original HFH-LP model can be found in Lowenberg-DeBoer *et al.* [14].

The three factors used to develop the four additional scenarios are: (i) the required number of human interventions in a given field operation (beyond setup, refuelling and input replenishment); (ii) the supervisor's location, which affects the time to respond to a problem and the time needed to travel to the field and back to the original location; and (iii) the number of crop robots being used in that operation, which depends on the size of the farm and the capacity of the individual robots. These factors and their ranges used to construct the scenarios were identified by the HFH and HFF team, who have more expertise in producing grain crops with autonomous equipment than anyone else in public sector agricultural research. Considering that the HFH and HFF projects were designed as demonstration and development fields for crop robots rather than research projects dedicated to reliability data collection from commercial systems, it was not possible to utilise HFH and HFF data directly to build the scenarios. This is because the available HFH and HFF data are not representative of what would occur on a commercial farm since they do not segregate human interventions for engineering development reasons from those required when routine operational problems occur.

Since there is very little publicly available data on field robot reliability and downtime, the HFH and HFF team devised scenarios based on their field experience to test farmer supervision choices at either end of the human intervention frequency range. In scenarios 1 ("on-site-trouble-free") and 3 ("remote-trouble-free"), the autonomous equipment only requires 1 human intervention per person-day (1 person-day = 8 hours). In scenario 1, the machine operator remains on-site and is occupied with other farm-related tasks. When HAAAE has an incident, the on-site operator needs 1 minute to respond to the incident call, and 5 minutes to travel to the equipment. It then takes a 5-minute-intervention for the human operator to resolve the issue, and additional 5 minutes to travel back to the original location (total incident time: 16 minutes). Additional machine time for an incident is 11 minutes because the machine resumes operating immediately after the 5-minute human intervention is finished and does not need to wait for the supervisor to return to the original control location. In scenario 3 ("remote-trouble-free"), the operator is supervising crop robots remotely. The "remote" site might be a farm office or another farm enterprise (e.g., intensive livestock production, food processing unit, or farm shop). Considering that the remotely located supervisor is occupied with tasks that may not be farm-related, the time to respond to the incident call is increased to 5 minutes. In this scenario, it is assumed that the supervisor must travel to the field by vehicle. It takes the supervisor 60 minutes to travel back and forth to the remote location, and 5 minutes to resolve the incident (total incident time: 70 minutes for the farm operator and 40 minutes for the machine). Scenarios 2 ("on-site-troublesome") and 4 ("remote-troublesome") add identical response, travel and intervention times but assume that 10 machine incidents occur over a person-day instead of just 1. The number of incidents is intentionally kept high to entirely cover their possible range. Total incident times in scenarios 2 and 4 are 160 and 700 minutes, respectively, for the farm operator, and 110 and 400 minutes, respectively, for the machine.

Table 1 summarises the six scenarios explored in this study. Scenarios A (autonomous) and B (conventional) are the baseline scenarios developed by Lowenberg-DeBoer and colleagues (2021c) [14]. For scenario A, Lowenberg-DeBoer *et al.* (2021c) [14] assumed that well-functioning commercial autonomous equipment requires 10% of human supervision, including initial setup, fuel refill and input replenishment. Human field times for scenarios 1 to 4 assume 10% supervision time plus the times to resolve minor machine or operation problems as explained above.

To maintain comparability with Lowenberg-DeBoer *et al.* (2021c) [14] and to avoid overcomplicating the model in the absence of real-world HAAAE incident data, several assumptions were made:

- *Workday duration.* The HFH economics study assumed 10-hour workdays for conventional equipment. It is technically possible to do many conventional farm operations around the clock with shifts of drivers, but very few UK farms operate through the night mainly due to operation in the dark being more difficult and workers being reluctant to continue through the night. In scenarios 1 and 2, this logic is extended to the supervision of crop robots, assumed to operate for 10 hours per day. On the other hand, in scenarios A, 3, and 4, the autonomous equipment is assumed to operate for 22 hours per day because the human supervisor does not need to remain on-site. The remaining 2 hours are available for setup, refuelling and input replenishment. However, an exception is made for harvesting operations occurring for 10 hours a day in all scenarios owing to night dew in the UK.
- *Constant intervention time.* Since crop robot incidents consist of minor operational issues rather than major breakdowns, intervention time across incident scenarios is always 5 minutes. The intervention time is constant across scenarios and across different operations within scenarios because data on interventions duration is absent.
- *Exclusion of simultaneous incidents.* After attending an incident, the supervisor has the time to return to their on- or off-site position before another incident occurs i.e., multiple incidents do not occur simultaneously even when using more than one robot per field operation on larger farms.
- *Harvesting operations.* During harvest, a combine and a grain hauling tractor are simultaneously used. As the hauling tractor must travel on public roads, it requires a human driver 100% of the time. The human operator supervises the autonomous combine but not the hauling tractor. The tractor driver does not attend to the combine in case of incidents.
- *Individual supervision of crop robots.* Machines are individually supervised i.e., they are not considered as a fleet under unified control and require 10% supervision each.
- *Competing solutions.* In case of competing wheat production cost solutions that use different amounts of available land, solutions that utilise 100% of the available land are selected as optimal solutions.
- *Incidents not added to the conventional scenario.* In the conventional baseline scenario, blockages and minor mechanical issues are

Table 1
Operator location, machine supervision, response time, travel time, frequency of incidents and intervention time assumptions for the six scenarios.

