Harper Adams University

Proceedings of the 4th Symposium on Agri-Tech Economics for Sustainable Futures

20th – 21st September 2021, Harper Adams University, Newport, United Kingdom.

Global Institute for Agri-Tech Economics,

Food, Land and Agribusiness Management Department,

Harper Adams University

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Website: https://www.harper-adams.ac.uk/research/giate/

Symposium Website: https://www.agritechecon.co.uk/

ISBN: 978-1-7398183-2-6

Edited by K. Behrendt and D. Paparas

Published by **HAU Publications (Ebooks)**

Cover Image: Hands Free Hectare, Harper Adams University

Citation: [Authors, 2021. Title.] In: K. Behrendt and D. Paparas (eds.) *Proceedings of the 4th Symposium on Agri-Tech Economics for Sustainable Futures*. Global Institute for Agri-Tech Economics, Food, Land & Agribusiness Management Department, Harper Adams University. HAU Publications, Newport, United Kingdom, 20-21 September 2021, [pp].

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Economic Implications of Field Size for Autonomous Arable Crop Equipment

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Abstract

Research shows that smaller field size favours biodiversity and it is hypothesized that autonomous arable crop equipment would make it possible to farm small fields profitably. To test this hypothesis algorithms were developed for machine time over a range of field sizes. The Hands Free Hectare (HFH) linear programming model was used to assess the economic implications of field sizes. The study considered rectangular fields in the West Midlands from 1 to 100 ha farmed with tractor sizes of 38 hp, 150 hp and 296 hp. Results showed that field times (hours/hectare) were longer for small fields with equipment of all sizes and types, but field size had the least impact for small equipment. The results showed that autonomous equipment reduces costs on farms with fields of all sizes. If temporary labour is available, conventional farms with small fields use the smaller equipment, but the extra hiring increases wheat production costs by £30-£40/ton over costs on farms with autonomous equipment. The larger 150 hp and 296 hp tractors were not profitable on the farms with small fields. The economic viability of autonomous equipment irrespective of field sizes shows that it could facilitate biodiversity gains and environment schemes, such as Environmental land management schemes (ELMS) in the United Kingdom and Agri-environment schemes (AES) in the European Union and elsewhere.

Keywords

Autonomous swarm robotics; Field sizes; Equipment selection; Economic viability; Mathematical programming; Commodity crop production.

Presenter Profile

A. K. M. Abdullah Al-Amin is recognised as Elizabeth Creak Fellow and working as a PhD researcher at Harper Adams University, Newport, Shropshire, UK. Mr. Al-Amin also works for Department of Agricultural Economics at Bangladesh Agricultural University, Mymensingh, Bangladesh as an Assistant Professor. Mr. Al-Amin has awarded Prime Minister Gold Medal-2014 for his excellent academic performance at graduate level. Al-Amin's research interests encompasses the economics of agricultural technology, especially precision agriculture and autonomous crop robotics, climate change, environmental impact assessment, and ecosystem services conservation.

Introduction

The changes of arable landscape structure are a matter of concern with substantial reduction of biodiversity (Firbank et al., 2008; Flick et al., 2012; Lindsay et al., 2013; MacDonald and Johnson, 2000; Haines-Younga et al., 2003; Robinson and Sutherland, 2002). In many parts of the world, to promote conventional agricultural mechanization, comparatively large rectangular fields are encouraged and most of the land consolidation studies around the world in the last decades have been motivated by the desire for larger fields (Kienzle et al., 2013; Lindsay et al., 2013; Robinson and Sutherland, 2002; Van den Berg et al., 2007). In the United Kingdom, field size has increased through removing hedgerows and in field trees to encourage increasing use of larger machinery and ensure economics of size (MacDonald and Johnson, 2000; Pollard et al., 1974; Robinson and Sutherland, 2002). Small fields are largely neglected and considered as non-economic for conventional mechanization, for instance, the United States abandoned most of the small irregular-shaped fields and the European Union and Switzerland treated small fields with subsidized agriculture (Lowenberg-DeBoer et al., 2021). Nevertheless, under the umbrella of landscape management, small fields are promoted both by the researcher and policymakers in the European Union, United Kingdom, United States and Canada to conserve biodiversity (Europe, 2008; Fahrig et al., 2015; Stanners and Bourdeau, 1995). Research in Canada and the United States found increasing biodiversity in smaller fields (Fahrig et al., 2015; Flick et al., 2012; Lindsay et al., 2013). Likewise, studies in the United Kingdom and Europe, also showed that small fields and a more fragmented landscape have higher biodiversity (Europe, 2008; Firbank et al., 2008; Gaba et al., 2010; González-Estébanez et al., 2011). Keeping the ongoing debate of arable crop farm size in mind, unlike conventional mechanization, the present study hypothesized that autonomous arable crop equipment (i.e., autonomous crop robotics) would make it possible to farm small fields profitably.

