An economic assessment of autonomous equipment for field crops

A thesis submitted in partial fulfilment of the requirements of Harper Adams University for the degree of Doctor of Philosophy.

By

A. K. M. Abdullah Al-Amin

MS in Agricultural Economics (Production Economics) (Bangladesh Agricultural University)

B.Sc.Ag.Econ.(Hons.) (Bangladesh Agricultural University)

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Department of Food, Land and Agribusiness Management

Harper Adams University, Edgmond, Newport, Shropshire, TF10 8NB, UK

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Paper	Published
Paper 1	Al-Amin, A.K.M. Abdullah, Lowenberg DeBoer, J., Franklin, K. and Behrendt, K. (2023) 'Economics of field size and shape for autonomous crop machines', Precision Agriculture, p. 0123456789. Available at: https://doi.org/10.1007/s11119-023-10016-w (Accessed: 12 July 2023) ***Note:*** *The preliminary versions of the first paper were published as proceedings papers as:* Al-Amin, A.K.M. Abdullah, Lowenberg DeBoer, J., Franklin, K. and Behrendt, K. (2022) *'Economics of Field Size for Autonomous Crop Machines.*', in A paper from the Proceedings of the 15th International Conference on Precision Agriculture Minneapolis, Minnesota, United States. pp. 1–15. Available at: https://ageconsearch.umn.edu/record/322755?ln=en (Accessed: 12 July 2023). Al-Amin, A.K.M. Abdullah, Lowenberg-DeBoer, J., Franklin, K. and Behrendt, K. (2021) *'Economic Implications of Field Size for Autonomous Arable Crop Equipment.'* In: K. Behrendt and D. Paparas (2021) 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. pp. 25–44. Available at: https://ageconsearch.umn.edu/record/316595?ln=en (Accessed: 12 July 2023).
Paper 2	Al-Amin, A. K. M. Abdullah, Lowenberg-DeBoer, J., Erickson, B. J., Evans, J. T., Langemeier, M. R., Franklin, K., & Behrendt, K. (2024) 'Economics of strip cropping with autonomous machines', Agronomy Journal, 1–18. Available at: https://doi.org/10.1002/agj2.21536 (Accessed: 12 February 2024)
Paper 3	Al-Amin, A.K.M. Abdullah, Dickin, E., Monaghan, J.M., Franklin, K. and Lowenberg-DeBoer, J. (2023) *'Economics of autonomous machines for regenerative agriculture'.* Proceedings at the 14th European Conference on Precision Agriculture, 2-6 July 2023. Bologna, Italy. Precision Agriculture' 23. Wageningen Academic Publishers. pp. 749-755. Available at: https://www.wageningenacademic.com/doi/10.3920/978-90-8686-947-3_94?fbclid=IwAR19C5uYtaNb96lWo5mdXwz6dx96kBAf2_YD9sdwcc8u7S1-Tjx_EiAzOBA (Accessed: 18 July 2023).

Contributions of authors

The contributions of authors on publications included in this PhD thesis are as follows:

Paper	Authors	Contributions
Paper 1	A. K. M. Abdullah Al-Amin	Conceptualization, Data curation, Initial and Formal analysis, Investigation, Methodology, Validation, Visualization, Writing - original draft, Writing - review & editing
	James Lowenberg-DeBoer	Conceptualization, Data curation, Funding acquisition, Investigation, Methodology, Project administration, Software, Supervision, Validation, Writing - review & editing
	Kit Franklin	Methodology, Project administration, Supervision, Writing - review & editing
	Karl Behrendt	Conceptualization, Funding acquisition, Investigation, Project administration, Supervision, Writing - review & editing
Paper 2	A. K. M. Abdullah Al-Amin	Conceptualization, Data curation, Initial and Formal analysis, Investigation, Methodology, Validation, Visualization, Writing - original draft, Writing - review & editing
	James Lowenberg-DeBoer	Conceptualization, Data curation, Funding acquisition, Investigation, Methodology, Project administration, Software, Supervision, Validation, Writing - review & editing
	Bruce J. Erickson	Conceptualization, Data curation, Investigation, Methodology, Project administration, Supervision, Writing - review & editing
	John T. Evans	Conceptualization, Investigation, Methodology, Resources, Supervision, Writing - review & editing
	Michael R. Langemeier	Conceptualization, Investigation, Methodology, Writing - review & editing
	Kit Franklin	Conceptualization, Methodology, Project administration, Supervision, Writing - review & editing
	Karl Behrendt	Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Supervision, Writing - review & editing
Paper 3	A. K. M. Abdullah Al-Amin	Conceptualization, Data curation, Initial and Formal analysis, Investigation, Methodology, Validation, Visualization, Writing - original draft, Writing - review & editing
	E. Dickin	Conceptualization, Methodology, Writing - review & editing
	J.M. Monaghan	Conceptualization, Methodology, Writing - review & editing

	Kit Franklin	Methodology, Project administration, Supervision, Writing - review & editing
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Research outcomes dissemination

Objective	Seminar Presentation
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Objective 2	• Presented at the 5th Online Symposium on Agri-Tech Economics for Sustainable Futures, organized by Global Institute for Agri-Tech Economics, Food, Land and Agribusiness Management Department, Harper Adams University, Newport, Shropshire, TF108NB, UK on 19-20 September 2022. Available at: https://www.youtube.com/watch?v=xNmSUkKn6Ww&t=425s
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Abbreviations

AI	Artificial Intelligence
AES	Agri-Environment Schemes
BREXIT	British Exit from the European Union
BPS	Basic Payment Scheme
CSS	Countryside Stewardship Scheme
ELMS	Environmental Land Management Scheme
GAMS	General Algebraic Modelling System
GBP	Great British Pound
GHG	Greenhouse Gas
GNSS	Global Navigation Satellite Systems
GPS	Global Positioning System
HFH	Hands Free Hectare
HFF	Hands Free Farm
HFH-LP	Hands Free Hectare Linear Programming
ICT	Information and Communication Technology
LP	Linear Programming
PA	Precision Agriculture
PAR	Photosynthetically Active Radiation
PPFD	Photosynthetic Photon Flux Density
RAS	Robotics and Autonomous Systems
ROLMRT	Return to Operator Labour Management and Risk Taking
SI	Sustainable Intensification
DSS	Decision Support System
MIDAS	Model of an Integrated Dryland Agricultural System
UK	United Kingdom
US	United States

Declaration

The author hereby confirms that the research is originally based on the experience of the Hands Free Hectare (HFH) and Hands Free Farm (HFF) demonstration project at the Harper Adams University in the United Kingdom. The author himself wrote the report, with a few definitions adopted from different sources and references cited properly. The report has not been partially and fully submitted to achieve institutional qualification or award to any university.

A. K. M. Abdullah Al-Amin
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Dedication

The PhD thesis is dedicated to the departed soul of my beloved father (late) who was a close friend of mine. I would like to extend my profound gratitude to him as he launched the voyage to educate me going against his socio-economic constraints that was totally unfavourable for him to start with. His lifelong sacrifices pushed me ahead.

My father is still alive in the great thoughts and good deeds of mine. Have a great time in ‘haven’ dear. We will meet again.

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“Try to educate yourself and achieve the highest degrees of the world and use the acquired knowledge for the welfare of the universe” is a lifetime learning for the author.

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The Author

A. K. M. Abdullah Al-Amin

Abstract

Research suggests autonomous machines in open field arable farming can enhance biodiversity conservation and ecosystem services restoration. It is hypothesized that autonomous equipment could be a profitable alternative to conventional machines with human operators irrespective of field size and shape or cropping systems. However, lack of agronomic, economic and technical data has constrained economic assessment. Noting this, this study evaluated the economics of field size and shape, and mixed cropping with autonomous machines using the Hands Free Hectare and Hands Free Farm (HFH&HFF) demonstration experience of Harper Adams University, UK. Using the Hands Free Hectare Linear Programming (HFH-LP) optimization model results indicated that autonomous machines in British farming decreased wheat production cost by €15/ton to €29/ton for small rectangular fields and €24/ton to €46/ton for small non-rectangular fields. Sensitivity scenarios of increasing wage rates and labour scarcity shows that autonomous farms adapted easily and profitably to changing scenarios, whilst conventional mechanized farms struggled. The ex-ante economic analysis of corn-soybean strip cropping in the North American Corn Belt of Indiana found that per annum return to operator labour, management and risk-taking (ROLMRT) was $568.19/ha and $162.58/ha higher for autonomous strip cropping as compared to whole field sole cropping and conventional strip cropping. Conventional strip cropping was only feasible with a substantial amount of labour availability. The ex-ante economic analyses of wheat - barley - flower mix - spring bean regenerative strip cropping practices show that for Great Britain autonomous regenerative strip cropping ROLMRT was £57,760 and £25,596 higher compared to whole field sole cropping and conventional regenerative strip cropping practices. The profitability of autonomous machines in small fields irrespective of field size and shape, strip cropping systems and regenerative practices imply that autonomous machines could offer a win-win farming solution that help achieve the production and environmental goals of arable farming.

Chapter 1

General introduction

"Autonomous field management represents the next evolutionary step in agricultural technology. ... The integration of multifaceted objectives into a common decision-making process poses a great challenge to human farmers and their capacities. Liberated from labour constraints, autonomous systems have the potential to align decisions with the complex requirements of multiple − even contradicting – goals more easily, and to execute them accordingly without exhaustion."

Gackstetter et al. (2023): Agricultural Systems, 206, p.103607.

1.1 Introduction

Robotics and autonomous systems (RAS) for arable open-field crop farm operations are being introduced worldwide to reduce social, economic and environmental costs of farming (Duckett *et al.*, 2018; Rose and Chilvers, 2018; Lowenberg-DeBoer *et al.*, 2021a; Pearson *et al.*, 2022). The robots for livestock rearing (e.g., performing operations like milking, feeding, barn cleaning and silage handling) have developed more rapidly as this technology is similar to industrial robots and requires less mobility and decision-making capacity due to the structured environment. The pioneers among crop robots were the greenhouse robots operated on rails in a controlled environment (Lowenberg-DeBoer *et al.*, 2020; Daum, 2021). However, the farming environment of arable open-field crops is more complex and unstructured. Arable crop farm operations depend on the risk and uncertainty of weather, soil attributes, travelling between fields, rolls and slopes, and other farm level challenges, and legal and policy constraints (Bechar and Vigneault, 2016; Grieve et al., 2019; Fountas et al., 2020; Shockley et al., 2021; Kubota, 2023).

Open-field crop robots are currently used for agricultural tasks (i.e., land preparation, transplanting, seeding, plant protection, weed control and harvesting) and supporting tasks (i.e., guidance, navigation, mapping, and localization) to maximize production, and environmental and food safety (Bechar and Vigneault, 2016; Bellon-Maurel and Huyghe, 2017; Davies, 2022; Finger et al., 2019). The development of mechatronic technology, information and communication Technology (ICT), increasing agricultural labour scarcity and higher demand for food and nutritional security has pushed arable crop farming towards crop robotics (Duckett et al., 2018; Lowenberg-DeBoer et al., 2020). Arable farm machines having some autonomy and mobility in operations are simultaneously termed 'robots', 'field crop robots', 'automated machines', and 'autonomous machines'.

The term 'robots' refers to the equipment with decision making capacity through the use of artificial intelligence (AI) (Kyriakopoulos and Loizou, 2006; Lowenberg-DeBoer et al., 2021a). In this study 'field crop robot' indicates "a mobile, autonomous, decision making, mechatronic device that accomplishes crop production tasks (e.g., soil preparation, seeding, transplanting, weeding, pest control and harvesting) under human supervision, but without direct human labour". The term 'automated machines' refers to the partially robotized mechatronic technology that accomplish arable field operations such as seeding, weeding, and harvesting, but with mobility assured by a human operator (Lowenberg-DeBoer *et al.*, 2020). In this study 'autonomous machines' (or 'autonomous crop robots' or 'autonomous crop machines') are a subset of field crop robots which have autonomy in arable field operations using predetermined field paths and itinerary often with relatively little decision-making capacity.

Autonomous machines are precision agriculture (PA) technology because they have the potential of cost effectively increasing the precision of input applications and to collect very detailed data on agricultural production. Autonomous machines considered in this study are modelled on the arable field crop machines of the Hands Free Hectare (HFH) (https://www.handsfree.farm/) project demonstrated at the Harper Adams University (HAU) in the UK (Hands Free Hectare (HFH), 2021). The HFH autonomous machines are also labelled as 'swarm robots' (or 'swarm robotics') because multiple units of smaller equipment were used to accomplish arable farm operations that would typically be done by a larger conventional machine with a human operator (Lowenberg-DeBoer *et al.*, 2021a).

1.2 Autonomous machines for arable field crops

Worldwide autonomous machines for arable field crops are in an early wave of the development and commercialization processes (Shockley *et al.*, 2021; Lowenberg-DeBoer, 2022b). The market for autonomous machines is expanding with a robust growth in large and medium scale farming contexts, such as Australia, the UK, US and European Union. Research in the US and UK found that small and medium sized farms could purchase low cost small autonomous machines as such farms are potentially profitable with autonomous farming (Shockley, Dillon and Shearer, 2019; Lowenberg-DeBoer et al., 2021a). Autonomous machines could be the future of arable farming (Hekkert, 2021). Recent market report shows that autonomous machines manufacturers are investing substantially in research and development of equipment where industry players expect that the market for autonomous machines would be a US$ 150 billion industry by the near future in 2031. The report also pointed out that apart from large and medium scale farming, smallholders farming could be the thriving market for autonomous tractors and harvesters (Claver, 2021).