Scenario	Operator location	Baseline machine supervision (%)	Response time (min)	Travel time (min)	Number of incidents (per person-day)			Intervention time (min)
					Drilling	Spraying	Harvesting	
A: baseline robot	In field or off-farm	10%	N/A	N/A	N/A	N/A	N/A	N/A
B: baseline conventional	On machine	100%	N/A	N/A	N/A	N/A	N/A	N/A
1: on-site-trouble-free	In field	10%	1	5	1	1	1	5
2: on-site-troublesome	In field	10%	1	5	10	10	10	5
3: remote-trouble-free	Off-farm	10%	5	30	1	1	1	5
4: remote-troublesome	Off-farm	10%	5	30	10	10	10	5

already included in the field time calculations presented by Lowenberg-DeBoer *et al.* (2021c) [14]. In light of the nature of the minor operational issues analysed in this study, incident times were not added to the conventional scenario (scenario B). Indeed, if the human operator is driving the conventional equipment, the time needed to intervene is minimal because the human operator immediately responds to an issue and does not need to travel to the equipment from a different location. For example, with conventional equipment, a seed blockage may be resolved by hydraulically lifting the seeder to drop out the crop residue without leaving the tractor seat. Likewise, an unexpected obstacle in the field would not require much time for a human driver to circumvent it.

3. Results

The results generated by the HFH-LP for the six scenarios under comparison include human and machine field times, gross margins and ROLMRT, initial equipment investment, and wheat production costs. These are separately presented in the following subsections.

3.1. Human and machine field times

The estimated yearly human and machine field times per hectare are presented in Figs. 1 and 2. These represent the per hectare amount of time that either a human worker or agricultural equipment spend in the field to supervise or conduct operations across the year. As expected, human and machine field times increase when the incidents are more frequent and when the supervisor operates HAAAE from a remote location and must travel to the farm to deal with problems. As a consequence of the added incident times, the autonomous incident scenarios always require human and machine field times that are higher than in the baseline autonomous case (scenario A). This effect is more evident when a farmer operates a larger farm requiring additional crop robots to compensate for the machine time lost in waiting for the human operator to intervene. For example, on the largest 500 ha farm, both scenarios 1 (“on-site-trouble-free”) and 4 (“remote-troublesome”)

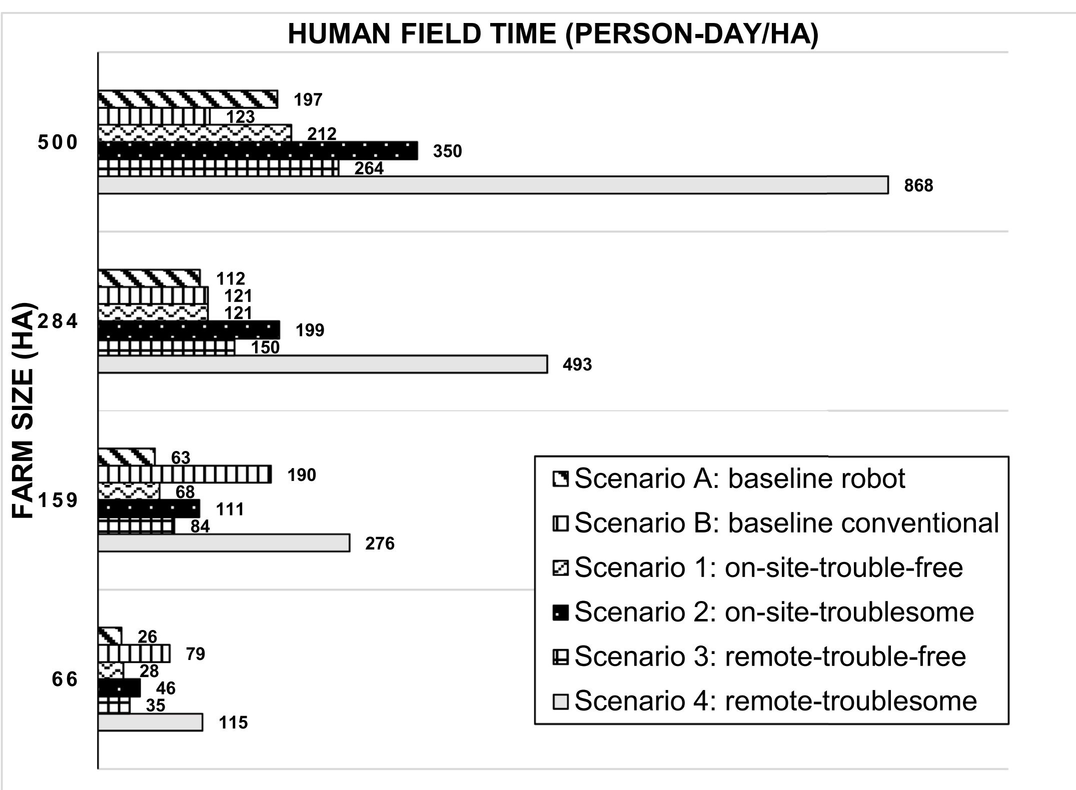

Fig. 1. Human field times (person-day/ha) by farm size for the six scenarios.