Autonomous crop robotics in this study refer to the mechatronic devices which have autonomy in operation through predetermined path or itinerary. More specifically, the autonomous crop robots are mobile, having decision making capability, and accomplish arable farm operations (i.e., drilling, seeding, spraying fertilizer, herbicides, pesticides, and harvesting) under the supervision of human, but without the involvement of direct human labour and operator (Daum, 2021; Lowenberg-DeBoer et al., 2021; Lowenberg-DeBoer et al., 2021, 2020). In this study, autonomous crop robotics, demonstrated at the Hands Free Hectare (HFH) project (https://www.handsfreehectare.com/) in Harper Adams University, United Kingdom, represent the swarm robotics as the robots incorporate multiple smaller equipment's to accomplish arable farm operations like the larger conventional machine with human operator. The autonomous crop robotics of the HFH project are constructed through the retrofitting process of the conventional tractors (Lowenberg-DeBoer et al., 2021). The autonomous crop robotics are considered as the game changing technology to revolutionise precision agriculture and facilitate the 'fourth agricultural revolution' usually termed as Agriculture 4.0 (Daum, 2021; Klerkx and Rose, 2020; Lowenberg-DeBoer et al., 2021; Lowenberg-DeBoer et al., 2021). Owing to population and economic growth, agricultural labour scarcity, technological advancement, increasing requirements of operational efficiency and productivity, and mitigating environmental footprint, autonomous crop robotics are suggested as a sustainable intensification solution (Duckett et al., 2018; Fountas et al., 2020; Future Farm, 2021; Guevara et al., 2020; Lowenberg-DeBoer et al., 2021; Santos sand Kienzle, 2020). Even though the robotic systems of livestock and protected environment has developed more rapidly, research in autonomous crop robotics mostly concentrated on the technical feasibility (Duckett et al., 2018; Fountas et al., 2020; Lowenberg-DeBoer et al., 2020; Shamshiri et al., 2018). Considering the complexity of arable crop field operations, it is important to focus on the overall systems analysis (i.e., from drilling to harvesting) and understand the economic implications of autonomous crop robotics (Daum, 2021; Fountas et al., 2020; Grieve et al., 2019; Lowenberg-DeBoer et al., 2020). Economic implications of autonomous crop robotics play a crucial role in attracting investment, guiding adoption decisions, and further understanding of environmental and social benefits (Lowenberg-DeBoer et al., 2021, 2020; Santos and Kienzle, 2020).

The existing economic studies on autonomous crop robotics focused on one or two horticultural crops or rarely on cereals using prototype testing and experimental data (Edan et al., 1992; Gaus et al., 2017; McCorkle et al., 2016; Pedersen et al., 2017, 2008, 2006; Sørensen et al., 2005). Lack of information on economic parameters and machinery specifications act as a bottleneck in economic feasibility assessment because autonomous crop robotics are at an early stage of the development and commercialization processes (Fountas et al., 2020; Lowenberg-DeBoer et al., 2021; Lowenberg-DeBoer et al., 2021; Shockley et al., 2021). Most of the economic studies used partial budgeting where the changes of costs and revenues supported by all other constant assumptions are the problem, as the analysis is unable to present the real scenarios of economic impacts of crop robotics (Lowenberg-DeBoer et al., 2020). To date, four studies considered system analysis (Lowenberg-DeBoer et al., 2021; Shockley et al., 2019; Shockley and Dillon, 2018; Sørensen et al., 2005). Using Linear Programming (LP) models, the most successful systems analysis was performed by Lowenberg-DeBoer et al. (2021) and Shockley et al. (2019).

In the context of the United States, Shockley et al. (2019) showed that relatively small autonomous machines are likely to have economic advantages for medium and small farms. The most up to date study by Lowenberg-DeBoer et al. (2021) assessed the economic feasibility of swarm robotics from seeding to harvesting operations using on-farm level demonstration data of economic parameters and collected equipment time information from agricultural engineering textbook of Witney (1988). The study assumed 70% field efficiency from drilling to harvesting operations for both autonomous crop robotics and conventional equipment sets. They showed that autonomous equipment is technically and economically feasible for medium and small sized farms. The study also mentioned that autonomous crop robotics diminished the rule of thumb of mechanized agriculture that is “get big or get out”. Based on their preliminary analysis, they hypothesized that in the context of the United Kingdom, autonomous crop robotics would make it economically feasible to farm small fields. Nonetheless, the study did not test that hypothesis because of data deficiency on machine times and field efficiency.

To contribute to this knowledge gap, the objective of the study is to assess the economic implications of field sizes for autonomous crop robotics. Using the experience of the HFH project, demonstrated at Harper Adams University in the United Kingdom, the study developed algorithms to estimate equipment times and field efficiency for different sized rectangular fields. The study modified the LP model of Lowenberg-DeBoer et al. (2021) and updated the HFH-LP model by incorporating the equipment times and field efficiency parameters estimated through the developed algorithms. The modified HFH-LP model will facilitate farm management and machinery selection decisions. In addition, the inclusion of field size scenarios will have implications for environmental management and promote the ELMS and AES followed by the United Kingdom, European Union, and other countries.

Methods

Estimation of field time and field efficiency for different sized rectangular fields

The study developed algorithms to estimate equipment times (or field times) and field efficiency because the existing studies on arable crop machinery performance lack information on equipment times subject to field sizes. In this study, field time refers to hours required to complete per hectare arable field operation. The study estimated field efficiency as the ratio of theoretical field time based on machine design specifications like the estimates of theoretical field time to its actual field productivity. The field efficiency was presented in percentage. Even though logistics software is well developed in trucking and other transportation sectors (Software Advice, 2021), to date, there is no readily available commercial software to estimate equipment times. In farm equipment path planning literature, field times were sometimes generated as a by-product (Hameed, 2014; Jensen et al., 2012; Oksanen and Visala, 2007; Spekken and de Bruin, 2013). The agri-tech economic studies often rely on the general estimates of agricultural engineering textbooks like Hunt, (2001) and Witney (1988) to have equipment times and field efficiency estimates (see Lowenberg-DeBoer et al., 2021).