The interest in autonomous machines is increasing in smallholder's contexts because of the challenges of agricultural labour scarcity, aging of farmers, reluctance of young people to choose agriculture as a career and their desire for off-farm employment opportunities in the city (Feike et al., 2012; Yanmar, 2017; Tofael, 2019; Devanesan, 2020; Al-Amin and Lowenberg-DeBoer, 2021; World Bank, 2021a). Recent market reports identified that the autonomous equipment market for smallholders is swelling dramatically (Devanesan, 2020; Xinhuanet, 2020; Business Wire, 2021; PR Newswire, 2022). Countries like China and Bangladesh are taking initiatives for rural revitalization strategies, national digitalization vision and smart farming strategy that include automation (Business Wire, 2021; Bangladesh Delta Plan, 2018; Al-Amin and Lowenberg-DeBoer, 2021; Globe Newswire, 2022; Al-Amin, Lowenberg-DeBoer and Mandal, 2023). Among smallholders of Asia, more proactive autonomous on-field trails have been demonstrated by universities, research institutes, and agribusinesses in Japan (Farm Equipment, 2021; Ministry of Agriculture Forestry and Fisheries (MFF), 2022; Nature, 2022; Yanmar, 2022), China (New China, 2018; Aguilar, 2021; Qin, 2021), Philippine (Bautista *et al.*, 2021) and Thailand (Precision Farming Dealer, 2022c).

Apart from developing new machines, retrofitting conventional machines for autonomy has received growing attention worldwide (Karsten, 2019a; Koerhuis, 2021a; Azevedo, 2022; Lowenberg-DeBoer, 2022b; Torres, 2022). Agribusiness innovators have been marketing retrofit kits for autonomy (Andrews, 2020; Advanced Navigation, 2022; Claver, 2022a; Future Farming, 2022; Precision Farming Dealer, 2022a; Sveaverken, 2022).

Autonomous machines as a service model (i.e., custom hire service) has also been initiated by service companies (Claver, 2020a, Claver, 2022d; Wilde, 2020). Academics and researchers hypothesized that part of the future market may be captured by the service model, like Uber or other modes of custom hire services (Lowenberg-DeBoer et al., 2020; Al-Amin and Lowenberg-DeBoer, 2021; Daum, 2021; Al-Amin, Lowenberg-DeBoer and Hasneen, 2022; Al-Amin et al., 2023).

The initial development of autonomous machines for arable field crops were prototypes that were demonstrated by universities and research institutes on parking lots and playgrounds. A few on-field trials were carried out for specific crop(s) and/or operation(s)

(Lowenberg-DeBoer *et al.*, 2020; Lowenberg-DeBoer, 2022b). In the last few decades, commercial manufacturers worldwide, ranging from commercial giants to start-ups have initiated development of autonomous machines to revolutionize arable crop farming. Many companies have developed autonomous prototypes and a smaller number have moved towards commercialization. It is often not exactly clear which are prototypes or commercial because limited information is publicly available about technology scaling up. This study classified the example initiatives as prototype or commercial. Commercial initiatives are considered those which have public news available about commercialization or the company itself announces this as commercial. Example initiatives of autonomous prototype (Table 1.1) and commercial (Table 1.2) machines mainly for arable field crops are given as follows.

Table 1.1: Example initiatives of autonomous prototype machines for arable field crops.

Year	Autonomous milestones	Primary operation considered	Enterprise	Company or organization	Country	Reference
2011	Autonomous operating systems	Till, puddle, transplant and harvest	Rice	National Agriculture Research Organization (NARO)	Japan	Nagasaka et al. (2011)
2017	Autonomous machines	Whole farm operations (Plant to harvest)	Wheat, oilseed rape, barley, beans and grass ley	Harper Adams University (HAU)	UK	Hands Free Hectare (HFH), (2021)
2018	Driverless tractors	Plough, rake, seed, fertilizer and mulch	Cotton	Lovol, and South China Agricultural University (SCAU)	China	New China (2018)
2019	Autonomous ground vehicle	Plant, spray, fertilizer, crop health monitor and cover crop seed	Wheat, soybeans, corn and sorghum	Easton Robotics	US	Groeneveld (2021a) and Easton Robotics (2023)
2019	Autonomous weeders	Weed	Vegetables	FarmWise and Roush	US	Claver (2019) and FarmWise (2023)
2020	Autonomous rice-transplanter	Transplant	Rice	Kubota Tractor Corporation	Japan	Kubota (2023)

Table 1.1: Example initiatives of autonomous prototype machines for arable field crops (Continued).

2020	Yanmar's agro-bot	Monitor crops, detect and treat diseases, soil sample, and spray	Vineyard and spinach	Yanmar R&D Europe (YRE) and Florence University	Italy	Claver (2020b)
2020	Fendt Xaver robots	Plant, protect, weed control and fertilizer	Grains	AGCO	US	Fendt (2020) and Fendt (2023)
2021	Autonomous implement carriers	Seed, plant, weed and grass cut	Cereals, vegetables and vineyard	3D Radar AS and Norwegian University of Science and Technology	Norway	AutoAgri (2023)
2021	Uncrewed agricultural machinery	Transplant and harvest	Wheat and rice	AIForce Tec	China	Qin (2021)
2021	Autonomous Hand Tractor	Till	Rice	University of Santo Tomas	Philippine	Bautista et al. (2021)
2021	Autonomous tractor swarm	Till	Open field	Yanmar and Hokkaido University	Japan	Yanmar (2021)
2021	Autonomous asparagus harvester	Harvest	Asparagus	University of Waikato and Robotics Plus	New Zealand	Groeneveld (2021b)
2022	Autonomous electric planter	Plant	Corn and soybean	Salin 247	US	Salin 247 (2022)
2022	Autonomous diesel-electric field robots	Cultivate, plough, sow, mow, ted and rake	Forage	Krone / Lemken	Germany	Krone (2022)
2022	Horsch autonomous robot tractor	Plant	Open field	Horsch	Germany	TractorLab (2022) and Azevedo (2023a)
2022	Autonomous weeding robot	Weed	Carrot and onion	Ulf Nordbeck	Sweden	Koerhuis (2022b) and Ekobot (2022)

Table 1.1: Example initiatives of autonomous prototype machines for arable field crops (Continued).						
2022	Autonomous weeding robot	Weed	Carrot and onion	Odd.Bot	The Netherlands	Koerhuis (2022b) and Odd.Bot (2023)
2023	Autonomous Flex-Ro Robot	Phenotype data collect	Cereals	University of Nebraska (UNL) and Farmobile	US	Asscheman (2023) and University of Nebraska - Lincoln (UNL) (2023)
Source: *Author's own compilation.*						

Table 1.2: Example initiatives of autonomous commercial machines for arable field crops.						
Year	Autonomous milestones	Primary operation considered	Enterprise	Company or organization	Country	Reference
2011	Naio Technologies	Hoe, weed, furrow, seed, transport and harvest	Vegetables and vineyards	Naio Technologies	French	Naio Technologies (2023)
2019	ROBOTTI autonomous robot	Seed, weed and spray	Cereals, oilseeds, vegetables and grass for seeds	Agrointelli	Denmark	Agrointelli (2019)
2019	Ecorobotix	Weed	Row crops, vegetable crops and grassland	Ecorobotix SA	Switzerland	EcoRobotix 2023)
2019	GUSS autonomous herbicide sprayer	Spray	Orchard	GUSS (Global Unmanned Spray System)	US	Agromillora (2023) and GUSS (2023)
2019	Greenbot and X-pert	Plough, mow, sow and fertilizer	Vegetables, horticultural crops, orchard and golf courses	Precision Makers	The Netherlands	Van Hattum (2019) and Precision Makers (2023)
2019	Pixelfarming Robot One	Plant, hoe and crop protect	Cereals, vegetables and flower	Pixelfarming Robotics	The Netherlands	Pixelfarming Robotics (2019)

Table 1.2: Example initiatives of autonomous commercial machines for arable field crops (Continued).

2019	XAG R150 Unmanned Ground Vehicle	Spray, weed, crop monitor and on-farm transport	Orchard and vegetables	XAG	China	XAG (2023)
2020	Autonomous electric robot	Seed and weed	Rapeseed and vegetables (e.g., sugar beets, onions, spinach, and salad)	FarmDroid	UK	FarmDroid (2020)
2020	Monarch MK-V tractor	Till, weed and spray	Vineyard	Monarch	US	Monarch (2023)
2020	Sitia autonomous robot	Till, spray and hoe	Gardens, tree crops, and vineyards	Sitia	France	Sitia (2023a)
2020	Harvest CROO	Harvest	Strawberry	Harvest CROO Robotics	US	Harvest CROO (2020) and Koerhuis (2020)
2021	H2L autonomous robotics	Crop protect	Flower (tulip)	H2L Robotics	The Netherlands	H2L Robotics (2021)
2021	E-tract	Weed, spray and trail	Vegetable, vineyard and flowers	Elatec	France	Koerhuis (2021b) and Elatec (2023)
2021	EarthAutomations Dood	Plough, spray, top, shoot remove, disease detect and pest detect	Cereals, vegetables and vineyard	EarthAutomations	Italy	EarthAutomations Dood (2023) and Future Farming (2023)
2021	Pek Automative Slopehelper	Till, fertilizer, prune and spray	Orchard	Pek Automative	Slovenia	Pek Automative (2021)
2022	Autonomous larger tractor	Plough	Commodity crops	John Deere	US	John Deere (2022)
2022	CNH autonomous solutions	Till, spray and harvest	Commodity crops	CNH Industrial	Italian-American multinational corporation	CNH Industrial (2023)

Table 1.2: Example initiatives of autonomous commercial machines for arable field crops (Continued).

2022	La Chevre	Weed	Vegetables	Nexus Robotics	Canada	Agtecger (2022) and Nexus Robotics (2022)
2023	Raven autonomous solutions	Till, spray and harvest	Cereals and vegetables	Raven Industries	US	Bedord (2022) and Raven (2023)
2022	AgBots	Soil and seedbed prepare, seed, spray, roll and mow	Cereals, cover crop, and grass	AgXeed	The Netherlands	AgXeed (2023)
2022	Swarm Farm Robotics	Crop protect, Mow and slash	Grain, cotton and grass	Swarm Farm Robotics	Australia	Groeneveld (2023a) and SwarmFarm Robotics (2023)
2022	AIGRO UP	Weed and mow	Orchared	AIGRO	The Netherlands	AIGRO (2023)
2022	Amos Power A3/A4	Till, inter-seed, mow and spray	Cereals and vineyards	Amos power	US	Precision Farming Dealer (2022b) and Amos (2023)
2022	Directed Machines Land Care Robot	Light plough, spray, mow and trim	Grass and orchard	Directed Machines	US	Bloch (2022) and Directed Machines (2023)
2022	Exxact robotics	Till and spray	Vineyard, cereals and vegetables	Exxact Robotics	France	Exxact Robotics (2023)
2022	Robotics Plus Unmanned Ground Vehicle	Spray, weed control, mulch, mow and crop analyse	Orchard	Robotics Plus	New Zealand	Power and Motion (2022) and Robotics Plus (2023)
2022	VitiBot Bakus	Plough, weed, mow and spray	Vineyard	SAME Deutz Fahr (SDF Group)	French	Vitibot (2023)
2023	Korechi RoamIO	Cultivate, seed, weed, mow, soil sample and data-log	Cereal, vineyard, golf course,	Korechi	Canada	Korechi (2023)

Table 1.2: Example initiatives of autonomous commercial machines for arable field crops (Continued).

2023	Smart Machine Oxin	Mow, mulch, trim and spray	Vineyard	The Smart Machine Company	New Zealand	Koerhuis (2023) and Oxin (2023)
2023	Trabotyx autonomous robot	Weed	Carrot	Trabotyx	The Netherlands	Trabotyx (2023)
2023	Tevel Flying Harvest Robots	Pick, thin, and prune	Orchard	Tevel Aerobotics Technologies	Israel	Agtecher (2023) and Tevel Tech (2023)
2023	Solix Hunter and Sprayer	Monitor, map, protect and spray	Soybean, corn, sugarcane and cotton	Solinftec	Brazil	Azevedo (2023b) and Solinftec (2023)

Source: *Author's own compilation.*

Although autonomous machines are increasingly used for the production of grain-oilseed (Shockley, Dillon and Shearer, 2019; Lowenberg-DeBoer et al., 2021a), forage, vegetables, fruits and tree nursery (Sitia, 2020; Edwards, 2021; Koerhuis, 2021b; H2L Robotics, 2023; Sitia, 2023b), the present study concentrated on autonomous grain-oilseed farms because of data availability from Hands Free Hectare and Hands Free Farm (HFH & HFF) and the worldwide market implications of autonomous grain-oilseed production. The grain-oilseed farms, especially for medium and large-scale farming contexts are already mechanized, so the transition towards autonomous farming should be relatively easy (Gackstetter *et al.*, 2023) compared to the fruit and vegetable farms which still depend heavily on manual labour. The engineering challenge for grain-oilseed farms is primarily making already mechanized systems autonomous.

The HFH & HFF also demonstrated autonomous grass ley cutting that could have implications for forage harvesting. Prototypes such as Krone and Lemken developed autonomous combined powers for forage production including operations such as cultivating, ploughing, sowing, mowing, tedding and raking (Claver, 2022c; Krone, 2022). There are few commercial autonomous initiatives for grass ley production as detailed in Table 1.2.

The HFH & HFF at Harper Adams University, UK, were the world's first whole farm commercial autonomous grain-oilseed farming public demonstration (including planting, spraying and harvesting). HFH was initiated in 2016 with the first harvest in 2017. Major agricultural machinery companies have had autonomous machine development programs for many years and may have completed full cropping cycles with autonomous machines, but their results are proprietary. HFH was a simplified farming system with one hectare of a single crop. The HFH focus was on cost effective retrofitting of conventional farm machines for autonomy using modified open-source drone software. HFF scaled up autonomous farming to 35 hectares with several crops, using commercial auto-guidance systems. At the initial stage, HFH was concentrated on whole field sole cropping (Lowenberg-DeBoer *et al.*, 2021a). In 2023, the HFF has extended the focus with demonstration trials of strip cropping to show the relevance of autonomous machines for agroecological and regenerative farming (Franklin, 2022; Harper Adams University (HAU), 2023). Most autonomous initiatives worldwide other than HFH & HFF for grain-oilseed farming are highly concentrated on specific field operations (e.g., seeding, weeding and spraying) rather than whole farm production operations.