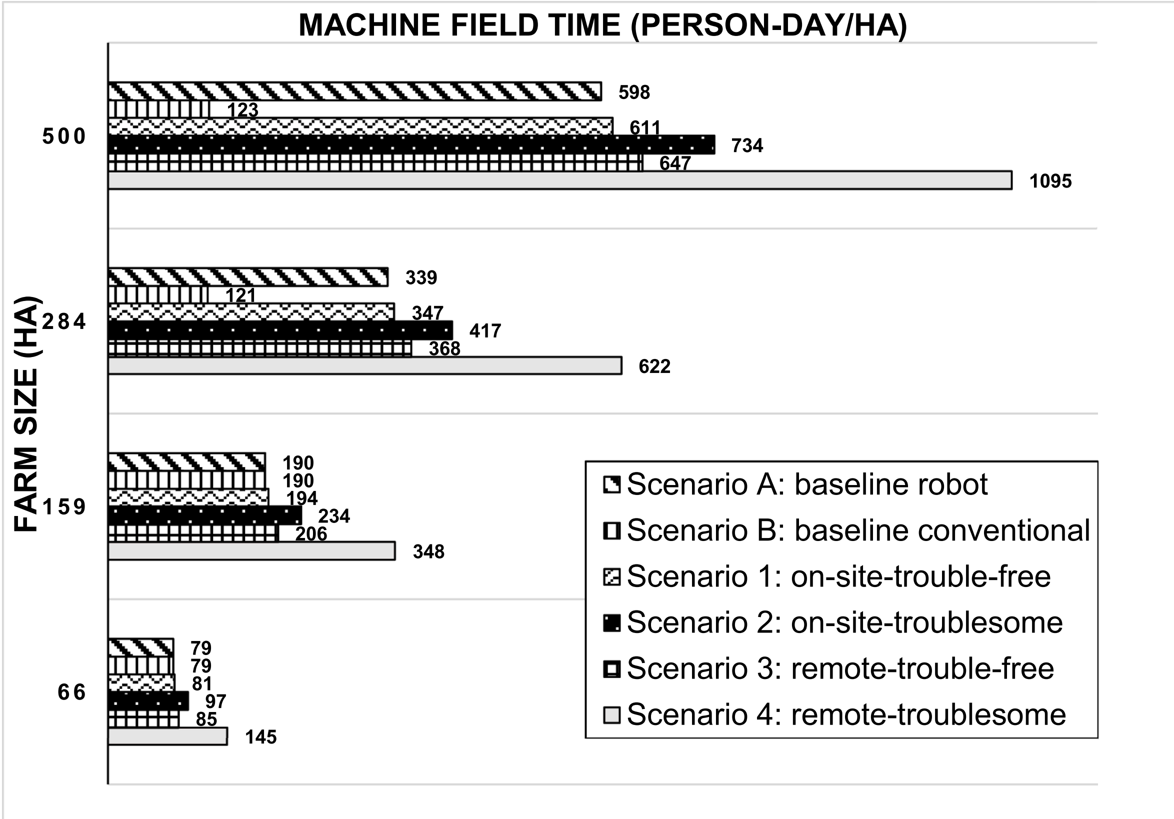

Fig. 2. Machine field times (person-day/ha) by farm size for the six scenarios.

require 5 crop robots for a single operation, or 2 additional robots than in the baseline autonomous scenario. In scenario 2 ("on-site-troublesome") this requirement is even greater with 6 robot units per operation, or 3 extra robots if compared to the baseline case. On average across all farm sizes, the increases in human field times over the baseline autonomous scenario (scenario A) are 8%, 77%, 34%, and 340% for the four incident scenarios, respectively. The machine field times average increases are 2%, 23%, 8%, and 83%. The increases in machine field times are lower than those for human field times because the baseline human field times in scenario A are much lower than machine field times (i.e., the assumed 10% supervision), and because incident times for the machine exclude the farm operator's return trip time.

Table 2
Gross margin (£/year) and ROLMRT (£/year) for the six scenarios.

Scenario	Farm area (ha)	Operator time (person-day/ha)	Labour hired (person-day/ha)	Optimal machine units	Gross margin (£/year)	Return to operator labour, management, and risk taking (£/year)
A: baseline robot	66	26	0	1x 28 kW	47,048	12,301
	159	54	8	1x 28 kW	112,691	46,891
	284	62	50	2x 28 kW	198,587	78,340
	500	76	121	3x 28 kW	347,015	141,936
B: baseline conventional	66	79	0	1x 28 kW	47,048	15,848
	159	118	72	2x 28 kW	107,759	36,344
	284	89	31	1x 112 kW	200,017	54,178
	500	87	35	1x 221 kW	353,677	90,743
1: on-site-trouble-free	66	28	0	1x 28 kW	47,048	12,301
	159	58	10	2x 28 kW	112,578	34,068
	284	68	52	3x 28 kW	198,384	65,428
	500	87	125	5x 28 kW	346,658	116,159
2: on-site-troublesome	66	46	0	1x 28 kW	47,048	12,301
	159	89	23	2x 28 kW	111,557	33,047
	284	112	87	3x 28 kW	193,118	60,161
	500	132	219	6x 28 kW	339,361	96,153
3: remote-trouble-free	66	35	0	1x 28 kW	47,048	12,301
	159	69	15	1x 28 kW	112,195	46,395
	284	89	61	2x 28 kW	197,701	77,454
	500	110	154	3x 28 kW	344,418	139,339
4: remote-troublesome	66	106	9	1x 28 kW	46,342	11,595
	159	139	137	2x 28 kW	102,629	24,120
	284	168	325	3x 28 kW	177,090	44,133
	500	180	688	5x 28 kW	302,726	72,227

3.2. Gross margins and ROLMRT

Gross margins and the ROLMRTs for the six scenarios are listed in Table 2 along with operator time, labour hired, and optimal machine units. The figures for the two baseline cases (scenarios A & B) were obtained from Lowenberg-DeBoer *et al.* [14], while those for the four incident scenarios (scenarios 1 to 4) were generated anew in the HFH-LP model.