However, in conventional mechanization and precision agriculture literature, few studies estimated field efficiency (Adamchuk et al., 2011; Bochtis et al., 2010; Buick and White, 1999; Peterson et al., 1981; Renoll, 1970, 1969; Grisso et al., 2004; Grisso et al., 2002; Janulevičius et al., 2019; Shamshiri et al., 2013; Taylor et al., 2001; Taylor et al., 2002). But prior studies treated headlands as non-productive areas (for details see Bochtis et al., 2010; Gónzalez et al., 2007), excluded overlap percentage (for overlap see Lowenberg-DeBoer et al., 2021), amalgamating productive field times (i.e., field passes, headlands turning, and headlands passes) and non-productive field times (i.e., replenish inputs, refuelling, and blockages), and ignoring headlands turning types (for headland types see Han et al., 2019; Jin and Tang, 2010; Tu and Tang, 2019). These characteristics are important in the estimation of field times and field efficiency. For instance, Lowenberg-DeBoer et al. (2021) assumed overlap as 10% and pointed out that future study should consider reduce overlap. It is evident that the precision agriculture literature assumed 10% benchmark overlap (Griffin et al., 2005; Lowenberg-DeBoer, 1999; Ortiz et al., 2013). A very few studies suggested that future research should separately calculate the headlands turning time, and stoppages time (Bochtis et al., 2010; Shamshiri et al., 2013; Taylor et al., 2001; Taylor et al., 2002) because productive times and non-productive times play a significant role in field efficiency estimation (Bochtis et al., 2010; Jensen et al., 2015; Shamshiri et al., 2013; Spekken and de Bruin, 2013).

Keeping these points in mind, the study developed algorithms to estimate field times and field efficiency for autonomous crop robotics and conventional machinery with human operators (i.e., 38 hp HFH conventional equipment, 150 hp and 296 hp conventional machine) subject to different sized rectangular fields. Using the experience of the HFH demonstration project, the algorithms encompassed productive times and non-productive times separately, and incorporated the overlap percentage, and headlands turning type (for details see the technical note of Al-Amin et al., 2021a). The study assumed that the equipment entered the field from the entry side and completed the headlands first. Afterwards the machine made a “flat turn” to start the interior passes (i.e., the longest side of the field). Subsequently followed the "flat turn" for interior headland turns (i.e., the shortest side of the field) as shown in Figure 1.

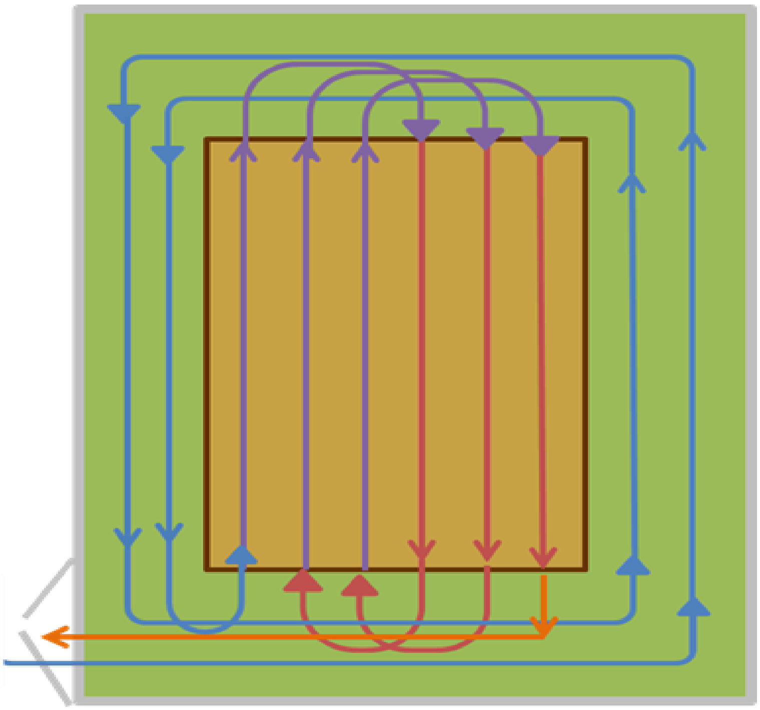

Figure 1: Typical field path considered in the algorithms based on the HFH demonstration project experience.

The study adopted and modified the flat turning algorithm of Jin and Tang (2010). The HFH autonomous equipment (i.e., tractor for drilling and combine for harvesting) followed the "flat turn" with skipping two swaths (i.e., during headlands turning the machine skipped two swaths nearer and enter in the interior field after skipping those swaths) (for typical "flat turn" see Jin and Tang, 2010). The speed of the implement in the interior headlands turning was assumed to be one third of the interior field speed. The algorithms were calibrated following the experience of the HFH project and the equipment specifications of conventional technologies with human operators. Finally, the study assumed that the equipment ends on the entry side of the field. The algorithm was developed in an excel spreadsheet to allow for use and modification by researchers and students who are not familiar with coding (for details of the algorithms see Al-Amin et al. 2021b).

Modelling the economic implications of field sizes on equipment use

The study modified the HFH-LP model to capture the economic implications of field sizes based on Lowenberg-DeBoer et al. (2021). The HFH-LP model is a decision-making tool which assesses the economic viability of autonomous crop robotics compared to conventional machines with human operators. The objective of the model was to maximize gross margin (i.e., return over variable costs) subject to primary farm resource constraints. The HFH-LP model is a one-year "steady state" model for arable crop farming, where the model assumes a monthly time step from January to December. The concept of "steady state" was adopted from the Orinoquia model (for details see Fontanilla-Díaz et al., 2021). Following Boehlje and Eidman (1984), the HFH-LP deterministic economic model can be expressed as:

The objective function:

$$Max\ \pi = \sum_{j=1}^{n} c_j X_j \qquad \dots \dots (1)$$

Subject to:

$$\sum_{j=1}^{n} a_{ij} X_j \ \leq \ b_i \ for\ i = 1, \dots \dots, m; \qquad \dots \ \dots (2)$$

$$X_j \geq 0\ for\ j = 1, \dots \ \dots, n; \qquad \dots \ \dots (3)$$

where, π is the gross margin, X_j is the level of *j*th production activities, c_j is the gross margin per unit over fix farm resources (b_i) for the *j*th production activities, $a_{ij}$is the amount of *i*th resource required per unit of *j*th activities, b_i is the amount of available *i*th resource. Net returns (i.e., total sales revenue minus total costs allied with variable and fixed factors of production) of the farm were examined.