1.3 Autonomous machines for sustainable intensification solutions

Autonomous machines are the potential successors of large conventional machines with human operators that could lead to a paradigm shift of arable farming (Goense, 2005; Shockley, Dillon and Shearer, 2019, Shockley et al., 2021; Revell, Powell and Welsh, 2020). It is hypothesized that autonomous machines have the possibility to revolutionize PA and facilitate the ‘Fourth Agricultural Revolution’ which is also labelled as ‘Agriculture 4.0’ (Klerkx and Rose, 2020). A number of potential benefits are hypothesized for autonomous arable farming that could promote sustainable intensification solutions (Duckett *et al.*, 2018; Daum, 2021).

Autonomous machines could help to solve the problem of agricultural labour shortage and thereby help to feed the growing population of the world (Kolodny and Brigham, 2018). The list of economic benefits of autonomous machines usually start with labour saving because worldwide agricultural labour is scarce and agricultural real wage rate is increasing over time (Lowenberg-DeBoer *et al.*, 2021a; Lowenberg-DeBoer, 2022b). The availability of agricultural labour is one of the prime challenges for medium and large-scale arable farming (OECD, 2020; Charlton and Castillo, 2021; World Bank, 2021a; The Environment Food and Rural Affairs Committee, 2022) owing to the economic and political reasons (e.g., BREXIT, new immigration policies for COVID-19 pandemic) (Shockley et al., 2021; Sandford and Hanrahan, 2022; The Migration Observatory, 2022). Smallholders around the world also face labour scarcity in agriculture (World Bank, 2021b) due to socio-economic reasons (Devanesan, 2020; Al-Amin and Lowenberg-DeBoer, 2021; Yanmar, 2021).

Small autonomous machines have numerous benefits beyond labour saving potential such as efficiency, reliability, accuracy, economies of size, lower machinery investment costs, higher field work rates, timeliness of operations, working 24/7, increasing labour and land productivity, and profit maximization (Shockley, Dillon and Shearer, 2019, Shockley et al., 2021; Farm Equipment, 2021; Lowenberg-DeBoer et al., 2021a). Autonomous machines have the potential of reducing off-target application with localized on-the-go application of pesticides, herbicides and fertilizer, plant specific husbandry and collection of on-field data supporting farm management decision making (Duckett *et al.*, 2018; Daum, 2021; Lowenberg-DeBoer, 2022b).

Apart from facilitating production goals (i.e., least cost of production and profit maximization) (Shockley, Dillon and Shearer, 2019; Lowenberg-DeBoer et al., 2021a) autonomous machines have the potential to support environmental goals of farming (Ditzler and Driessen, 2022; Pearson et al., 2022; Gackstetter et al., 2023). In the longer run, the biggest impact of autonomous machines may not only be confined to technical and economic (i.e., techno-economic) feasibility, rather extend to environmental sustainability. Small autonomous machines are expected to reduce environmental footprints of agriculture through reducing soil compaction and carbon footprint (Chamen et al., 2015; Asseng and Asche, 2019; Karsten, 2019b; McPhee et al., 2020; Revell, Powell and Welsh, 2020; Keller and Or, 2022; AutoAgri, 2023).

Autonomous machines are expected to help restore in-field biodiversity that has been reduced through whole field sole cropping with larger conventional machines with human operators (Blackmore, Have and Fountas, 2001; Robinson and Sutherland, 2002; Duckett et al., 2018; Santos and Kienzle, 2020; Lowenberg-DeBoer et al., 2021a). Autonomous machines are hypothesized to be capable of farming small, irregularly shape fields that will reduce land consolidation pressure, promote hedges, wetlands and in-field trees (Lowenberg-DeBoer *et al.*, 2021a). Agricultural intensification solutions are suggested through addressing spatial and temporal (i.e., spatio-temporal) heterogeneity with autonomous mixed cropping systems (Slaughter, Giles and Downey, 2008; Ward, Roe and Batte, 2016; Tanveer et al., 2017; van Oort et al., 2020; Ditzler and Driessen, 2022; Donat et al., 2022) that could reduce synthetic input use, pest and diseases infestation, improve soil health, ecosystem services, and soil carbon and nitrogen.

Although many of the early-stage autonomous machines are powered by fossil fuels (i.e., typical diesel-powered combustion engines) (e.g., HFH & HFF autonomous machines), an increasing number of autonomous machines are powered by alternative renewable electricity from solar, wind, methane and hydrogen, etc. (FarmDroid, 2020; Hekkert, 2020;

Fuel Cells Works, 2021; Vale, 2021; Claver, 2022b; Groeneveld, 2022; Hein, 2022; Karsten, 2022). For example, battery-based autonomous electric machines are suggested to reduce greenhouse gas emissions and increase driveline efficiency. Research in the context of Swedish agriculture using systems analysis, economic analysis and life cycle assessment found that autonomous electric tractors reduced energy use, per annum costs, soil compaction and greenhouse gas emissions (Lagnelöv, 2023).

Autonomous machines could facilitate sustainable intensification by integrating multifaceted goals in a common decision-making process. Integrating those goals is often too complex with human operated conventional machines. The diverse goals of individuals (i.e., increasing productivity and/or profit maximization) and society as a whole (i.e., environmental sustainability) could be jointly optimized with use of autonomous machines. For instance, autonomous machines could facilitate the net zero agricultural goal through facilitating agroecological and regenerative farm management. These cropping systems will help to achieve simultaneously food and nutrition security, and environmental sustainability (DEFRA, 2020; Davies, 2022; Pearson *et al.*, 2022).

As part of the agricultural intensification solution of autonomous machines, the present study considered labour saving potential, opportunity costs of capital investment, higher field work rates, and timeliness of operations. Moreover, the advantage of mixed cropping systems (i.e., agroecological strip cropping and regenerative agriculture) with autonomous machines was also considered to reconcile the production and environmental goals of arable open-field crop farming. Other anticipated benefits mentioned above were not included in the present study due to lack of data.

1.4 The research problem

Research on autonomous machines shows that autonomous machines could solve the real-world problems of arable crop farming as part of sustainable intensification solutions (Lowenberg-DeBoer, 2022b). The technical potential of autonomous machines are well accepted through worldwide prototypes and commercial on-farm demonstrations (Shamshiri *et al.*, 2018; Fountas *et al.*, 2020; Hands Free Hectare (HFH), 2021). Economic research has been focusing on guiding wide scale adoption through farm profitability assessment with autonomous farming systems. Prior to 2018, the economic research on autonomous operations mostly concentrated on horticultural crops (Lowenberg-DeBoer *et al.*, 2020). Recently, some studies focused on the economics of autonomy for arable cereal farming. For instance, most recent autonomous farming research focused on the profitability of this precision agriculture technology on whole field sole cropping commodity crops production considering the context of the UK (Lowenberg-

DeBoer et al., 2020, Lowenberg-DeBoer et al., 2021a) and the US (Shockley, Dillon and Shearer, 2019). Some studies also examined the implications of regulation on economics of autonomous farming (Shockley *et al.*, 2021; Maritan *et al.*, 2023). The study of Lowenberg-DeBoer *et al.* (2021a) hypothesized that autonomous machines could facilitate biodiversity by superseding the ''get big or get out'' rule of thumb of conventional mechanization through facilitating farm operations in small, irregularly shaped fields farmed with whole field sole cropping systems. But they were unable to assess the hypothesis owing to the lack of data on field times (h/ha) and field efficiency (%).

Apart from whole field sole cropping, heterogeneous within field mixed cropping systems are also envisaged with autonomous machines (Slaughter, Giles and Downey, 2008; van Oort et al., 2020; Juventia et al., 2022; Ward, Roe and Batte, 2016). Research also hypothesized that autonomous machines would facilitate the regenerative agriculture practice which could help to achieve the net zero target in addition to the production goals of arable cereal farm (Davies, 2022; Pearson et al., 2022; Manshanden et al., 2023).

Delving into the state of the knowledge it is clear that research on autonomous machines in whole field sole cropping system is still unable to address the implications of field size and shape (Lowenberg-DeBoer *et al.*, 2021a). Understanding the economics of field size and shape for autonomous machines is crucial because over the last few decades, conventional machines with human operators have been largely motivated by the rule of thumb of conventional machines (i.e., ''get big or get out'') to achieve labour productivity in arable farming. Beyond unlocking the economics of autonomous machines for whole field sole cropping system subject to field size and shape, this study attempted to address the economics of autonomous machines for mixed cropping and regenerative agriculture. Mixed cropping systems and regenerative agriculture are suggested with autonomous machines to simultaneously achieve both the production goals of productivity and profitability, and environmental goal of limiting environmental footprints of arable crop farming (Duckett *et al.*, 2018; Daum, 2021; Pearson *et al.*, 2022; Davies, 2022). In this study, strip cropping system is considered to represent mixed cropping and regenerative agriculture practice because strip cropping is the simplest mixed cropping system. It is feasible with conventional mechanization with human operators, but requires more labour than conventional whole field production (Ward, Roe and Batte, 2016; Exner *et al.*, 1999; van Apeldoorn *et al.*, 2020; Alarcón-Segura *et al.*, 2022). The mixed cropping and regenerative strip cropping practices may be less profitable for conventional mechanized farms operated with human operators, while autonomous machines may the change the cost calculus. This study assumed that profitability assessment will guide the autonomous machines adoption because farm economics is one of the prime drivers for technology adoption and scaling up (Lowenberg-DeBoer et al., 2021a; Tey and Brindal, 2022). The context of the of the UK and the US was considered to achieve the following objectives because of economic, agronomic, and technical data availability. The case study contexts are described in detail in the respective objective sections.

1.5 Research objectives

The overall objective of this study was to assess how autonomous machines could maximize the profitability of arable field crop production compared to farming with conventional machines with human operators both in whole field sole cropping and mixed cropping systems considering agroecological and regenerative agriculture. The specific objectives were to:

(i) Assess how field size and shape impact the profitability of autonomous crop machines (detailed in Chapter 3);

(ii) Estimate the profitability of strip cropping with autonomous machines (detailed in Chapter 4); and

(iii) Determine the profitability of autonomous machines for regenerative agriculture (detailed in Chapter 5).

1.6 Research hypotheses

The following hypotheses were examined to achieve the specific objectives of the study:

(i) Autonomous crop machines make it possible to farm small, non-rectangular fields profitably, thereby preserving field biodiversity and other environmental benefits;

(ii) Autonomous machines make strip cropping profitable, thereby allowing farmers to gain additional agroecological benefits; and

(iii) Autonomous machines make regenerative strip cropping profitable, thereby supporting the agricultural transition plan to improve soil health, biodiversity and achieve carbon net zero target.

1.7 Theoretical grounds

Based on microeconomic theory and opinion of farm management experts, the choice of cropping systems (e.g., whole field sole cropping and/or within field heterogeneous crop mixes such as strip cropping and/or regenerative agriculture) and farm mechanization levels (e.g., whole farm conventional mechanization with human operators and/or autonomous machines) should maximize utility (Henderson and Quandt, 1958; Boehlje and Eidman, 1984; Lowenberg-DeBoer, 2022b). However, utility maximization encompasses numerous factors such as profit, leisure time, risk, capital, resource constraints and transaction costs.

Maximizing profit is the starting point to analyse farm management decisions in the short run. The cropping systems and farm mechanization levels should at least cover the costs of production. The economic payoffs would motivate wide-scale adoption (Lowenberg-DeBoer, 2022b). In farm mechanization levels and crop choices, economic benefits are considered as the prime driver (Lowenberg-DeBoer et al., 2021a; Tey and Brindal, 2022).

Consequently, the theoretical grounds of the research would be consistent with typical neoclassical microeconomic farm theory (Shockley, Dillon and Shearer, 2019). The objective function of the research was to maximize gross margin (i.e., return over variable costs) subject to primary farm resource constraints. The net return to operator labour, management and risk-taking (ROLMRT) was examined to address the impacts of overhead costs in mechanized farming (Lowenberg-DeBoer *et al.*, 2021a).

1.8 Research approach

Farmers and farm management specialists traditionally make less complex farm management decisions using budgeting (Hazell and Norton, 1986). A review study conducted in 2018, found that most production economics studies on automation (i.e., automated, and autonomous machines) to that point mostly used partial budgeting methods, where only some specific costs and returns associated with automation were changed while crop rotations, field operation timing, and other aspects of production were unchanged (Lowenberg-DeBoer et al., 2020). Although budgeting can account for a whole farming system, it is feasible only for very simple farming systems. With scenario-based budgeting, in complex cropping and farming systems, the analyst quickly gets lost in the alternatives and options for enterprise rotations, plant and harvest time, labour hiring, etc. Rarely budgeting could find the optimal or most profitable plan (Boehlje and Eidman, 1984). Deterministic linear programming (LP) is computationally easier compared to tedious and burdensome budgeting (Hazell and Norton, 1986; Boehlje and Eidman, 1984). The LP does not require substantial additional data but automates optimization that best allocate farm resources (Boehlje and Eidman, 1984).

Apart from deterministic LP models, there are various options for whole farm planning that could capture more complex interactive effects such as integer mathematical programming, non-linear programming and/or simulation studies. Simulation can capture more of the biological and physical details of farming, but it was not used in this study because it fails to capture the key human tendency to optimize. Also, interpretation of simulation results can be challenging because it involves comparisons of many options and scenarios.

The choice of optimization model depends on the trade-offs between model complexity and the credibility of results given limited data. In an ex-ante analysis, data is usually very limited. Often the parameters must be estimated by extrapolating from experimental results and expert opinion. Constructing a complex optimization model based on this limited data is often not credible. In contrast, LP requires only slightly more data than budgeting but can provide insights at the farming system level.

To achieve the objectives of this study, whole farm deterministic LP model was used as the simplest analytic tool for a farming system level analysis. The LP model utilizes a set of "optimizing rules" to identify the most profitable plan to quickly sort through thousands of potential crop rotations, technologies, and plant and harvest timing options (Hazell and Norton, 1986; Boehlje and Eidman, 1984). Through shadow prices LP capture important interactions between resource availability, constraints, and choice of activities. This study considered LP model to maximize gross margin subject to the binding constraints of land, human labour, and equipment time.