Since direct costs and yields are assumed to be the same across the scenarios, gross margins are relatively similar at all farm sizes. For the smallest farm, gross margins are identical at £ 47,048 in all scenarios except for scenario 4 ("remote-troublesome"). This occurs because in the two baseline scenarios, as well as incident scenarios 1, 2 and 3, the HFH-LP model is able to plant and harvest wheat and oilseed rape in the optimal period without needing to hire temporary workers. In scenario 4, a farm manager would need to spend an extra £ 706 to hire temporary labour for 9 person-days, thus reducing the yearly gross margin to £ 46,342. On larger farms, gross margins differ across all six scenarios due to the different human field time requirements resulting from the different types of equipment used (conventional or autonomous) and from the additional human intervention times incorporated in the incident scenarios. Except for the smallest farm for the reason explained, gross margins across the incident scenarios are always lower than in scenario A ("baseline robot") due to additional variable costs resulting from increased labour requirements when incidents or problems occur. On the three largest farms, the cost differences over scenario A for the additional time spent on-farm by the farm manager and the hired labour range from £ 1,324 to £ 3,805 in scenario 1, £ 13,235 to £ 27,197 in scenario 2, £ 5,790 to £ 14,553 in scenario 3, and £ 39,908 to £ 80,859 in scenario 4. These figures justify why gross margins are particularly lower when HAAAE is troublesome and the supervisor's location is remote. Indeed, in scenario 4, the yearly gross margin is almost 13% lower than that in the autonomous baseline case for the largest 500 ha farm. In the three remaining incident scenarios, gross margins are slightly lower when field operations undergo frequent incidents (scenario 2) but remain relatively similar to those generated in scenario A despite the additional human field times costs. Indeed, excluding the two larger farms in scenario 2 for which gross margins are at least 2% lower than in scenario A, all other instances hardly exceed a 1% difference, with many cases close to no difference (e.g., 0.1% difference in scenario 1 for the 159, 284 and 500 ha farms).

Unlike what is observed for the gross margins, the ROLMRT varies to a greater extent across the six scenarios (Table 2). At the smallest farm size, all values for the autonomous scenarios are identical, except for scenario 4 ("remote-troublesome") where the gross margin is lower, hence resulting in lower ROLMRT. The ROLMRT for the smallest 66 ha farm in the conventional case is the highest, as already highlighted by Lowenberg-DeBoer *et al.* in the original HFH-LP study [14]. However, as the size of the farm increases, autonomous equipment shows a higher ROLMRT in most cases. Indeed, at the second smallest farm size, scenarios A (baseline robot) and 3 ("remote-trouble-free") are over 20% more profitable than the conventional case. At the same farm size, ROLMRT for the on-site incident scenarios (scenarios 1 and 2) are just about 6-9% lower than in the conventional scenario (scenario B). In scenario 4 ("remote-troublesome"), nearly half of the ROLMRT is lost on the three largest farms. For the two largest farms, the autonomous scenarios are always more profitable except for scenario 4 ("remote-troublesome"). As fixed costs include annual machine expenditures, ROLMRTs are lower when the number of machines being used is greater. This justifies the differences in ROLMRT across the autonomous scenarios. Indeed, the yearly returns in scenarios 3 ("remote-trouble-free") and A ("baseline robot") are almost identical owing to the same number of crop robots being used. When several additional robots are added as on the 500 ha farm in scenarios 1, 2 and 4, 18%, 32%, and 49% of the yearly ROLMRTs in the baseline autonomous scenario are lost, respectively.

3.3. Initial equipment investment

Although ROLMRTs are reduced in the autonomous incident scenarios, the upfront capital investment to purchase autonomous equipment for the larger two farm sizes is always lower than in the conventional case (scenario B). The initial equipment investments by farm size for the six scenarios are shown in Fig. 3.

The cost for the equipment set with a conventional 28 kW tractor is £ 67,900, which can be retrofitted at a cost of £ 23,262, resulting in a total investment of £ 91,162 for an autonomous 28 kW tractor. Additional information on the retrofitting components for an autonomous 28 kW tractor is available in the electronic supplementary material attached to the Lowenberg-DeBoer *et al.* (2021c) study [14]. Since the 66 ha farm with autonomous and conventional equipment uses the same size and number of tractors and harvesters (i.e. 1 each), the autonomous farm has higher capital costs as a result of the retro-fit expense. Owing to a 159 ha conventional farm requiring two 28 kW tractors, equipment investment in this case is double that of the smallest farm. For the 284 and 500 ha conventional farms, a 112 kW tractor and a 221 kW tractor are used, respectively. As estimated by Lowenberg-DeBoer *et al.* [14], a 112 kW equipment set costs £ 389,500, while a 221 kW equipment set costs £ 723,500. These two cases represent the largest investment requirements across the six scenarios. Indeed, for the two largest farm sizes, autonomous equipment requires a lower capital investment than the conventional equipment because multiple smaller and less costly robots can be used more intensively to perform the same tasks. This advantage persists even for troublesome operations and remote supervision (scenario 4).