The constraints of the HFH-LP model encompassed land, human labour, equipment times (i.e., tractor use time for drilling and spraying, and combine use time for harvesting), and cashflow. The land constraint was considered with the lens of field sizes. For instance, the 66 ha farm (i.e., representing the smallest average farm in the regions of the United Kingdom and the West Midland's average farm) (DEFRA, 2018a) with 90% tillable area (i.e., 59.4 ha) consisted of 59 fields of 1 ha each and 6 fields with 10 ha each. The study used the same principles for other farm sizes. To estimate the equipment time constraints, the study initially estimated field efficiency through the developed algorithms. In the subsequent stage, using the equipment specifications, 10% overlap percentage, and estimated field efficiency, the study calculated equipment times (i.e., hr/ha) from drilling to harvesting operations for the equipment sets with a reference to 1 ha and 10 ha sized rectangular fields. Finally, the equipment times were used to estimate the coefficients of human labour constraint and equipment time constraints. For details of the land, human labour, and cash flow constraints see Lowenberg-DeBoer et al. (2021). The details of the equipment time constraints were available at the technical notes of Al-Amin et al. (2021a). The HFH-LP model was coded in the General Algebraic Modelling System (GAMS) (https://www.gams.com/), where the data exchange (https://www.gams.com/35/docs/UG_DataExchange_Excel.html) option (i.e., Microsoft Excel to GAMS) were used considering the future user-friendly implications (for details of the GAMS code see Lowenberg-DeBoer et al., 2021).

Case Study and Data Sources

The study was conducted based on the experience of the HFH project demonstrated at Harper Adams University, Newport, United Kingdom. The HFH-LP model represented the arable agricultural grain-oil-seed farm in the West Midlands in the United Kingdom. The land constraints were selected following DEFRA (2018a, 2018b) to represent the average farm size in the West Midlands, average cereals farm, average cereals farms over 100 ha, and an arbitrary larger farm in the United Kingdom (Lowenberg-DeBoer et al., 2021). To calibrate the

HFH-LP model, the study used parameters from different sources. The information about commodity produced and the costs estimates were collected from the Agricultural Budgeting and Costing Book (Agro Business Consultants, 2018) and the Nix Pocketbook (Redman, 2018). The study followed the field operation timing of Finchet al. (2014) and Outsider's Guide (1999). The equipment specifications and field specifications were collected from HFH demonstration experience (https://www.handsfreehectare.com/), conventional large and small machine specifications from John Deere (https://www.deere.co.uk/en/index.html), and Arslan et al. (2014) (for details of the data sources see the technical notes of Al-Amin et al., 2021a).

Results

Effects field sizes on field efficiency and equipment times

The estimated average field efficiency of the whole cropping cycle for the four equipment sets differed substantially between 1 ha and 10 ha fields, but for a given equipment set the field efficiency was almost the same for fields of 10 to 100 ha (Figure 2). In this case the whole cropping cycle included direct drilling, five spray applications and harvesting. The interesting finding of the whole farm field efficiency is that the HFH equipment set (i.e., small 38 hp conventional machine with human operator and autonomous crop robotics were considered identical) had comparatively higher field efficiency, whereas 150 hp and 296 hp conventional equipment sets with human operator were not efficient for small fields. As beyond 10 ha, the field efficiency for a given equipment set was similar for all field sizes (i.e., 20 ha, 50 ha, 75 ha, and 100 ha), the study endeavoured to focus on the economic implications of 1 ha and 10 ha field sizes.