In keeping with the concept of using the simplest model that captures farming system changes, the choice of machinery sets (i.e., tractor, implements, combine) was done manually by comparing solutions with specific machinery assumptions. Because machines within a machinery set must be compatible, choosing machinery sets within the algorithm would require integer programming. This integer programming approach was used by Shockley et al. (2019, 2021). In this case integer programming would add to the complexity of the model, without adding substantially to the insights.

The whole farm deterministic LP model used in this study was adopted from the Hands Free Hectare-Linear Programming (HFH-LP) model of Lowenberg-DeBoer et al. (2021a). The HFH-LP model follows the 'Steady State' concept, which refers that the solutions could be repeated annually over time. This steady state HFH-LP model was originally based on the Purdue Crop/Livestock Linear Program (PC/LP) model for Midwestern farmers (Dobbins et al., 1994). The PC/LP model was later adapted for use in various countries of the world (Fontanilla-Díaz et al., 2021; Lowenberg-DeBoer et al., 2021a).

The whole farm deterministic HFH-LP model used in this study can be expressed as follows following Boehlje and Eidman (1984):

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 fixed 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.

Following Lowenberg-DeBoer et al. (2021a) the primary constraints considered in this study were:

(i) Land: This study assumed that the sum of land in productive activities is less than or equal to the arable crop land available. For example, if in each rotation the crops are q, the used land for a unit of a rotation is the fractional unit 1/q of each crop. Taking for example, one hectare of a wheat-oilseed rape (OSR) rotation is equal to half a hectare of wheat and half a hectare of OSR.

(ii) Human labour: This study assumed that the sum of the labour needed in each month for each crop in the rotation multiplied by the fractional unit (1/q) of each crop in each rotation. Here in this study the sum of the human labour required must be less than the labour available from the operators, permanent farm labour and temporary farm labour on the number of good field days.

(iii) Equipment time: The equipment time is that the sum of equipment time per crop in each month on good field days, weighted by the rotation fraction (i.e. 1/q), must be less than or equal to the amount of equipment time available.

(iv) Cashflow: Sum of the variable costs for each crop in a rotation in each month multiplied by the rotation fraction (1/q) must be less than or equal to the working capital available. This study considered that the cashflow is not binding.

The optimization model used in this study was coded in the General Algebraic Modelling Systems (GAMS) software (GAMS Development Corporation, 2020). Although the R software has also been used for optimization modelling of PC/LP type models (Griffin et al., 2023), this study used the GAMS software because it is a standard mathematical optimization algorithm used around the world and the HFH-LP was already available in the form of GAMS code (Lowenberg-DeBoer et al., 2021a).

1.9 Outline of the thesis

The outlines of the PhD thesis are represented in Figure 1.1. Chapter 1 explains the general difference between 'robots', 'field crop robot', 'automated machines', and ’autonomous machines'. Subsequently, it provides examples of autonomous initiatives worldwide with the implications for agricultural intensification solutions. The knowledge gaps and rationale of the study are identified in 'The Research Problem' section. The research objectives, research hypotheses, theoretical background and research approach are explained briefly to give a general overview of the research. Chapter 2 shows the state of the art and limitations of the existing research which is linked with research objectives and hypotheses. Chapter 3 represents the outcomes of first research hypothesis regarding how field size and shape impact the economics of autonomous machines for grain-oilseed farms. Chapter 4 estimates the ex-ante economic scenarios of the economics of strip cropping with autonomous machines. Chapter 5 analyses the economics of regenerative agriculture with the ex-ante scenarios. Finally, Chapter 6 contains the general discussion and conclusions with the limitations of the study. Worldwide implications of the research and future research directions are also suggested.

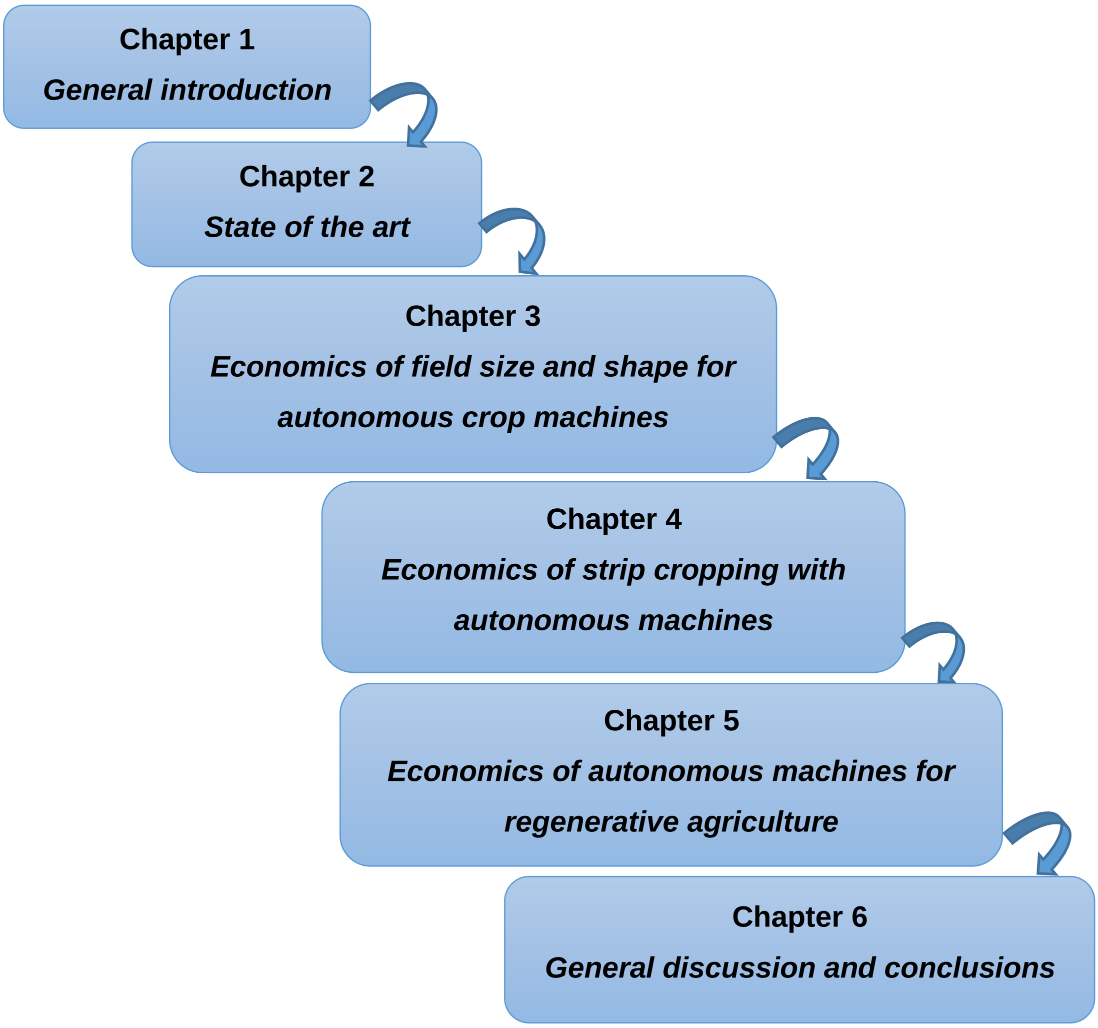

Figure 1.1: Structure of the thesis and chapters overview.

Chapter 2

State of the art

" … your task is to build an argument, not a library."

Rudestam and Newton (1992)*: Surviving your dissertation. Fourth Edition. p. 49.*

2.1 Introduction

The review of literature as presented in this chapter explored the existing state of the art of the economics of field crop robotics and autonomous systems (RAS) and associated literature. The objective is to contribute to the scientific knowledge. The review mainly concentrated on three research objectives regarding the economics of field size and shape for whole field sole cropping system, and mixed cropping (i.e., within field heterogeneous agroecological strip cropping systems and regenerative agriculture) with different levels of mechanized farms. Mechanization levels here refer conventional machines operated with human operators and autonomous machines (i.e., HFH retrofitted autonomous machines). This chapter identified the limitations of the existing production economics studies on autonomous machines. The chapter also proposed simulation methodology to compare arable open field farming with conventional mechanization and autonomous machines.

Simulation methods other an econometric approach is suggested because the autonomous machines for field crops considered in this study are not yet widely marketed and adopted for the context of large, medium and small-scale farming. The technologies are in the pipelines and on the verge of commercialization processes (Shockley *et al.*, 2021). The HFH autonomous machines are prototypes that were demonstrated in the context of the UK. The ex-post scenarios evaluation using econometric analysis was not feasible here. To understand the economic potential of whole field sole cropping subject to field size and shape and autonomous farming beyond whole field sole cropping simulation methodology (here Linear Programming (LP)) is the right choice because it goes beyond the biological and physical relationships to incorporate human motivation and drive to seek better solutions. Consequently, LP analysis was suggested to fill the research gaps that usually incorporates the basic elements of human decision making and overcome the limitations of partial budgeting. In partial budgeting only crop and enterprise specific changes in costs and revenues are considered with all other things remaining the same assumption.

This research anticipated that the profitability analysis of autonomous machines using optimization LP model irrespective of field size and shape for whole field sole cropping and farming beyond whole field sole cropping would facilitate the game changing autonomous machines to achieve both production goals of productivity and profitability and environmental goals of agroecological and regenerative farming to limit environmental footprints of agriculture. The implications of this research for agri-tech economists, engineers, agronomists, environmentalists, agribusinesses innovators, and policy makers and planners are also pointed out in this chapter.

2.2 Economics of field crop robotics and autonomous systems (RAS)

The state of the knowledge of the economics of field crop robotics and autonomous systems (RAS) reveals that the RAS used in arable open-field crop operations are viewed in two perspectives: *Firstly,* automated machines (or automated crop robots) (i.e., partially robotized mechatronic technology that accomplish arable field operations such as seeding, weeding, and harvesting, but with mobility assured by a human operator). *Secondly,* autonomous machines (or autonomous crop robots) (i.e., are a subset of field crop robots which have autonomy in arable field operations using predetermined field paths and itinerary with relatively little decision-making capacity) (Lowenberg-DeBoer *et al.,* 2020).

The most updated review of literature as of 2018 addressed the economics of automated operations of one or two horticultural crops (detailed in Table 2.1). The economic studies on automated machines for field crops are primarily focused on the cost saving potentials of one or two field operations in production of horticultural crops. The production economics literature on automated machines to date does not cover the broader implications of the technology (e.g., the implications of machinery performance subject to field size and shape and biodiversity conservation). The existing studies mostly concentrated on horticultural crops, ignoring the whole farm systems analysis of commodity crops production (Table 2.1) (Lowenberg-DeBoer *et al.,* 2020). However, this study did not delve in into the economics of automated machines because this is out of the scope of this study. The HFH demonstration experience at Harper Adams University in the UK represents autonomous machines, also known as autonomous crop robots or swarm robots or swarm robotics. Considering the research objectives, the review of literature in the subsequent sections concentrated the focus on the economics of autonomous machines to identify the knowledge gaps and to contribute to the state of the art.

Table 2.1: State of the arts of automated crop robotics.

Authors and year	Country	Economic tools used	Goal	Arable operation considered	Machinery performance	Crops
Tillett (1993)	UK	Partial budget	Labour cost saving	Harvest	No	Tomato and fruit
Arndt *et al.* (1997)	US	Partial budget	Recovery rate of breakeven harvest	Harvest	Yes: Harvest rate (28% and 15%)	Asparagus
Tsuga (2000)	Japan	Partial budget	Cost saving	Transplant	No	Cabbages and lettuces
Ruhm (2004)	Germany	Partial budget	Recovery rate of breakeven harvest	Harvest and grade	No	Asparagus
Clary *et al.* (2007)	US	Partial budget	Breakeven harvest recovery rate	Harvest	Yes: Harvest rate (70% and 80%)	Asparagus
Cembali *et al.* (2008)	US	Partial budget	Breakeven harvest recovery rate	Harvest	Yes: Spear collection rate (85%)	Asparagus
Fennimore *et al.* (2014)	US	Partial budget	Max. net return	Weed and Thin	No	Leafy vegetables
Mazzetto and Calcante (2011)	Italy	Partial budget	Cost saving	Transplant	No	Vineyard
Pérez-Ruíz *et al.* (2014)	US	Partial budget	Cost saving	Weed control	No	Tomato
Zhang, Pothula and Lu (2016)	US	Partial budget	Max. net return	Harvest	Yes: Commented	Apples

Source: *Lowenberg-DeBoer et al. (2020) and author's compilation.*

The research on the economics of autonomous machines primarily focused on the cost saving potential (Gaus *et al.,* 2017; Goense, 2005; Pedersen *et al.,* 2006; Pedersen *et al.,* 2017). A very few production economics research pointed out the significance of machinery performance in terms of field efficiency and equipment times (Lowenberg-DeBoer *et al.,* 2021a; Revell, Powell and Welsh, 2020; Sørensen, Madsen and Jacobsen, 2005). From 1990 to 2018, a total of eight studies investigated economics of autonomous machines in arable open-field farms (Lowenberg-DeBoer *et al.,* 2020). In 2018 onwards, nine studies focused on the economics of autonomous machines (Table 2.2). The production economics research on autonomous machines did not cover how machinery performance subject to field size and shape in the whole field sole cropping system impacts the economics of autonomous machines. A detailed overview of existing literature, limitations and contribution of the present study are provided as follows:

Using partial budgeting approach, Edan, Benady and Miles (1992) assessed the potentiality of automation for melon harvesting, where in sensitivity analysis they considered autonomy. They found that if the manual harvesting operation is less than US$494/ha, then autonomous operation is economically viable for a 202.4 ha harvesting operation. They showed that breakeven investment lies within the range of US$ 50,000 to US$250,000. Goense (2005) investigated the economics of autonomous equipment and examined how autonomous implement size affects mechanization cost in row crop cultivation of different sized farms. The study showed that row crop cultivation with autonomous technology is an attractive alternative to manually operated machinery, if the navigation is cost effective and large areas are covered.