When comparing the four incident scenarios with the baseline robot case, it is noted that the equipment investment for the smallest farm does not vary. This is because one crop robot unit is sufficient for all scenarios as there is enough unused machine capacity to absorb the additional incident time on the smallest farm. Conversely, larger farms are unable to absorb additional incident times in many cases and thus need additional 28 kW crop robot units. The more crop robot units are required, the more investment cost advantage of autonomous farming is eroded. For the three largest farms across the four incident scenarios, this economic advantage is only preserved in scenario 3 ("remote-trouble-free"), where the number of robot units being used is always identical to scenario A ("baseline robot"). It is also noted that, except for the largest 500 ha farm, the initial equipment investments for the on-site incident scenarios (scenarios 1 and 2) are identical regardless of the number of incidents. This effect is not reflected in the remote incident scenarios (scenarios 3 and 4) as a result of the 22-hour workday assumed. Indeed, the shorter 10-hour day expected for an on-site supervisor makes it harder to achieve timeliness of operations even in a relatively trouble-free scenario. Thus, scenario 1 ("on-site-trouble-free") requires one or two additional robot units than scenario 3 ("remote-trouble-free") at the three largest farm sizes even if the number of incidents does not vary between the two scenarios.

When the number of crop robots is selected to minimize wheat production cost for a given farm area, the shadow prices of robotic tractors and harvesters are zero in all cases except for tractors in September and October on the 284 ha farm in the "on-site-troublesome" scenario (scenario 2). In this case, the shadow price for Sept is 1,217 £/ha and for Oct is 313 £/ha, but if an additional robot unit is added the overall cost of wheat production rises.

The estimated initial equipment investments across the scenarios rely on the assumption from Lowenberg-DeBoer *et al.* [14] that the farm owns the crop equipment being used. However, with the risk of rapid technological obsolescence and the formidable upfront investment for crop robots, rental and leasing arrangements are very likely to become common practice once HAAAE is fully commercially available, making it a potential new market for agricultural contractors. In the case where an autonomous farm is operated by using third-party service providers, a farmer would not incur machine purchase costs and, possibly, machine operator costs. Exploring the economic parameters for the six scenarios

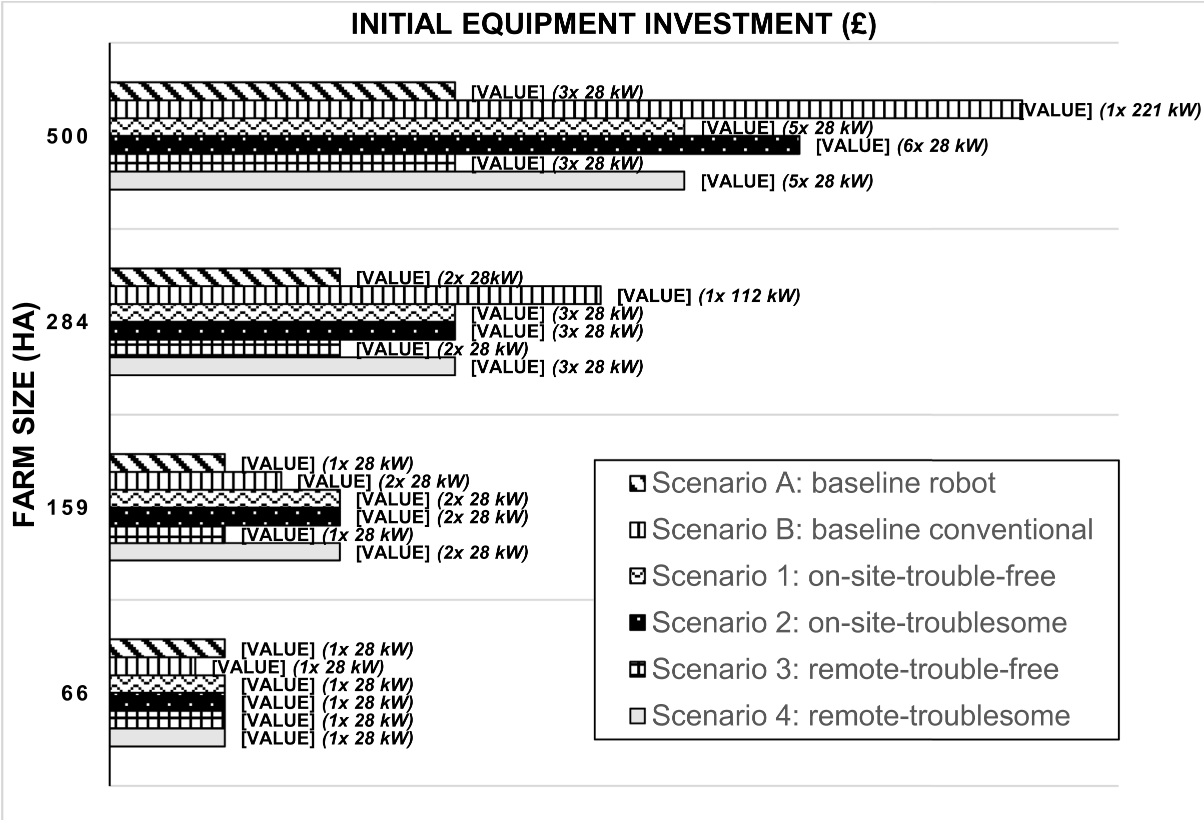

Fig. 3. Initial equipment investment (£) by farm size for the six scenarios.

under such an arrangement is beyond the scope of this study. However, many of the conclusions obtained by using owned equipment would still apply to a farm operated with rented equipment, though the supervision-related choices would have to be made by the crop robot provider.