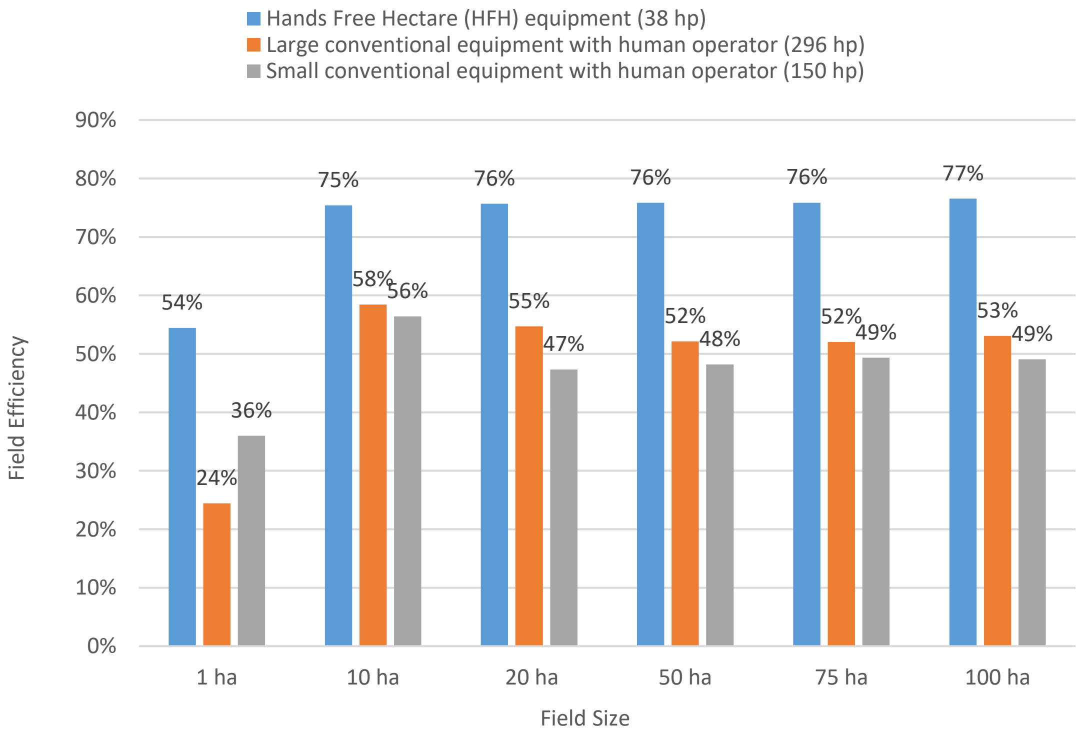

Figure 2: Estimated (weighted average) whole farm field efficiency of HFH equipment (assumed same for both HFH small conventional equipment with human operator and autonomous swarm robotics), large conventional machine, and small conventional technology in different sized rectangular fields.

The result of the equipment times depicted that field times (hr/ha) were longer for small 1 ha fields operated with equipment of all sizes and types, but field size had the least impact for HFH small equipment (Table 1). The extra time required for small 1 ha fields was associated with the lumpiness of non-productive times (i.e., replenishing seed and spray materials, and refilling fuel), interior headlands turn, and interior field passes. In spraying operations, irrespective of autonomous crop robotics and conventional equipment sets, the lower field efficiency reflects the reality. For example, the HFH 38 hp sprayer implement covered a 7 m wide swath with relatively fast speed (i.e., interior field speed was 5 kph, where the interior headland turning speed was 1/3 of the interior field speed), consequently, the input refill (i.e., seed and spray materials) became a bigger issue. If the capacity of the sprayer tank and drill bin (i.e., for seed) closely matched what was needed for whole rounds, then the field efficiency was slightly higher. On the contrary, if the sprayer tank and drill bin capacity did not match the requirements of the whole rounds (i.e., a substantial amount remained in the tank or bin, but not enough for a whole round) then field efficiency was lower. The study showed that small fields required more headlands and interior rounds for non-productive times. In addition, the lumpiness associated with the interior headlands turn and interior field passes were also a bigger issue for 150 hp and 296 hp conventional equipment sets because small fields required manual intervention leading to the conclusions that the comparatively larger conventional equipment sets were not suitable for small fields (for details see the developed algorithms at Al-Amin et al., 2021b).

Economic implications of field sizes on machinery use

The result of the equipment scenarios showed that return over variable costs were higher for small 1 ha fields operated with autonomous crop robotics irrespective of farm types (i.e., average farms in the West Midlands, average cereal farms, average cereals farms over 100ha, and larger arbitrary farms), whereas larger farm with 10 ha sized fields equipped with 296 hp conventional equipment set had a higher gross margin (Table 2). The interesting findings of the study are that 1 ha fields were more feasible with autonomous crop robotics, whereas 10 ha field sizes were similar to the findings of Lowenberg-DeBoer et al. (2021) which supported larger conventional equipment for arbitrarily larger fields, if the ownership costs were not considered. However, inclusion of ownership costs revealed that net returns to operator labour, management, and risk taking were higher for crop robotics, except for the typical smallest farms in the West Midlands. The smallest farm with 1 ha and 10 ha sized fields operated by autonomous crop robotics and conventional equipment sets produced similar gross margins. This may be because the smallest farms operated with four equipment scenarios did not face any operator and labour time constraints and as such planted and harvested wheat-OSR rotation at optimal times.

Although irrespective of 1 ha and 10 ha field sizes, the net returns were higher for the smallest farms operated with 38 hp HFH conventional equipment, and the smallest conventional equipment set required higher operator time than the autonomous crop robotics. The higher profit may be because the study did not exclude the operator compensation. In addition, the autonomous crop robotics included the investment of retrofitted equipment as the autonomous crop robotics were developed through the retrofitting process. It is also evident that in arable crop field operations, the smallest 38 hp HFH conventional equipment set required higher amounts of human labour and operator time than all other equipment sets. More specifically, the small 1 ha fields demanded more human labour and operator time than 10 ha fields. Nevertheless, throughout the world agricultural labour is difficult to hire. In the context of the United Kingdom, small conventional equipment will not be the feasible solution as the country is also facing agricultural labour scarcity. The study assessed economic feasibility with an average wage rate of £9.57/hr. However, with the increase in wage rate increases, the scenarios may change. There is uncertainty as to whether or not the labour could be always hired at this wage rate.

Table 1: Equipment times of the machinery sets for rectangular fields of 1 ha and 10 ha

Equipment	Width of the implement (m)**	Overlap percentage**	Field speed (km/hr)**	Field Efficiency (%) ***	Area/hr	hr/ha
1 ha Rectangular Field						
HFH equipment set (38hp)*:						
Drill	1.5	10%	3.25	73%	0.32	3.12
Sprayer	7	10%	5	46%	1.45	0.69
Combine	2	10%	3.25	80%	0.47	2.14
Larger conventional set (296hp):						
Drill	6	10%	5	24%	0.65	1.54
Sprayer	36	10%	10	23%	7.45	0.13
Combine	7.5	10%	3	32%	0.65	1.54
Small conventional set (150hp):						
Drill	3	10%	5	46%	0.62	1.61
Sprayer	24	10%	10	32%	6.91	0.14
Combine	4.5	10%	3	45%	0.55	1.83
10 ha Rectangular Field						
HFH equipment set (38hp):						
Drill	1.5	10%	3.25	84%	0.37	2.71
Sprayer	7	10%	5	70%	2.21	0.45
Combine	2	10%	3.25	92%	0.54	1.86
Larger conventional set (296hp):						
Drill	6	10%	5	82%	2.21	0.45
Sprayer	36	10%	10	49%	15.88	0.06
Combine	7.5	10%	3	82%	1.66	0.60
Small conventional set (150hp):						
Drill	3	10%	5	83%	1.12	0.89
Sprayer	24	10%	10	45%	9.72	0.10
Combine	4.5	10%	3	86%	1.04	0.96