Table 2.2: State of the art of autonomous crop robotics.

Authors and year	Country	Economic tools used	Goal	Arable operation considered	Machinery performance	Crops
Edan, Benady and Miles (1992)	Israel and US	Partial budget	Cost saving	Harvest	No	Melon
Sørensen, Madsen and Jacobsen (2005)	Denmark	Scenario planning	Cost saving	Weed	Yes: Weeding efficiency (80%)	Whole farm
Pedersen *et al.* (2006)	Denmark	Partial budget	Cost saving	Scout /Weed	No	Sugar beets and cereals
Pedersen, Fountas and Blackmore (2008)	Denmark /Greece /UK/US	Partial budget	Cost saving	Scout /Weed	No	Sugar beet
McCorkle *et al.* (2016)	US	Financial simulation	Cost saving	Prune and Thin	No	Vineyard
Pedersen *et al.* (2017)	Denmark	Partial budget	Max. gross margin	Seed	No	Sugar beet
Gaus *et al.* (2017)	Germany	Partial budget	Cost saving	Weed	No	Cereals
Shockley and Dillon (2018) and Shockley, Dillon and Shearer (2019)	US	Linear Programming (LP) (Whole farm)	Max. net return	All production operations	No	Maize and soybean
De Witte (2019)	Germany	Partial budgeting	Cost saving	Harvest and till	No	Grain crops

Table 2.2: *State of the art of autonomous crop robotics (Continued).*						
Lowenberg-DeBoer *et al.* (2019)	UK	Hands Free Hectare (HFH)-LP model (Whole farm)	Max. net return	All production operations	Yes: Field efficiency (70%) for all operations and equipment sets	Wheat, oilseed rape and barley
Revell, Powell and Welsh (2020)	Australia	Discounted Cash Flow (DCF) Analysis	Cost saving	Spray	Yes: Considered field time (h/ha)	Cotton, wheat and chickpea
Lowenberg-DeBoer, *Pope and Roberts* (2020),	UK	HFH-LP model (Whole farm)	Max. net return	Spray	No details are provided	Wheat, barley, oilseed rape, beans, and linseed
Lowenberg-DeBoer *et al.* (2021a)	UK	HFH-LP model (Whole farm)	Max. net return	All production operations	Yes: Field efficiency (70%) for all operations machines	Wheat, oilseed rape, and barley
Lowenberg-DeBoer *et al.* (2021b)	Worldwide, especially China, Brazil, UK, US, Australia, Belgium, Netherlands, Canada, and New Zealand.	Discussion	Policy lesson with discussion of max. net return	All production operations	No specific analysis, but inclusive of field efficiency in UK case study	UK and US case studies of maize, soybean, wheat, oilseed rape and barley
Shockley *et al.* (2021)	US and UK	Linear Programming (LP) (Whole farm)	Max. net return and policy lesson	All production operations	Yes: Field efficiency (70%) for all operations and equipment set	Corn and soybeans for the US and Wheat, oil seed rape and barley for the UK

Table 2.2: *State of the art of autonomous crop robotics (Continued).*

Maritan *et al.* (2022)	UK	HFH-LP model (Whole farm)	Max. net return	All production operations	Yes: Field time (hr/ha) and Field efficiency (70%) for all operations and equipment sets	Wheat, oilseed rape and barley
Lowenberg-DeBoer (2022b)	World wide	Qualitative	Economics of adoption	Miscellaneous	Performance discussion	Miscellaneous

Source: *Adopted from Lowenberg-DeBoer et al. (2020) and authors own compilation.*

Pedersen *et al.* (2006) compared economic feasibility of autonomous robotic systems in three different agricultural applications. The findings revealed that agricultural robotic operations were economically feasible compared to the conventional operating systems. In robotic weeding on sugar beet, micro spraying reduces herbicide application by 90% and total costs of robotic and conventional weeding were per annum €260.4/ha and €296.6/ha. It means that autonomous weeding reveals €36.20 cost advantage than conventional one. Likewise, robotic crop scouting ensured per annum cost savings of €3.80/ha. The study pointed out several benefits such as, weed mapping, working hour's advantage and improved efficiency in modern production. The robotic grass cutting had a cost saving advantage of more than €300/ha per annum. Pedersen, Fountas and Blackmore (2008) analysed economic feasibility of robotic weed scouting and robotic weeding for the US, UK, Greece, and Denmark. They pointed out that robotic weeding had a cost advantage for all of the countries studied except Greece. They found that autonomous operations are comparatively flexible and reduce labour expenses and had advantage of extended working hours.

Considering early seedling and re-seedling of sugar beet, Pedersen *et al.* (2017) quantified the economic perspectives of agricultural robots. They compared gross margins of new seeding systems (i.e., early seeding and reseeding) and conventional cultivation practice. The study mentioned that robotic operations lead to minimum overlaps, and it is possible to ensure economies of scale in small and medium sized farms. Among the three scenarios (conventional practice, early seeding, and re-seeding) considered, early seeding was the most profitable system. Even though they assumed a yield increase of 2.5%, the system is expected to offer cost advantage due to the use of robots that leads to labour savings. However, the expected increase of yield in re-seeding will be 5%, but the system will require conventional seeding due to its dual seeding operations. Results showed that in early seeding, the gross margin will increase by 7.7% and in re-seeding there is a possibility to increase gross margin of 6.5%. The study of Gaus *et al.* (2017) using partial budgeting techniques investigated economics of autonomous swarm robots for weeding in wheat. The study commented on the future product prices and robot's requirement for field operation. Results showed that swarm robots could be a possible alternative for crops, especially for crops with high costs intercultural operations. The production economics studies mentioned above used partial budgeting, whereas a very few studies considered methodological rigour in economic assessment to overcome the limitations of partial budgeting (Lowenberg-DeBoer *et al.,* 2019, Lowenberg-DeBoer *et al.,* 2020, Lowenberg-DeBoer *et al.,* 2021b; McCorkle *et al.,* 2016; Shockley, Dillon and Shearer, 2019; Shockley and Dillon, 2018; Sørensen, Madsen and Jacobsen, 2005).

In Denmark, using scenario planning Sørensen, Madsen and Jacobsen (2005) investigated the potentiality of organic crops robotic weeding. They found that the benefits of robotics weeding were highly sensitive to weed intensity and initial equipment price. Results showed that for robotic weeding, farmers paid up to €40,000, but they are still in a better off position than manual weeding. The study mentioned efficiency is the critical prerequisite for improved profitability and assumed 80% weeding efficiency for sugar beet and maize. McCorkle *et al.* (2016) investigated the economics of robotic technology in the production of wine grapes using a financial simulation model. They showed how substituting manual labour with robotic equipment affects vineyards of different sizes. Shockley and Dillon (2018) examined the economic feasibility of autonomous field machinery compared to conventional manned machinery using the whole farm planning model in corn and soybean production. Results showed that net returns were greater when the farm was operated with autonomous machinery. With the anticipated benefits of 10% reduction in input costs and 7% increase in yields, the net return increased significantly up to 19%. Findings of the sensitivity analysis showed that autonomous machinery had the potentiality to ensure greater profitability for different sizes of farm, especially for small sized farms.

De Witte (2019) pointed out that small autonomous equipment will be less capital intensive and hypothesized that in addition to labour cost saving potential, small autonomous machinery will positively influence profitability with yield increase and other resource savings in arable farming. Shockley, Dillon and Shearer, (2019) compared the economic feasibility of conventional and autonomous machinery to produce grain crops in the United States for a given farm size of 850 hectares. Results showed that autonomous machinery was profitable over conventional machinery when the intelligent control establishment was cost effective. They also found that relatively small autonomous machinery was likely to have economic advantage for various farm sizes, especially for small farms. Lowenberg-DeBoer *et al.* (2019) examined the economic impacts of autonomous equipment subject to farm size in the using Hands Free Hectare (HFH) demonstration experience. Although economic analyses of autonomous crop robotics throughout the world are constrained due to lack of data on economic parameters, the key strength of the HFH on-farm demonstration was that it provided first-hand experience with autonomous whole farm production operations. Using HFH demonstration experience they showed that crop production with swarm robots was economically feasible, where small and medium sized farms had cost advantage, and production costs of the United Kingdom were internationally competitive. Revell, Powell and Welsh (2020) examined the economic feasibility of autonomous tractors used in spraying operations for producing cotton in irrigated and dryland including cotton, wheat and chickpeas. They found that adoption of autonomous equipment was economically feasible.

Lowenberg-DeBoer, Pope and Roberts (2020) used HFH-LP model to investigate economics of arable autonomous technology for biopesticide application in break crop, namely, oilseed rape, beans, and linseed. They found that application of low cost biopesticide is feasible with both conventional and autonomous technology, but autonomous equipment still demands more human labour in field operation compared to conventional herbicide treatments. Lowenberg-DeBoer *et al.* (2021a) identified economic implications of autonomous equipment. The study showed technical and economic feasibility of autonomous equipment and found that medium sized farms had a cost advantage with autonomous technology. They also commented on the economic potentiality of autonomous technology in irregular shaped arable fields and restoration of in-field biodiversity. In another study, considering the context of the United Kingdom, Lowenberg-DeBoer *et al.* (2021b) suggested that economic and social implications of autonomous equipment adoption will be affected by the rules of autonomous equipment use. Using the context of the United States, Shockley *et al.* (2021) pointed out that profitability of autonomous equipment was sensitive to the rules of automation for arable farming. They found that small farms gain more through using autonomous machinery in arable farm operation. Maritan *et al.* (2022) investigated economically optimum farmer supervision time for open-field autonomous machines. The study found that for field crop production economically optimum supervision time lies between 13% to 85% depending on the reliability of the machine and type of supervision (i.e., on-site or remote). Lowenberg-DeBoer (2022b) pointed out the economics of digital technology adoption worldwide, where autonomous machines adoption and implications for large, medium and small-scale economies are vividly described.

The state of the art of economics of autonomous machines (i.e., autonomous crop robots) reveals that research on autonomous machines economics highly concentrated the focus on costs saving potential. In economic analysis, a very few studies encompassed or commented on the implications of farm size (Edan, Benady and Miles, 1992; Gaus *et al.,* 2017; Goense, 2005; Lowenberg-DeBoer *et al.,* 2019, Lowenberg-DeBoer *et al.,* 2021a; McCorkle *et al.,* 2016; Pedersen *et al.,* 2017; Shockley, Dillon and Shearer, 2019; Shockley and Dillon, 2018). Nevertheless, apart from economic parameters, how machinery performance subject to field size and shape impact the farm economics of autonomous arable open-field farming are still unexplored. On the contrary, in conventional mechanized farms, farm size and shape received substantial attention to increase labour productivity and economies of size. Relatively larger rectangular fields are preferred which support the ‘get big or get out’ rule of thumb of conventional mechanization (Robinson and Sutherland, 2002; Lowenberg-DeBoer *et al.*, 2021a).

The economic and technical data limitations of autonomous farming are the prime reason for such a research gap (Lowenberg-DeBoer *et al.*, 2020). The technological development and research of autonomous machines are well advanced (Shamshiri *et al.*, 2018; Fountas *et al.*, 2020). Academic, researchers and agribusiness innovators envisioned that autonomous machines will be able to reconcile techno-economic and environmental goals (Duckett *et al.*, 2018; Daum, 2021; Pearson *et al.*, 2022; AutoAgri, 2023). Up-to-date production economics research are based on autonomous whole field sole cropping cost economies, whilst machinery performances subject to field geometry are yet to be explored (Shockley, Dillon and Shearer, 2019; Lowenberg-DeBoer *et al.*, 2021a; Shockley *et al.*, 2021; Maritan *et al.*, 2023). Similarly, open-field autonomous arable crop farming beyond whole field sole cropping (i.e., mixed cropping to address spatial and temporal heterogeneity) need investigation to guide win-wing farming synergies. The multifaceted benefits to reconcile both production goals (i.e., productivity and/or profitability) and the goals of the society as a whole (i.e., limiting environmental footprint of agriculture) are yet to be answered.

To address the production economics research gaps on autonomous machines and to navigate the game changing technology innovation and adoption, the present study examined the economics of field size and shape for autonomous machines in the whole field sole cropping system (Objective 1). In addition, the study extended the research focus beyond autonomous whole field sole cropping economics to reconcile production goals and environmental goals through evaluating the economics of autonomous agroecological strip cropping systems (Objective 2) and the economics of autonomous regenerative agriculture (Objective 3). The following sections dealt with objective specific state of the knowledge, limitations and the contribution of the present study to scientific knowledge:

2.3 Field size and shape (AND/OR) autonomous machines: Whole field sole cropping (Objective 1)

Field size and shape received substantial attention in the field of geography (Davis, 1926; Miller, 1953; Boyce and Clark, 1964; White and Renner, 1957) and more importantly in the last decades in agricultural sciences (Batte and Ehsani, 2006; Griffel *et al.,* 2018; Janulevičius *et al.,* 2019; Larson *et al.,* 2016; Zandonadi *et al.,* 2013). Research in agricultural sciences, considered field size and/or shape to examine machinery performances (Amiama, Bueno and Álvarez, 2008; Gónzalez, Marey and Álvarez, 2007; Oksanen, 2013; Spekken and Bruin, 2013), input application overlap (Luck, Zandonadi and Shearer, 2011; Jernigan, 2012; Zandonadi *et al.*, 2013), and agricultural production economics literature to investigate profitability of precision agriculture technology, especially on Global Navigation Satellite Systems (GNSS) guidance and related technologies such as boom control (Batte and Ehsani, 2006; Larson *et al.,* 2016; Shockley *et al.,* 2012).