3.4. Wheat production costs

Economic theory and history show that in the long run firms will tend to use business practices which minimise production costs (Duffy, 2009; Hallam, 1991) [17,18]. Thus, as in Lowenberg-DeBoer *et al.* [14], minimum wheat production costs are calculated. These include per

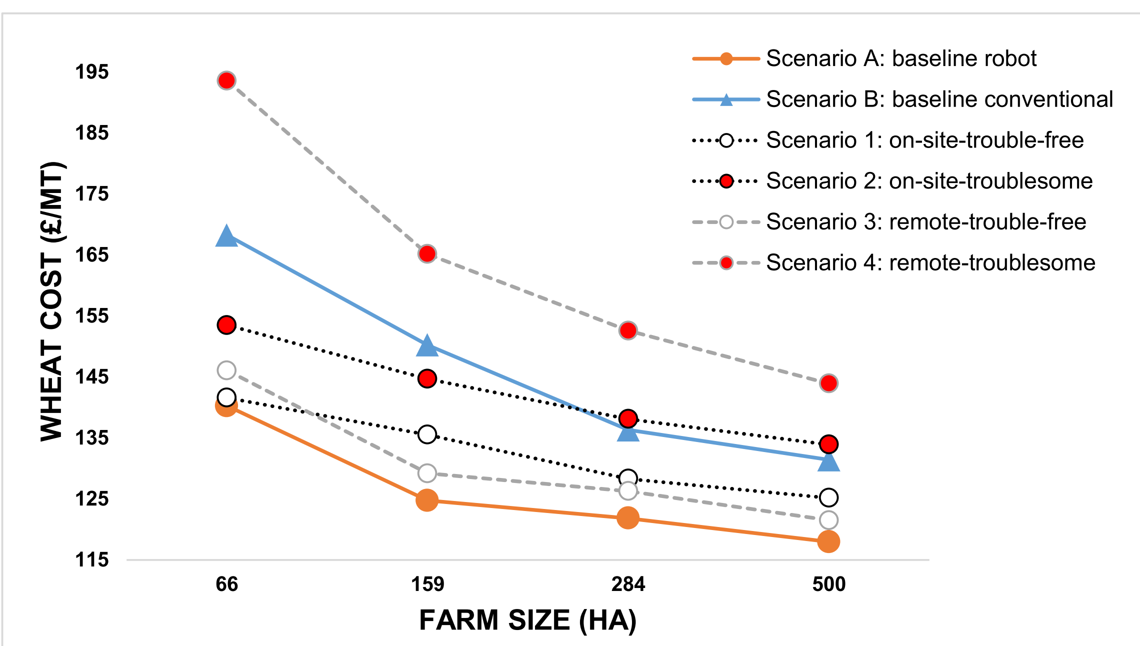

Fig. 4. Minimum wheat production costs (£/MT) by farm size for the six scenarios.

hectare wheat variable costs, labour compensation, and fixed costs [14]. Across the four incident scenarios, wheat production costs become increasingly higher, with both the "on-site-troublesome" and "remote-troublesome" scenarios losing economic advantage over the conventional scenario at some or all farm sizes (Fig. 4). On the other hand, in scenarios 1 ("on-site-trouble-free") and 3 ("remote-trouble-free"), the economic advantages of autonomous wheat production are largely preserved.

The wheat production cost curves for scenarios 1 and 3 intersect. At the smallest farm size, despite the gross margins and ROLMRTs of these two scenarios being equal, wheat production cost is lower in the "on-site-trouble-free" scenario because of the lower variable costs resulting from shorter human field times when the operator is on-site. At all other farm sizes, this effect is cancelled by higher machine-related fixed costs in the scenario where the operator is on-site since a 10-hour workday requires more machine units to perform the same task in a 22-hour workday. If the operator is located off-site and must frequently intervene (scenario 4), wheat is more expensive to produce with autonomous equipment than it is conventionally at any farm size. However, in case the operator must stay on-site (scenario 2), wheat production costs are higher than in the conventional scenario only at the two largest farm sizes. For the smaller 66 ha and 159 ha farms, even though machine costs are lower in the conventional scenario, its variable costs are higher owing to the compensation for the operator driving conventional equipment far exceeding that of an operator supervising HAAAE for only 10% of the time plus infrequent incidents.

4. Discussion

In the absence of crop robot supervision regulations, decisions about crop robot supervision times would be governed by economic parameters such as gross margins, ROLMRT, initial equipment investment, and wheat production costs. Factors affecting the economically optimal level of HAAAE supervision are: (i) the required number of human interventions in a given field operation; (ii) the supervisor's location; and (iii) the number of crop robots being used in that operation. The combination of these factors in the autonomous incident scenarios provides mixed effects. When incidents are added to the baseline autonomous scenario, human and machine field times are substantially greater across all farm sizes, especially at the highest incident frequency. Gross margins in both the baseline cases and the incident scenarios remain relatively similar, except for the "remote-troublesome" scenario where as much as 13% of gross margins are lost on the largest farm. Conversely, ROLMRTs vary to a greater extent. The baseline conventional scenario has higher returns than the autonomous scenarios on the smallest farm size. However, as the farm size increases, the autonomous scenarios show similar or higher profitability except for the "remote-troublesome" scenario. The highest initial equipment investments occur on the two largest conventional farms, exceeding even those required in the "remote-troublesome" autonomous scenario. As to minimum wheat production costs, these are always lower than conventional when farm operations are relatively trouble-free. When the frequency of incidents increases, minimum wheat production costs are higher than conventional if the farm operator's location is remote ("remote-troublesome" scenario) at all farm sizes, but higher than conventional only at the two largest farm sizes if the farm operator remains on-site ("on-site-troublesome" scenario). This indicates that smaller farms better absorb machine incidents in terms of production costs when the farm operator remains on-site.