Note: * HFH equipment sets representing both 38hp conventional machine with human operator and 38hp autonomous swarm robotics. **The machine specifications and overlap assumptions were collected from the HFH experience and Lowenberg-DeBoer et al. (2021). *** The authors developed algorithms to estimate the field efficiency of rectangular fields (for details of the estimation procedures and algorithms see the technical note in the supplementary material).

Table 2: HFH-LP outcomes on the economic viability of technology choice subject to field sizes. The technology selection scenarios encompassed HFH small conventional equipment with human operator and autonomous crop robotics, large conventional machine with human operator, and small conventional technology with human operator.

Scenario*	Farm size (ha)	Field size (ha)	Arable area (ha)**	Labour hired in the farm (days)	Operator time required in the farm (days)	Whole farm gross margin (£ per annum)	Return to operator labour, management and risk taking (£ per annum)	Wheat cost of production with allocated operator labour (£ per ton)
Conv 38 hp	66	10	59.4	0	66	47048	15848	160
Conv 38 hp	66	1	59.4	0	83	47048	15848	171
Conv 38 hp^{2}	159	10	143.1	41	118	110140	38725	148
Conv 38 hp^{2}	159	1	143.1	63	138	108452	37037	155
Conv 38 hp^{3}	284	10	255.6	140	144	191499	69185	138
Conv 38 hp^{3}	284	1	255.6	191	167	187583	65269	143
Conv 38 hp^{4}	500	10	450	323	171	330716	127117	130
Conv 38 hp^{4}	500	1	450	435	194	302777	99178	143
Conv 38 hp^{5}	500	1	450	450	179	321300	108538	135
Robot 38 hp	66	10	59.4	0	19	47048	12301	136
Robot 38 hp	66	1	59.4	0	23	47048	12301	138
Robot 38 hp	159	10	143.1	0	46	113343	47543	122
Robot 38 hp	159	1	143.1	0	5	113343	47543	124
Robot 38 hp^{2}	284	10	255.6	21	61	200782	80535	121
Robot 38 hp^{2}	284	1	255.6	31	66	200014	79767	122
Robot 38 hp^{3}	500	10	450	71	73	350879	145800	117
Robot 38 hp^{3}	500	1	450	88	83	349528	144449	118

Note: *The superscript with equipment specification under scenario indicates the number of equipment sets. **Based on the experience of HFH demonstration project, the study assumed that the arable crop farm was 90% tillable, where remaining 10% were occupied for ecologically focused area such as, lanes, hedgerows, drainage ditches, farmstead, etc.

Table 2: HFH-LP outcomes on the economic viability of technology choice subject to field sizes (Continued)

Scenario*	Farm size (ha)	Field size (ha)	Arable area (ha)**	Labour hired in the farm (days)	Operator time required in the farm (days)	Whole farm gross margin (£ per annum)	Return to operator labour, management and risk taking (£ per annum)	Wheat cost of production with allocated operator labour (£ per ton)
Conv 150 hp	66	10 ha	59.4	0	25	47048	-26001	210
Conv 150 hp	66	1 ha	59.4	0	45	47048	-26001	223
Conv 150 hp	159	10 ha	143.1	0	60	113343	9242	155
Conv 150 hp	159	1 ha	143.1	21	87	111668	7567	164
Conv 150 hp	284	10 ha	255.6	17	90	201096	55257	136
Conv 150 hp	284	1 ha	217.1	65	99	166931	35360	146
Conv 150 hp[2]	284	1 ha	255.6	91	102	195363	-1487	162
Conv 150 hp	500	10 ha	383.8	58	104	299526	106111	126
Conv 150 hp[2]	500	10 ha	450.0	82	107	350053	81080	136
Conv 150 hp	500	1 ha	213.5	65	99	166931	36718	144
Conv 150 hp[2]	500	1 ha	434.3	212	116	327466	64323	140
Conv 296 hp	66	10 ha	59.4	0	15	47048	-70973	287
Conv 296 hp	66	1 ha	59.4	0	40	47048	-70973	303
Conv 296 hp	159	10 ha	143.1	0	35	113343	-35731	183
Conv 296 hp	159	1 ha	143.1	11	84	112478	-36596	197
Conv 296 hp	284	10 ha	255.6	0	63	202449	11638	151
Conv 296 hp	284	1 ha	227.6	53	99	176086	-4317	165
Conv 296 hp[2]	284	1 ha	450.0	70	101	197007	-161910	276
Conv 296 hp	500	10 ha	450.0	24	88	354591	91657	131
Conv 296 hp	500	1 ha	227.5	53	99	176086	-4317	165
Conv 296 hp[2]	500	1 ha	450.0	185	115	341980	-16938	160

Note: *The superscript with equipment specification under scenario indicates the number of equipment sets. **Based on the experience of HFH demonstration project, the study assumed that the arable crop farm was 90% tillable, where remaining 10% were occupied for ecologically focused area such as, lanes, hedgerows, drainage ditches, farmstead, etc.