In arable field operations, field size and shape received significant attention. Studies showed that conventional agricultural mechanization always favoured large sized rectangular fields and most of the land consolidation studies around the world in the last decades have been motivated by the desire for larger fields (Kienzle, Ashburner and Sims, 2013; Lindsay *et al.,* 2013; Robinson and Sutherland, 2002; Van den Berg *et al.,* 2007). Likewise, machinery performances are always sensitive to field sizes and shapes (Keicher and Seufert, 2000; Spekken and de Bruin, 2013; Janulevičius *et al.*, 2019). Majority of the research on machinery performance subject to field size and shape mainly concentrated on two domains of field operations: (i) Numerous studies focused on the path planning to minimize non-productive time in agricultural field operations (Oksanen, 2013; Spekken and de Bruin, 2013), and (ii) research generally highlighted machinery performance, especially time efficiency during agricultural operations (Anigacz, 2015; Ebadian *et al.,* 2018; Fedrizzi *et al.,* 2019; Griffel *et al.,* 2018; Janulevičius *et al.,* 2019).

In southern Finland, Oksanen (2013) aimed to find a computationally faster method of examining the relationship between field shape and operational efficiency. They compared their findings of a path planning algorithm with a set of real plots. Likewise, considering field shape, Oksanen and Visala (2007) developed a coverage path planning algorithm which is applicable to any kind of agricultural equipment. Spekken and de Bruin (2013) focused on route optimization with a reference to different field sizes to reduce non-productive time in field operations. Janulevičius *et al.* (2019) provided a method for estimating time efficiency of farm tractors during tillage operation in fields of different sizes. In Bangladesh, Islam, Kabir and Hossain (2017) investigated existing plot size and shape to understand the effects on operational efficiency of mechanical walk behind type rice transplanter. Gonzalez, Alvarez and Crecente (2004) considered plot size and shape to evaluate land distribution in Spain and presented an index considering plot size and shape factor. Similarly, Gónzalez, Marey and Álvarez (2007) examined effects of plot shape and size on effective field capacity of machinery operation in potato farming. In Spain, Amiama, Bueno and Álvarez (2008) considered field shape and proposed two new shape indices to investigate the effects of field shapes on the effective field capacity of self-propelled forage harvester. The study of Koniuszy *et al.* (2017) investigated power performance of farm tractors in tillage operation subject to different field sizes.

Agricultural scientists considered field size and/or shape to minimize input application overlap in PA literature. For instance, Jernigan (2012) considered field shape to examine the relationship between diversified fields and planter overlap in Tennessee, US. Luck, Zandonadi and Shearer (2011) in Kentucky, US, examined the effects of field size and shape on overlap errors of automatic section control and manual application. In Central Kentucky, US, Luck *et al.* (2010a) investigated pesticide and nutrient savings based on three different irregularly shaped grain fields. In another study, Luck *et al.* (2010b) compared effectiveness of automatic section control with manual section control to investigate pesticide application overlap in fields of different shapes and sizes in Kentucky, US. Zandonadi *et al.* (2011) developed a computational method based on field shape to calculate overlap errors of machinery and concluded that off-target spray application area varied depending on shape and size of field boundary. Likewise, Zandonadi *et al.* (2013) evaluated field shape descriptors to calculate off-target application area.

However, most of the existing research on the effects of field size and/or shape on arable field operations are mainly concentrated on technical aspects of machinery management. A very few production economics studies addressed field size and shape issues in economic feasibility assessment of PA technology. In Tennessee, US, Larson *et al.* (2016) examined effects of field size and shape on profitability of chemical application with PA equipment. They concluded that field size and shape significantly affect profitability of precision spraying using automatic section control. Batte and Ehsani (2006) compared economic benefits of farmer-owned precision sprayers with a traditional non-precision system in three differentiated field shapes (i.e., a rectangle, parallelogram, and trapezoid). They analyzed a set of hypothetical farm fields each of which was 40.47 ha sized with and without the inclusion of grass waterways through the fields at 45^0 and 60^0 angles. In Kentucky, US, Shockley *et al.* (2012) investigated impacts of field size and shape on automatic section control profitability. The study was conducted for planting and spraying operations in four fields and within the fields there were a spectrum of shape, size, and obstacles. Smith *et al.* (2013) considered on-farm field parameters (i.e., field size and shape) to evaluate the profitability of precision spraying technologies in Colorado, Kansas, and Nebraska, US. They found profitability was sensitive to size and shape of the irregular fields. Although the existing studies investigated profitability of PA technologies considering field size and shape, most of the studies were based on partial budgeting methods and concentrated on one or two crop operations (i.e., weeding and/or harvesting). The review of the existing literature reveals that the economics of PA technologies with a reference to field sizes and shapes focused on the input savings potentials in economic assessment. Nevertheless, the economic implications of machinery performance subject to field sizes and shapes considering whole farm operations from planting to harvesting (i.e., systems analysis) were unexplored.

Autonomous machines have the potential to revolutionise PA (Lowenberg-DeBoer *et al.*, 2020, Lowenberg-DeBoer *et al.,* 2021a). Even the studies on the economics of automated machines considered different sized farms (Tsuga, 2000; Ruhm, 2004; Mazzetto and Calcante, 2011) and commented on the operational efficiency in field operations (Clary *et al.*, 2007; Cembali *et al.*, 2008). Nonetheless, the economic implications of field sizes and shapes with the lens of machinery performance are still unexplored. For example, in Japan, Tsuga (2000) showed that automated transplanters can economically compete with human labour with a minimum area covered over 8.2 ha. Ruhm (2004) evaluated economics of harvesting, grading and cultivation of asparagus in Germany. The study showed that automated asparagus grading technology would be cost-effective if the area is more than 13 ha and the optimum size of the field for automated technology is 29 ha. They pointed out that future effort should concentrate on efficient production with minimum costs. In Italy, Mazzetto and Calcante (2011) developed an innovative system for completely automated transplant operation of vine cutting. They considered farm size and tested the developed method in various field topographic conditions. They found that the automated system reduced the requirements of labour and increased the transplanting rate by 15% compared to the conventional system. The cost curve estimation revealed that automated transplanter had lowest cost potentiality with annual area transplanted over 23 ha. Zhang, Pothula and Lu (2016) conducted an economic assessment of a self-propelled harvesting and automated in-field sorting machine systems in the US apple industry. The study mentioned that farm size played an important role in cost savings and automated machines increased harvest efficiency. Cembali *et al.* (2008) determined the efficiency level for profitable automation asparagus harvesting and compared it with manual harvesting methods. The study assumed the spear collection and collateral damage efficiency as the primary trial was unable to demonstrate exact efficiency. They concluded that the efficiency of the spear collection rate should be 85% with 5% collateral damage for profitable selective mechanical harvesting compared to manual methods. These studies focused on farm size but did not analyse the impact of the field size within the farm.

Similarly, the economic feasibility assessment of autonomous machines incorporated farm size in arable field crops and fruit production. For example, Edan, Benady and Miles (1992) found that if manual harvesting operation was less than US$494/ha, then autonomous operation was economically viable for 202.4 ha harvesting operation. In the US, McCorkle *et al.* (2016) showed how substituting manual labour with robotic equipment affects different sized vineyards. Pedersen *et al.* (2017) mentioned that robotic operations lead to minimum overlaps, and it was possible to ensure economies of scale in small and medium sized fields. Goense (2005) showed that row crop cultivation with autonomous technology was an attractive alternative to manually operated machinery, if large areas were covered. The above production economics studies were unable to disclose the economic implications of field sizes and shapes, in addition, these studies lacked systems analysis.

To date, only very few studies focused on systems analysis in their economic assessment and mentioned the significance of farm sizes. However, economic implications of field sizes and shapes subject to the performance of machineries' were overlooked (Lowenberg-DeBoer *et al.,* 2019, Lowenberg-DeBoer *et al.,* 2021a; Shockley, Dillon and Shearer, 2019; Shockley and Dillon, 2018). Shockley and Dillon (2018) examined the economic feasibility of autonomous field machinery to produce corn and soybean in the US. They concluded that farm size should be considered into market size determination. Likewise, Shockley, Dillon and Shearer, (2019) found that relatively small autonomous machines are likely to have economic advantages for medium and small-scale farms. Shockley *et al.* (2021) examined how regulation will impact the commercial viability of the use of autonomous equipment in the US. They mentioned that smaller farms had the advantage to gain more from farming with autonomous equipment. Lowenberg-DeBoer *et al.* (2019) went beyond the study of Shockley, Dillon and Shearer (2019), they assessed the economic feasibility of swarm robots incorporating seeding to harvesting operations based on field data. They found small and medium sized farms with swarm robotic operations had cost advantage. Similarly, using systems analysis, Lowenberg-DeBoer *et al.* (2021a) identified economic implications of autonomous equipment for grain-oil-seed farms in the UK. They found that medium sized farms had a cost advantage with autonomous technology. They also commented on the economic potentiality of autonomous technology in irregular shaped arable fields. In their analysis, they assumed all farms had 70% field efficiency for all operations and equipment sets, but did not reflect the economic implications of field efficiency differences subject to field sizes and shapes. Sørensen, Madsen and Jacobsen (2005) mentioned efficiency is a critical prerequisite for improved profitability and assumed 80% robotic weeding efficiency. However, these studies assumed constant field efficiency for different farm sizes and operations. They overlooked the crucial question about economic implications of field sizes and shapes on the use of autonomous crop robotics.

On the contrary, the ecological management studies, especially studies conducted in the US, UK, Canada, and European Union considered field sizes with utmost importance to promote environmental schemes *(*Clough, Kirchweger and Kantelhardt, 2020; Europe, 2008; Fahrig *et al.,* 2015; González-Estébanez *et al.,* 2011; Stanners and Bourdeau, 1995). For instance, Fahrig *et al.* (2015) considering Canadian context, found that field size had a strong relationship with biodiversity. Results showed that higher biodiversity exists in small arable crop fields. They suggested for ensuring biodiversity conservation, field size reduction should be considered. Likewise, in the context of eastern Ontario, Canada, Flick, Feagan and Fahrig (2012) examined effects of the structure of landscape on the diversity of butterfly species. The results showed there was a positive relationship between declining patch size and richness of butterfly species. Lindsay *et al.* (2013) investigated the relationship between structure of farmland and bird species composition, diversity and richness in six watersheds in the Midwest, US. They found avian richness decreased with the increase of field size. In the context of Great Britain, Robinson and Sutherland (2002) found increased use of machinery promoted the expansion of field size that resulted in 50% removal of the stock of hedgerows. In northwest Spain, González-Estébanez *et al.* (2011) found that butterfly diversity is higher in smaller fields. They mentioned landscape attributes are important for biodiversity conservation. Gaba *et al.* (2010) examined the richness and diversity of weed species in France. The study found increased richness and diversity of weed in small fields. They suggested that fields having more crop edges could shelter numerous species of weed. Clough, Kirchweger and Kantelhardt (2020) pointed out that in European landscapes, biodiversity declined with the increase in field size. They suggested that ecological and economic trade-offs should be addressed in policy and research, where field size could be the mediator to mitigate the trade-offs.

The state of the art reveals that small fields are advantageous for environmental management. On the contrary, the performance of conventional agricultural mechanization has an inverse relationship with small fields. Nonetheless, it has yet to be demonstrated how and to what extent autonomous machines performance is sensitive to field sizes and shapes, and what would be the economic implications of field size and shape on autonomous machines. Although the most up to date study conducted by Lowenberg-DeBoer *et al.* (2021a) estimated wheat costs of production subject to farm sizes (Figure. 2.1). They hypothesized that autonomous swarm robots will minimize the pressure to "get big or get out", indicating that small farms are economical with autonomous machines. However, they did not address the implications of field size and shape. Consequently, the economic implications of field sizes and shapes remain in question.

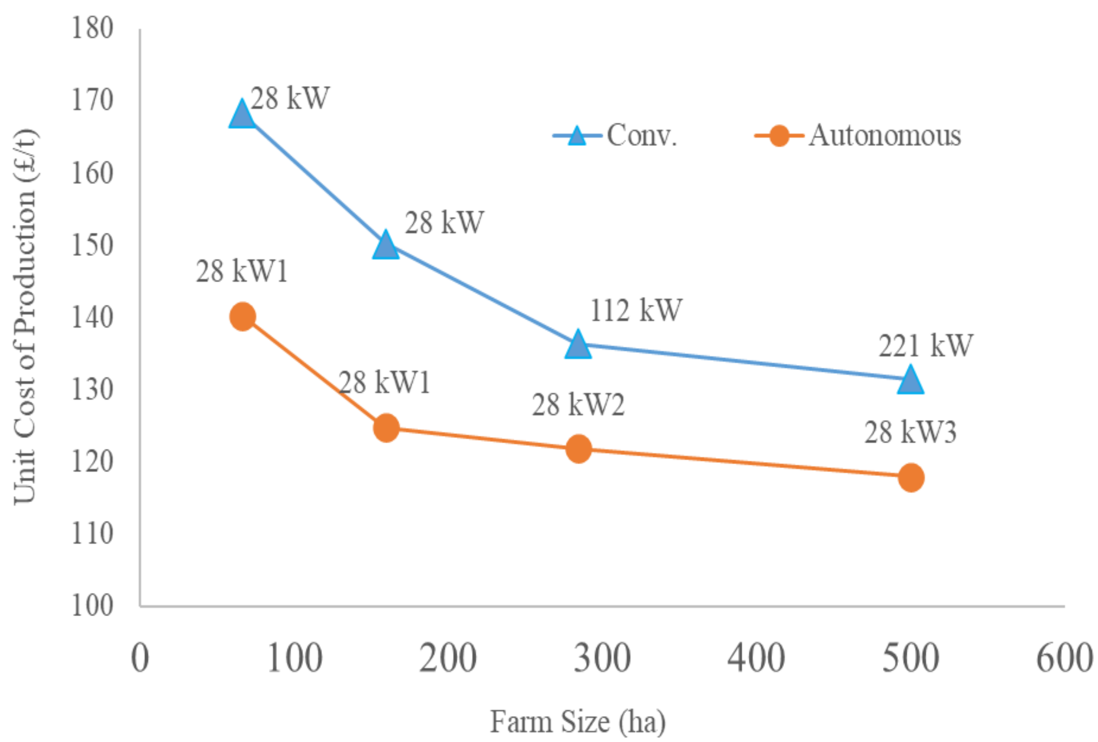

Figure 2.1: Costs of production of wheat for conventional (triangles) and autonomous equipment (circles) subject to farm sizes. ***Source:*** *Lowenberg-DeBoer et al. (2021a).*

To shed light on the research gap, the present study hypothesized that autonomous crop machines would make it possible to farm small, non-rectangular fields profitably, thereby preserving field biodiversity and other environmental benefits. The study took advantage of systems analysis considering autonomous arable farm operations from drilling to harvesting. Using HFH demonstration experience at Harper Adams University in the UK, the study investigated the economics of field size and shape on autonomous grain-oilseed production (Objective 1). The findings of the study have implications for the development and improvement of autonomous machines and facilitate the decision-making process of the farmers and agribusiness adopters, environmentalists, and policy makers and planners.