The economically optimal farmer supervision of crop robots for the four incident scenarios is 13%, 35%, 23%, and 85% of machine field time, respectively, or 3%, 25%, 13%, and 75% more than in the baseline autonomous scenario. These supervision levels are substantially lower than the 100% crop robot supervision mandated by regulations in the EU and California. In case of relatively trouble-free operations (scenarios 1 and 3), since the supervision requirements are relatively low for both the operator locations, a supervisor has the choice to stay on-site or to control HAAAE remotely, with the latter requiring about a twice as high supervision percentage. However, if the equipment or the operation requires frequent human interventions (scenarios 2 and 4), the supervisor would benefit from remaining on-site rather than controlling HAAAE remotely. When looking more closely at the "on-site-trouble-free" and "remote-trouble-free" scenarios in terms of minimum wheat production costs, these are 3.06% lower in the former on the smallest farm, but between 1.61% and 4.90% lower in the latter on the three largest farm sizes. Thus, in case of relatively trouble-free operations, a farm manager would choose to operate HAAAE remotely. This confirms the hypothesis that the voluntary supervision of crop robots is at least affected by the proposed three factors and that a farm manager would remain on-site for more time to oversee autonomous field operations in case frequent human interventions were required, even in the absence of supervision regulation.

The reason why human interventions are required depends on the nature of the field operation being performed. These may include plant debris removal during drilling, clogged nozzles during spraying, and sieves clearance during harvesting. It is also important to highlight that currently available field robots are not equipped with high AI capacity. They mostly follow predetermined field paths. If they encounter something unexpected, most of them just stop and wait for a human to decide or deal with the problem. As field robot AI capacity increases, the need for human intervention would be expected to diminish. If the differences in ROLMRTs between trouble-free and troublesome scenarios were interpreted as proxy for a farm manager's willingness to pay for AI, this would be particularly high on remotely controlled larger farms. For a farm manager remaining on-site, the willingness to pay for AI ranges from £ 0 on the smallest farm to £ 20,006 on the largest farm. For a farm manager remotely supervising operations, this ranges from £ 706 on the smallest farm to £ 67,112 on the largest farm, with a £ 22,275 willingness to pay for AI already at the second smallest farm size. Such a low willingness to pay for AI on smaller farms is in line with the minimum wheat production costs demonstrating that smaller farms are better capable of absorbing increased production costs resulting from machine incidents. This holds particularly true for small cereal and general cropping farms. On mixed crop and livestock farms or farms with non-farm enterprises, these figures might constitute an underestimation of the willingness to pay for AI in those cases where higher opportunity costs of labour are higher. Despite the higher willingness to pay for AI on remotely controlled larger farms, it must be noted that the need for human intervention might never disappear entirely as neither manufacturers or crop robots can anticipate every problem. Even the most capable AI will encounter some situations that are outside of its training. For instance, all farm operation types may require human intervention in case the crop robot's collision detection and avoidance system identifies an unexpected obstacle in the field and switches off the crop robot to safe mode.

Further to the incident scenarios analysis, the dichotomy between on-site and remote as well as between trouble-free and troublesome scenarios must not exclude the possibility for an operator (or for a farming services provider) to switch from a remote to an on-site control location across the year depending on the human intervention requirements of a specific operation. A sensitivity analysis conducted on the number of incidents during spraying activities showed that wheat production costs for the "on-site-troublesome" scenario would be below those of a conventional farm at all farm sizes if the number of spraying incidents was reduced from 10 to 1, i.e., as that of a trouble-free scenario. Thus, an operator could indeed retain the economic advantages of HAAAE by remaining on-site during more problematic activities such as drilling and harvesting, and by controlling relatively trouble-free spraying activities from a remote location. However, the economic advantages preserved by remotely controlling HAAAE during less problematic spraying operations could be lost in case the operator had to be additionally compensated for remaining on-site during drilling and harvesting activities. Indeed, a second sensitivity analysis on operator compensation in the same scenario indicates that minimum wheat production costs would exceed those in the conventional case (scenario B) at all farm sizes if the operator was compensated an additional 60%. Below this threshold, the economic advantages of autonomous equipment in the “on-site-troublesome” scenario are at least preserved for the two smallest farms (66 and 159 ha) as previously described.

A breakeven analysis conducted on the four incident scenarios showed that, in the on-site scenarios, autonomous farming would remain competitive with conventional farming if up to 22 and 16 incidents per person-day occurred on the 66 ha and 159 ha farms, respectively. On the other hand, the larger 284 and 500 ha farms in the on-site scenarios could only tolerate up 8 and 6 crop robot incidents, respectively. In the remote scenarios, these figures are as low as 5 incidents per person-day on the 66 ha farm, 4 incidents per person-day on the 159 ha farm, 2 incidents per person-day on the 284 ha farm, and 3 incidents per person-day on the 500 ha farm. This analysis modelled incident scenarios at opposite ends of the performance range from relatively trouble-free to quite troublesome. It is a preliminary analysis of the optimal supervision time for crop robots and it consequently has many limitations. As experience with autonomous crop equipment accumulates, it will become possible to more accurately identify the incident thresholds at which economic decisions would change from remote to on-site supervision of HAAAE or to conventional equipment use. In particular, the numerical results presented depend on the robotic technology modelled, the crops produced and other assumptions of the HFH-LP. The autonomous equipment modelled in this study has very little AI capacity and it mostly follows a predetermined field path. More advanced equipment would be expected to require fewer human interventions. The economic determinants of supervision time in the absence of regulation will probably be similar for other HAAAE technology and crops, but the numerical results will differ.