The wheat costs of production curves revealed that irrespective of field sizes (i.e., 1 ha and 10 ha) farming with autonomous crop robotics had higher economies of size advantage than the farms operated with conventional equipment sets (Figure 3).

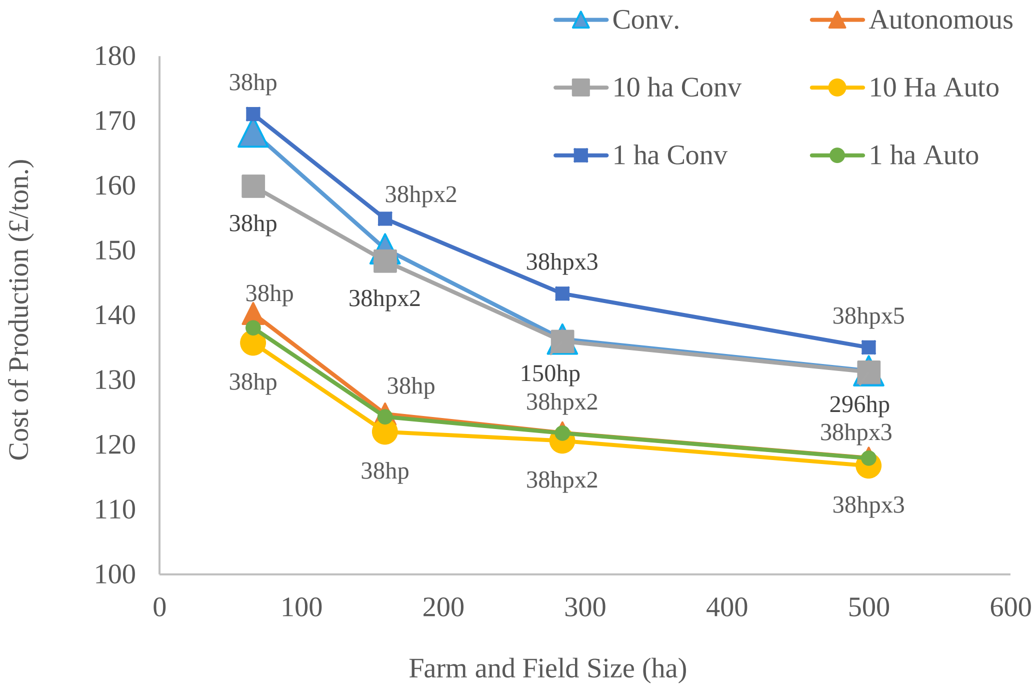

Figure 3: Wheat unit cost of production in pounds per ton with a reference to farm and field sizes. The labels on the data points are the size of the tractor used and the number of equipment sets.

The key finding is that the study found a substantial effect of field sizes on wheat cost of production farmed with conventional equipment sets (i.e., 38 hp; 150 hp, and 296 hp). The wheat costs of production showed that 10 ha sized farms equipped with conventional equipment sets had comparatively higher economies of size advantage (big squares) than the farms without field size in consideration as shown in the “L” shaped upper middle wheat costs of production curve (triangles) adopted from Lowenberg-DeBoer et al. (2021). For 1 ha farm scenarios, even if the small 1 ha farm is operated with the smallest 38 hp conventional equipment set, the costs (small squares) were higher than 10 ha fields with all conventional equipment sets. The cost curves were calculated based on the production of profitable farms, where the study found that farming with 150 hp and 296 hp conventional equipment sets was unprofitable for the two larger farms. The unprofitable farms would not stay in business for long. This means that for conventional farms, the wheat cost curve required hiring substantial amounts of temporary labour. Farming with autonomous crop robotics had similar costs of production for 1 ha (small circle) and 10 ha (big circle) sized fields, where the “L” shaped curve (triangular) represents the wheat production cost curve for autonomous crop robotics without field size in consideration.

Discussion

The contribution of the present study is that the study endeavoured to focus on the economic implications of field sizes on arable field crop operations equipped with autonomous crop robotics and conventional machinery with human operators in the context of the UK's typical farms. The results of study have significant implications for farm management and machinery selection decisions, agribusiness adopters, and environmental management. The previous economic studies on autonomous machinery use missed the implications of field sizes (Lowenberg-DeBoer et al., 2021; Shockley et al., 2019), whereas small fields received substantial attention in environmental conservation studies to protect biodiversity and encourage ELMS and AES (Europe, 2008; Fahrig et al., 2015; Firbank et al., 2008; Flick et al., 2012). To address the economic implications of field sizes, the study developed algorithms for estimating field efficiency and field times of different sized rectangular fields and equipment sets. This is the first attempt as prior studies more likely relied on the estimation of field efficiency and field time based on Hunt (2001) and Witney (1988). The estimation of the agricultural engineering books did not address the variability of equipment sets and field sizes. As such, the developed algorithms in this study would have future implications. The study ensured flexibility to address field and machine heterogeneity, calculate productive and non-productive times separately, and incorporated overlap percentage for achieving real farm scenarios. In agriculture, there is no readily available software to calculate field times and field efficiency. Consequently, the engineers and agri-tech economists can use the algorithms for analysing the future technical and economic potentials of arable crop machines.

The study found that field size had the least impact for the smallest equipment sets compared to the large conventional equipment sets with human operators. This means that the smallest equipment less likely favours field enlargement which in-turn conserves biodiversity. The finding supports the environmental management studies of small fields to conserve biodiversity (Fahrig et al., 2015; Gaba et al., 2010; González-Estébanez et al., 2011). The study assumed that HFH small 38 hp conventional equipment and autonomous crop robotics were identical. Future research should consider other small conventional equipment to address the equipment time issue with small fields. To empirically examine the on-field scenarios of field biodiversity, future research should incorporate field biodiversity, such as hedgerows, in field trees, and wetlands in the algorithms subject to field sizes.