2.4 Automating mixed cropping

Apart from the cost economies (i.e., economies of size) of autonomous machines for whole field sole cropping system (Shockley, Dillon and Shearer, 2019; Lowenberg-DeBoer *et al.*, 2021a), the mixed cropping farm management potentials of autonomous machines are in planning (Daum, 2021; Davies, 2022; Pearson *et al.*, 2022) and demonstration stage (Ditzler and Driessen, 2022; Harper Adams University (HAU), 2023). Autonomous machines are expected to reconcile the multifaceted goals of arable farming such as production goals of productivity and profitability and environmental goals of sustainability (Gackstetter *et al.*, 2023).

Research suggests several mixed cropping systems with the advent of autonomous machines, such as strip cropping (Ward, Roe and Batte 2016), pixel cropping (Ditzler and Driessen, 2022) and patch cropping (Grahmann *et al.*, 2021; Donat *et al.*, 2022). However, technical challenges of farm management constraints more complex mixed cropping due to different plant heights and growth patterns (Ditzler and Driessen, 2022). Strip cropping (refers to a farming practice of simultaneously growing two or more crops in adjacent strips, where the strips are wide enough for independent cultivation, whilst narrow enough for facilitating crop interaction) is considered as the simplest and most technically feasible mixed cropping systems even with conventional mechanization (Exner *et al.*, 1999; van Apeldoorn *et al.*, 2020; Alarcón-Segura *et al.*, 2022).

2.5 Strip cropping (AND/OR) autonomous machines: Objective 2

Strip cropping is considered as part of sustainable intensification solution because strip cropping has the potential to address within field spatial and temporal (i.e., spatio-temporal) heterogeneity, while increasing production and reducing synthetic inputs use (Cruse and Gilley, 2008; Du *et al.*, 2019; Juventia *et al.*, 2022). Agroecology (FAO, 2019) has been suggested to bring a new paradigm in arable crop farming through redesigning spatio-temporal heterogeneity. The agroecological farming systems has the potential to reconcile production and environmental sustainability while substituting external inputs use through optimizing the ecological processes (Lacombe, Couix and Hazard, 2018; Boeraeve *et al.*, 2020). Under the umbrella of agroecological farming, strip cropping is advocated with existing machinery to increase productivity and resource-use-efficiency (Munz *et al.*, 2014a; Song, 2020; Juventia *et al.*, 2022; Bejo, 2023; Chongtham, 2023). The agronomic (West and Griffith, 1992; Agyare *et al.*, 2006; Munz *et al.*, 2014a) and ecological (Alarcón-Segura *et al.*, 2022) benefits of strip cropping are well documented in research throughout the world.

Research in the large-scale farming context showed the agronomic benefits of strip cropping. For instance, Borghi *et al.* (2012) using field experiments in Brazil, investigated the effects of different row spacing on maize and forage intercropping. The study found that narrow-row spacing maize yields were higher compared to wide-row spacing at the same plant density. Field experiments in Argentina by Verdelli, Acciaresi and Leguizam´on (2012) found that strip cropping corn yield in three seasons increased 13 to16% in the border rows, whilst soybean yield decreased 2 to11% compared to whole field sole cropping (i.e., monocultures). The study found no significant difference in centre rows yield in strip cropping. The study pointed out that yield increase of corn in border rows was highly associated with the radiation interception and crop growth rates advantage of taller corn plants and the opposite happened for subordinate soybean that leads to yield penalty. West and Griffith (1992) conducted maize and soybean strip cropping trials from 1986 to 1990 in the Corn Belt of Indiana, US. The study found that the strip cropping system increased outside corn rows yield on average by 25.8% and decreased outside soybean yield by 26.6% compared to unstripped cropping system. The review study conducted by Francis *et al.* (1986) pointed out that in the Eastern and Midwest US, narrower strips corn had yield advantage of 10 to 40% and soybean yield reduction was 10% to 30% over sole cropping systems owing to the light water and nutrient competition between taller corn and smaller soybean plants. The study also mentioned that in wider strips the corn yield increase and soybean yield decrease were less than sole cropping. Ghaffarzadeh, Préchac and Cruse (1994) evaluated the yield response of corn-soybean-oat-legume strip intercropping in two experiments conducted in 1989 and 1990 in Iowa, US. Results showed that outside corn rows produced significantly higher yield, but competition of water caused yield loss. Rainfall and water adequacy affected soybean yield. The study suggested strip intercropping as a suitable alternative to current monocropping practices. Cruse and Gilley (2008) in Iowa, US found that corn yield was 10% to 30% higher in the edge rows whilst soybean yield decreased 5% to 10% compared to the strip in centres.

Experiments of medium scale farming context in Germany and small scale context in China by Munz, Claupein and Graeff-Hönninger (2014b) showed that strip widths have significant impact on crop yield. The study found that on average maize yield increase in border rows for 18 to four rows by 3% to 12% in Germany and 5% to 24% in China. Yang *et al.* (2014) used the experience of maize and soybean relay strip intercropping experiments in China and found that planting geometrics had yield effects. The study pointed out that spatial pattern differences have implications for soybean owing to the light environment. Results showed that total yield in strip intercropping systems was higher than that of sole cropping systems. Yang *et al.* (2015) found that maize yield increased with bandwidth reduction and plant spacing had significant impacts on yield. The yield of relay strip intercropping was higher compared to sole cropping maize and soybean farming. The optimum bandwidth and narrow-row spacing of maize were 200 and 40 cm. The study suggested appropriate reduction of narrow rows maize plant spacing and increased distance of maize-soybean rows for higher yield. Research in China by Iqbal *et al.* (2019) suggested appropriate planting geometry for yield increase, nutrition acquisition, and mechanical operations in maize-soybean strip intercropping systems. They suggested increasing distance between soybean and maize rows and decreasing distance of maize rows. Qin *et al.* (2013) using experimental trails in arid land of China found that maize based intercropping systems such as maize-pea and maize-wheat had significant yield advantages compared to sole cropping systems. The study also found land equivalent ratios of 1.2 to 1.5 (the benefit greater than 1 indicates intercropping benefits). The study also advocated that intercropping systems incorporating a legume such as pea has the capacity to increase crop productivity, reduce soil respiration and decrease carbon emission. Jun bo *et al.* (2018) in China found that increase of plant density resulted in higher maize and soybean yield and the land equivalent ratios as of 2.0. The study mentioned that the outer rows of maize and soybean were expanded enough to facilitate light use and equipment work efficiency. The simulation study of van Oort *et al.* (2020) using Chinese case study of wheat and maize relay strip intercropping found that wider strip decreased intercropping benefits. The study suggested optimum strip width less than 1 m. Liu *et al.* (2022) using three years maize and soybean experiments in southwest China found that soybean strip width had substantial effects on leaf photosynthetically active radiation (PAR) compared to maize strip width.

Agronomic studies also found the effects of strip orientation in strip cropping systems. The maize-soybean-oat strip cropping study of Jurik and Van (2004) on four farms of Iowa, US, found that outside edge rows of corn in north-south direction received 2% to 38% higher daily photosynthetic photon flux density (PPFD) (i.e., the number of photons per unit time on a unit surface) compared to inner rows in strip systems and the outside soybean row far away from corn received 36% to 140% greater PPFD. Cruse and Gilley (2008) found that in east-west oriented strip cropping systems, south border rows corn yield increased substantially compared to north borders. They also found that strips oriented in the north-south favoured corn yield on both side edges. Liu *et al.* (2022) based on three years of maize and soybean strip cropping experiments on North-south and West-east strip orientation in southwest China found more photosynthetically active radiation (PAR) (i.e., solar radiation that photosynthetic organisms capable to use in photosynthesis where the solar radiation lies between 400 to 700 nanometres) interception by soybean plants compared to maize plants while strip orientation angled increase from 0^0 to 90^0. Iragavarapu and Randall (1995) based on the experiment in southern Minnesota, US found that yield of corn increased by 3% when the corn and soybean strip cropping was oriented in East-west rows and 13% in North-south rows. On the contrary, soybean yield decreased by 10% for East-west rows and 7% for North-south rows. Iragavarapu and Randall (1996) showed that strip orientation has substantial effects on yield based on the experimental trials of southern Minnesota, US. The layout followed south side soybean, northside wheat and east-west side-oriented corn to maximize light interception and minimize shading. The four-year (1991 to 1994) average yield found that outside rows corn yield was 12% higher in east-west rows and 25% higher in north-south rows compared to non-border rows. In the case of soybean, the study found 13% yield penalty for east-west and 12% for north-south rows.

The study of Cruse and Gilley (2008) considering the North American context of Iowa pointed out that total application of pesticide and fertilizer was less in strip cropping systems compared to whole field sole cropping. The review synthesizes of Iqbal *et al.* (2019) found that intercropping helps in higher resource capture due to the advantage of capturing spatial and temporal dimensions. The inclusion of legumes in intercropping systems served as a strategy to save nitrogen owing to the biological nitrogen fixation process. They also pointed out that cereal-legume intercropping systems improve water use efficiency and soil fertility. The findings of meta-analysis showed that intercropping reduced anthropogenic inputs (i.e., less fertilizer N is required) compared to the sole cropping system (Xu *et al.*, 2020). Based on the southwestern Chinese context, the study of Du *et al.* (2019) found that legume-nonlegume intercropping such as maize and soybean intercropping systems reduce N input through biological N fixation. The study of Głowacka *et al.* (2018) using a field experiment in south Poland from 2008 to 2010 found that strip cropping is an effective strategy to improve maize biofortification (i.e., the process of improving food nutritional quality). The study found that strip cropping significantly increased Magnesium (Mg) and Calcium (Ca) accumulation in maize biomass (i.e., renewable organic matter) and grain.

Strip cropping systems also have the potential to maximize temporal variability and reduce the negative border effects. Small grains same in height such as oat and wheat could be considered to take the advantage of edge effects. Small grains typically sown a few months before the typical taller plant maize and subordinate plant soybean. This cropping system competes less for light. When the small grains (e.g., oat and wheat) reach maturity the taller plant (maize) ensures wind shelter that reduces grain lodging (Iragavarapu and Randall, 1996; Cruse and Gilley, 2008). The findings of meta analysis by Xu *et al.* (2020) showed that intercropping increased temporal variability by sowing or harvesting one crop earlier than others.

Apart from agronomic benefits, research shows ecological benefits of strip intercropping (Qin *et al.*, 2013; Tajmiri *et al.*, 2017b). For instance, based on a field experiment in China Ju *et al.* (2019) pointed out that strip intercropping increases crop biodiversity and could be used for successful conservation and biological control tools. The study of Alarcón-Segura *et al.* (2022) found that strip intercropping systems increased biodiversity and biological pest control in conventionally mechanized farms with larger 27-36m strips in German farms. Cong *et al.* (2015) conducted wheat, maize and faba bean strip cropping experiments from 2008 to 2011 in Northwest China. The study found that root biomass in intercrops was 23% higher compared to whole field sole cropping. Results also found soil carbon (C) sequestration, Nitrogen (N) fixation. The study pointed out that strip intercropping systems have aboveground productivity owing to species complementary and belowground productivity due to C sequestration and biological N fixation. The review study by Kremen and Miles (2012) pointed out that strip intercropping has less disease spread due to the spacing and enterprise diversity. The crop roots interaction in strip intercropping is less than other types of row intercropping. The review of Hiddink Termorshuizen and van Bruggen (2010) found that strip cropping and other mixed cropping systems reduced diseases in 74.5% of cases compared to whole field sole cropping. The study of Raseduzzaman and Jensen (2017) based on the metal analysis pointed out that cereals and grain legumes intercropping has the potential to promote biodiversity and sustainable intensification with higher yield stability. Using field experiments in south China, Liang *et al.* (2016) found that intercropping substantially lower disease infestation. The net rate of photosynthesis and leaf chlorophyll content were increased for rice in the edge rows of water spinach. Ning *et al.* (2017) found that in south China, rice and water spinach intercropping reduced diseases and pest infestation in rice. Chen *et al.* (2017) in their experiments in China found that maize and soybean relay strip intercropping increased land productivity and reduced environmental pollution.

The study of Cruse and Gilley (2008) considering the North American Corn Belt context of Iowa pointed out that due to the advantages of easily defined planting positions, no-till or ridge tillage and contour planting strip cropping system limit soil erosion. Moreover, inclusion of small grain/forage strips in the strip cropping system act as an efficient vegetation filter for sediment removal during water runoff. Strip cropping is a management system to control soil drift and improve water storage (Bravo and Silenzi, 2002).

Mohammadi *et al.* (2021) considered Iranian context and found that strip intercropping is an effective strategy to encourage pest predators. Study by Iqbal *et al.* (2019) in China showed that cereal-legume intercropping systems reduce weed infestation, soil erosion and improve water use efficiency and soil fertility. The study of Brennan (2013) in California, US, showed that lettuce and alyssum strip cropping is an effective strategy for biological aphids control. Using 2014 and 2015 cropping seasons of Iran, Tajmiri *et al.* (2017a) found that canola and alfalfa strip cropping increased pest predator species diversity. Another study of Tajmiri *et al.* (2017b) in Iran pointed out that potato and alfalfa strip intercropping could be an effective strategy to reduce pest density. Based on experimental outcomes from 2009 to 2011 in China, Qin *et al.* (2013) pointed out that adoption of strip intercropping is an effective strategy to reduce soil respiration and lower carbon emission.