Despite the limitations of this analysis, these results help identify priority areas for researchers, entrepreneurs, and crop robot manufacturers. This is particularly the case if agricultural health and safety regulators will allow for partial HAAAE supervision during certain or all field operations as the economically optimal farmer supervision of crop robots calculated through the HFH-LP model is much lower than 100% across all autonomous scenarios. At the initial stages, autonomous machines may be used for less troublesome operations while other operations could still be performed using conventional equipment. With the advance of field robotics, farmers could gradually shift to autonomous farming for all operation types, possibly utilising the existing inventory of conventional equipment for back up in case minor operational issues persist in some cases. Developing crop robots that can perform well even in difficult operations or in adverse weather and field conditions would encourage a faster HAAAE adoption by farmers. There is tremendous potential for the development of “smart” field robots that can adjust themselves when basic operational issues occur or that are able to autonomously recognise and circumvent unexpected obstacles. At first, these systems could partially rely on a remote or on-site human operator being notified (via text message or mobile phone app) about a problem. The human operator could quickly check the nature of the incident without needing to travel to the machine and give permission to the crop robot to adjust or “unblock” itself from afar. With time, the crop robot could be trained to independently resolve issues that were already encountered in previous situations, or that were incorporated into updated crop robot versions relying on real-world HAAAE incident and performance data accumulated over the years. Development of greater AI capacity would help farmers realise the multiple economic advantages of autonomous over conventional agricultural mechanisation.

5. Conclusion

This economic analysis used the HFH-LP optimisation model to explore factors affecting optimal farmer supervision of HAAAE (or crop robots) in the absence of regulation. Two HFH-LP baseline scenarios were compared to four new incident autonomous scenarios that reflected different human and machine time requirements according to: (i) the required number of human interventions in a given field operation; (ii) the supervisor’s location; and (iii) the number of crop robots being used in that operation. These three factors were selected by the HFH and HFF team based on their expertise in producing grain crops with autonomous equipment and were shown to affect the economically optimal farmer supervision of crop robots. More specifically, it was shown that a farm manager would voluntarily remain on-site for more time in case field operations required frequent human interventions and the crop robots being used were many as a result of a larger farm size. While worldwide some health and safety regulators are imposing constant human supervision of HAAAE as a one-size-fits-all solution to reduce on-farm risk, the results of this study underscore the need for tailoring crop robot supervision regulations to the specific autonomous technology being used. The economics, social, and environmental benefits of robotic agriculture may not be realized if high levels of human supervision are required for all HAAAE regardless of crop robot size, speed of operation and other factors.

The economically optimal farmer supervision of crop robots for the four incident scenarios is 13%, 35%, 23%, and 85% of machine field time, respectively. These supervision levels are lower than the constant supervision of crop robots required by jurisdictions such as the EU and California. In the absence of regulation, a farm manager prioritising profit maximisation would spend 25% more time on-site supervising HAAAE in case frequent human-interventions were required, but never reaching a level of 100% of machine field time. Regardless of the supervisor’s location, autonomous farming is characterised by lower than conventional production costs at any farm size in the case of relatively trouble-free field operations. Except for the case where the farm operator remains on-site on the two smallest farms, autonomous farming is less profitable than conventional agriculture if field operations are troublesome. In these cases, the human intervention frequencies would have to be reduced to 6-8 incidents per person-day in an on-site scenario or to 2-5 incidents in a remote scenario to preserve the economic advantages of autonomous farming. Further research is required to assess the economic effects of allowing an operator to simultaneously attend to multiple incidents in a single trip in a remote scenario or to evaluate the implementation of larger crop robots that might be used on larger farms but may require the farm manager to intervene more frequently.

The implications of these results for health and safety regulators are that requiring on-site human supervision of crop robots that is higher than economically optimal constitutes a penalty in terms of opportunity costs of human field time and greater investments in additional robot units required to operate the same area. Regulation should strive to balance the trade-off between financial gain and health and safety rather than imposing constant human supervision of HAAAE as a one-size-fits-all solution for all operation types and farm sizes. Autonomous and conventional equipment could co-exist, with the former being implemented under partial supervision for less troublesome operations and/or for smaller farms with an on-site operator. As health and safety risks decrease because of better crop robot reliability, supervision regulations could be relaxed even for troublesome operations and for all farm sizes. For researchers, entrepreneurs, and crop robot manufacturers, the development of crop robots that can perform well even in difficult operations or adverse conditions is an opportunity to preserve the competitive advantage of autonomous farming over conventional agriculture. While worldwide crop robot regulations are still in their infancy, priority should be given to the advancement of AI capacity or to equipment designs that place greater emphasis on reliability so that crop robots are safer and able to resolve problems without human intervention. These results show that moving autonomous equipment from the troublesome to the trouble-free category can substantially reduce costs of production and preserve the economic advantages of autonomous agriculture.

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