The findings of the return over variable costs more likely support autonomous crop robotics for small 1 ha fields. On the contrary, 10 ha sized fields favoured larger conventional equipment for larger arbitrary farms which is consistent with the findings of Lowenberg-DeBoer et al. (2021). The outcomes from mathematical programming (i.e., net return scenarios with all the equipment sets) showed that autonomous crop robotics were the most feasible solution to profitably operate all the arable crop farms, except for the smallest farms in the West Midlands (Table 2). For the smallest farm, HFH conventional 38 hp equipment was the profitable choice. However, this smallest farm demanded substantial amounts of temporary labour and operator time. As agricultural labour is difficult to hire and the world is facing scarcity of agricultural labour, conventional 38 hp equipment would become economically infeasible even on the smallest farm. Autonomous crop robotics could be considered as a sustainable solution for arable field crop operation with the increasing scarcity of agricultural labour. The experience of the HFH demonstration project showed that autonomous equipment still required hired labour and operator time for supervision, being 10% human supervision and 100% for hauling grain during peak harvesting time in July, August, and September. To make the autonomous crop robotics more economical and solve the problem of labour scarcity, the autonomous arable farms should endeavour to gear up the technological innovation and come up with autonomous (i.e., self-driving) equipment for public roads.

The findings of wheat costs of production also contribute to the economies of size literature. In agricultural production economics studies, the cost curves are typically used to analyse the economic-return-to scale of agricultural enterprises, spreading the fixed costs, and labour reducing technologies (Debertin, 2012; Duffy, 2009). To avoid the misuse of economies of scale (i.e., must follow the proportionate change in all input categories), based on the usual scenarios of agricultural farming, studies concentrated on economies of size (i.e., input categories do not change proportionately) (Debertin, 2012; Duffy, 2009; Hallam, 2017; Lowenberg-DeBoer et al., 2021; Miller et al., 1981). It is evident that agricultural production economic studies typically form the "L" shaped cost curve because the agricultural enterprises rarely showed diseconomies of size (i.e., increases production costs with increased production) (Debertin, 2012; Duffy, 2009). In the context of the United Kingdom, even though Lowenberg-DeBoer et al. (2021) investigated the economies of size of wheat costs of production, nevertheless, question remains on the implications of field sizes on the costs structure of arable field crop operations equipped with autonomous crop robotics and conventional equipment sets. The study found substantial effect of field sizes on wheat cost of production farmed with conventional equipment sets. This indicates that conventional equipment sets were unprofitable for larger farms and the smallest farms required substantial amounts of labour which is not a feasible option in the context of the United Kingdom. The autonomous crop robotics had the advantage of economies of size compared to conventional equipment sets irrespective of field sizes. This means that fields operated with autonomous crop robotics would be the possible solution from both an economic and environmental point of view. The advantage of small fields for enhancing biodiversity is already known for the United Kingdom, United States, Europe, and Canada. Therefore, the present study hypothesized a nexus between field sizes, autonomous crop robotics, and biodiversity enhancement which needs empirical investigation.

However, despite having significant contributions in farm management, agri-tech economics, and environmental management literature, the study had some limitations in the development of algorithms and existing economic modelling scenarios. The algorithms still need some manual intervention for interior headlands turning and interior field passes in the case of relatively small fields. For instance, if the field is too small relative to the size of the equipment, the algorithm breaks down and manual entries are needed. The algorithms also assumed zero blockages that should be extended based on field experience. The study fails to address the impacts of different field shapes which demands attention. In terms of economic model scenarios, the study only considered four equipment sets and there may be other equipment sizes (i.e., 50 hp, 60 hp, and 70 hp) that fit the given circumstance better, especially for small 1 ha fields. Future research could incorporate various field sizes of less than 10 ha because the field efficiency was similar for the larger fields. In addition, future endeavours should consider the economic implications of autonomous crop robotics on biodiversity enhancement and mitigation of environmental degradation.

Conclusions

Arable farms with small fields are promoted to conserve biodiversity and support the AES and ELMS followed by the European Union, United Kingdom, and other countries elsewhere. However, agri-tech economic studies on autonomous arable crop equipment's (i.e., autonomous crop robotics) have previously failed to address the implications of field sizes. To contribute to the scientific knowledge, the study hypothesized that autonomous crop robotics would make it possible to farm small fields profitably. To test the hypothesis, using the experience of the HFH project demonstrated at Harper Adams University in the United Kingdom, the study developed algorithms to calculate equipment times for different sized rectangular fields. The economic implications of field sizes were assessed with the modified HFH-LP model. Equipment time results reveal that small 1 ha fields required longer time for all equipment sets. The extra time was associated with the lumpiness of non-productive times (i.e., replenishing seed and spray materials, and refilling fuel), interior headland turns, and interior field passes. The results of the HFH-LP model show that irrespective of field sizes, the autonomous crop robotics were the most profitable solution for all arable crop farms, except for the smallest farms in the West Midlands. The smallest (i.e., 66ha) farm was profitable with 38 hp HFH conventional equipment, but the farm required more temporary labour and operator time. Given existing agricultural labour scarcity, even the small conventional equipment will not be the sustainable solution. The autonomous crop robotics will be the probable solution for arable crop farming because the autonomous crop robotics had the advantage of economies of size compared to conventional equipment sets irrespective of field sizes. The cost advantage even in small fields indicates that autonomous crop robotics ensured both the economic and environmental goals of arable farming.

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