The state of the knowledge of strip cropping shows agronomic and ecological (agroecological) benefits. Strip cropping has been practiced based on agronomic and/or environmental considerations in human intensive farming and/or conventional mechanized systems (Cruse and Gilley, 2008; Qin *et al.*, 2013; Brooker *et al.*, 2015; van Oort *et al.*, 2020; Rahman *et al.*, 2021). Mixed cropping is often evident in manual agriculture as compared to whole field sole cropping (Francis *et al.*, 1986; Brooker *et al.*, 2015). In conventional mechanized systems operated with human operators strip cropping is envisaged and practiced to maximize productivity and ecological benefits (Munz *et al.*, 2014c; Wang *et al.*, 2015; Alarcón-Segura *et al.*, 2022). However, questions about economics of strip cropping are yet to be answered as strip cropping economics is constrained by the substantial added labour requirements. Research in the large-scale farming context of the Midwest, US found that higher labour requirements and associated fixed costs in conventional mechanized systems offset the profitability of maize and soybean strip cropping (Ward, Roe and Batte, 2016; West and Griffith, 1992). The economics of strip cropping is even constrained for smallholder's context in China by labour scarcity (Feike *et al.*, 2012; Munz *et al.*, 2014c).

Researchers have hypothesized that economically feasible agricultural intensification with the strip cropping system could be possible with technological innovation. For example, Exner *et al.* (1999) in their strip intercropping study based on Iowa, US farms pointed out that precision management is demanded for strip cropping. The study of Lesoing and Francis (1999) in their study of corn-soybean and grain sorghum-soybean strip cropping in eastern Nebraska, US mentioned that new planting equipment could be more effective for cereal-legume strip intercropping. van Oort *et al.* (2020) pointed out that future machinery and crop growth models will enable farmers to achieve the benefits of intercropping. The study also suggested that intercropping and autonomous swarm robotics co-evolution will help to achieve maximum benefits of intercropping and labour productivity. The maize and soybean strip cropping study by Ward, Roe and Batte (2016) in the Corn Belt of the US found that strip cropping profitability is constrained by higher labour requirements and associated fixed costs related to conventional machines. Their study hypothesized that innovative technology such as small supervised autonomous machines (i.e., robots) could change the cost calculus of strip cropping.

The economic benefits of strip cropping as found in literature was measured using partial indicators such as Land Equivalent Ratio (LER), Gross Margin Ratio (GMR), Monetary Equivalent Ratio (MER) and/or harvested yields (Francis *et al.*, 1986; Smith and Carter, 1998; Lesoing and Francis, 1999; Yu *et al.,* 2015; van Oort *et al.,* 2020; Rahman *et al.*, 2021). A very few studies used partial budgeting (West and Griffith, 1992; Exner *et al.,* 1999; Ward, Roe and Batte, 2016; Kermah *et al.,* 2017). The most up-to-date economic analysis of strip cropping using partial budgeting was conducted by Ward, Roe and Batte (2016) considering the context of the Corn Belt of the US. However, the study was unable to test their robot hypothesis due to a lack of autonomous whole farm operations experience and data.

The existing strip cropping economics studies to date concentrated on partial assessment of economic scenarios instead of whole farm systems analysis capturing planting to harvesting operations. To help close this research gap, the study assessed the profitability of maize and soybean strip cropping with autonomous machines on a central Indiana, US farm. Maize and soybean farm of the Corn Belt of the US was considered because the study evaluated the hypothesis of Ward, Roe and Batte (2016), where agronomic benefits of yield increase for corn and penalty for soybean related to edge effects are available.

2.6 Regenerative agriculture (AND/OR) autonomous machines: Objective 3

The scientific definition of regenerative agriculture is not yet clear (Schreefel *et al.*, 2020). The existing definitions are based on processes (i.e., incorporating cover crops, livestock and tillage reduction or elimination), outcomes (i.e., improvement of soil health, carbon sequestration and biodiversity enhancement) and/or combination of both (Newton et al., 2020; Manshanden *et al.*, 2023). In this study, regenerative agriculture is considered with strip cropping practices that diversify crop production within the same field in strips to minimize soil disturbance, improve resource use efficiency of the farm through reducing synthetic chemical input use, and boost soil health, biodiversity, and farm productivity.

The combination of processes and outcomes based definition assumed in this study considered five soil health principles because soil health is the entry point to achieve the multiple objectives of arable farming, such as production and nature conservation

(LaCanne and Lundgren, 2018; Schreefel *et al.*, 2020; Schreefel *et al.*, 2022b). The soil health principles include minimising soil disturbance, maximizing crop diversity, keeping soil covered, maintaining living roots year round and including livestock components (Jaworski, Dicks and Leake, 2023; Manshanden *et al.*, 2023) as shown in Figure 2.2.

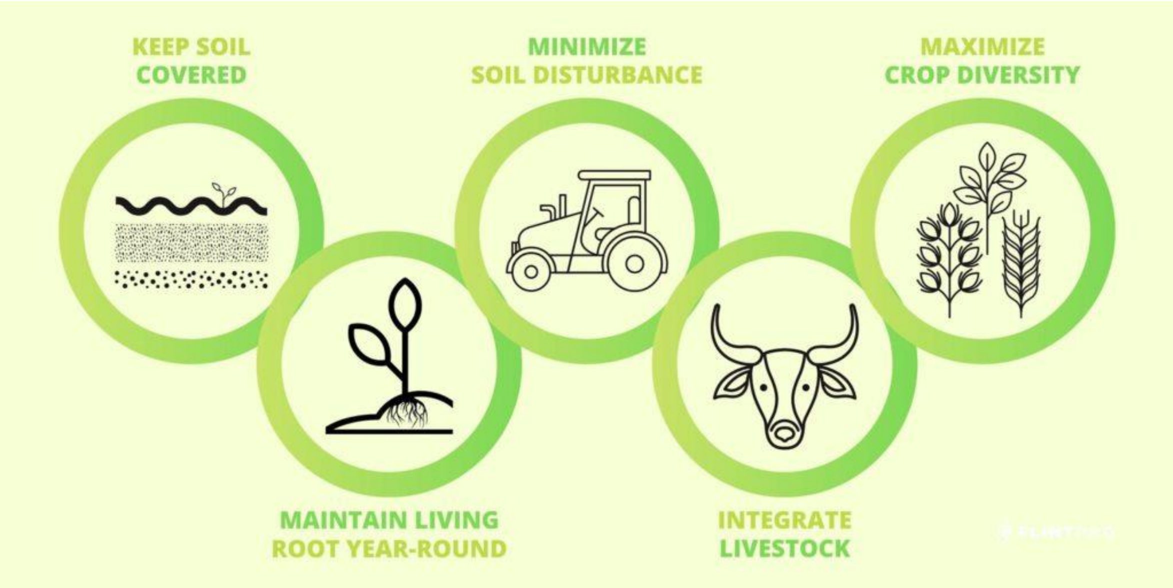

Figure 2.2: Five principles of regenerative agriculture.

Source: *Lower Blackwood Catchment. Adopted from: Cool Farm Tool. Available at: https://coolfarmtool.org/2020/12/regenerative-agriculture-and-climate-change/ (Accessed: 21 December 2022).*

Strip cropping systems are the simplest regenerative mixed cropping system. It is technically feasible even on conventional mechanized farms (Exner *et al.*, 1999; van Apeldoorn *et al.*, 2020; Alarcón-Segura *et al.*, 2022). This cropping system could also be considered as agroecological farming because strip cropping is an innovative agroecological practice to produce more (i.e., owing to edge effects) (Ward, Roe and Batte, 2016) with less external resources (FAO, 2019). Although the definitions of agroecology and regenerative agriculture differ, field biodiversity is a common element (FAO, 2019; Tittonell *et al.*, 2022). One of the key differences between agroecology and regenerative agriculture is that 'agroecology' refers 10 elements (FAO, 2019), which include 'political' or 'activist' elements as well as production aspects, whereas regenerative agriculture is increasingly supported by commercial and large-scale farming (Tittonell *et al.*, 2022; Manshanden *et al.*, 2023). At recent times, regenerative agriculture has been promoted by civil society, NGOs, media and multinational food companies considering agronomic and ecological grounds (Gosnell, Gill and Voyer, 2019; Giller *et al.*, 2021; Umantseva, 2022).

However, the production economics of regenerative agriculture shows mixed results (WBCSD, 2023; Schreefel et al., 2022a; Constantin et al., 2022). Profitability of regenerative practices are constrained by higher labour requirements and farm management challenges which limit the adoption and scaling up (Pearson 2007; Keshavarz and Sharafi, 2023). In this context, regenerative agriculture is envisaged with autonomous machines to reduce labour needs and enable intensive management (Davies, 2022; The Pack News, 2022). Research hypothesized that robotics and autonomous systems (RAS) could provide emerging opportunities that will help to achieve net zero agriculture targets with regenerative agriculture (Pearson et al., 2022).

The state of the knowledge of regenerative practices reveal that regenerative agriculture is a prominent alternative which could transform food production and ecosystem restoration degraded by industrial monocultures (Gordon, Davila and Riedy, 2023). For instance, considering the US farming systems, the study of Day and Cramer (2022) pointed out the significance of regenerative agricultural transformation through linking policy, process and education. Gosnell, Gill and Voyer (2019) mentioned that regenerative agriculture is a climate smart mitigation and adaptation measure supported by technological innovation, policy, education, and outreach. The study of Gremmen (2022) suggested scientific and technology driven as well as nature-based regenerative agriculture solutions to meet the demand for food of the increasing population. In the US, LaCanne and Lundgren (2018) found that corn pest abundance was more than 10-fold lower in regenerative multispecies cover crop systems compared to conventional systems. Regenerative agriculture directly conserves and restores soil health, increases biodiversity and ecosystem services, and sequesters atmospheric carbon (CO_2). Similarly, part of the co-benefits of regenerative agriculture is that it helps in producing healthy and nutritious food (White, 2020).

Using an Australian case study, Bartley *et al.* (2023) found that regenerative grazing (i.e., rotational grazing with rest included strategically) improved vegetation, and soil and land condition, but it took longer, a period of at least three to five years and a maximum fifteen to twenty years, to capture the benefits. The study found that regenerative grazing increased total nitrogen and soil organic carbon compared to control sites that did not follow regenerative grazing. Eckberg and Rosenzweig (2020) pointed out that regenerative agriculture is a farmer-led movement that adopts nature-based principles to restore soil health, biodiversity, and farm economics because cereal grain intensive food systems degrade natural resources. The study of Rehberger, West and Spillane, (2023) pointed out that regenerative agriculture increases soil organic carbon, soil health and biodiversity.

Using participatory monitoring and evaluation, the study of Soto, de Vente and Cuéllar (2021) in Spain, found that regenerative agriculture is a promising approach to restore degraded agroecosystems. Rhodes (2017) mentioned that regenerative agriculture not only increases soil organic carbon but also builds new soil that helps to improve soil health and structure, increase soil fertility and crop yield, facilitate water retention and aquifer recharge. McLennon *et al.* (2021) mentioned that regenerative agriculture helps to reduce external inputs dependency and restore and maintain natural systems. Hellwinckel and Ugarte (2011) argued that a regenerative agricultural transition is necessary to avoid locking into a system that depletes the soil and fossil fuels.

Although the food production and nature conservation potentials of regenerative agriculture is well known, the economics of regenerative agriculture has mixed literature depending on the specific regenerative practices considered (Bennett, 2021; Boston Consulting Group, 2023). A review study on the economics of regenerative agriculture in Western Australia conducted by Bennett (2021), found that the profitability of regenerative agriculture is lower compared to conventional agriculture. However, the regenerative agriculture production economics is sensitive to enterprise type. The study also pointed out that a loss of income is a significant barrier to scaling up regenerative practices' adoption. The study of Ogilvy *et al.* (2018) using financial data from sixteen regenerative agriculture grazing farms found that before interest and tax, the earnings from regenerative agriculture were more profitable compared to conventional grazing systems. However, this study was contested by Francis (2019) who found that using the same data, conventional systems grazing sheep achieved a return on assets of 4.22%, while regenerative agriculture practitioners' return on assets was only 1.66%. The difference was mainly because the study of Ogilvy *et al.* (2018) only considered enterprise or animal level analysis, not whole farm analysis considering all the factor costs and assets invested as used in the study of Francis (2019).

A survey study based on North American context found that in the short run for the first three to five years, farmers have to face loss of profitability, but in the long run the profit increased with regenerative practices (WBCSD, 2023). The study of LaCanne and Lundgren (2018) in the US, examined the profitability of regenerative corn and conventional corn production. The study found that regenerative corn yield was 29% lower compared to conventional corn production. However, profit was 78% higher for regenerative practice which was due to the reduced inputs costs and higher output price as there was positive association between organic matter and profit, not corn yield. The survey study of Taylor and Dobbs (1988) in South Dakota, US found that regenerative agriculture was more profitable compared to conventional farming due to the lower input costs for regenerative practice and improved prices for the regenerative agriculture products.

In the Dutch dairy case, the study of Schreefel *et al.* (2022a) using an ex-ante modelling approach found improved soil function at the expense of farm profitability. Another study of Schreefel *et al.* (2022b) considered arable, dairy and mixed farming system in the Netherlands. The study found that regenerative practices improve environmental performances at the expense of farm profitability on an average by 50% across all case study farms. Constantin *et al.* (2022) did a review of literature of comparative environmentally friendly farming systems and found that regenerative agriculture is not an economically feasible farming system, while suggesting large-scale practice to achieve farm profitability.

The study of Pearson (2007) pointed out that regenerative systems required higher labour. The study suggested technological innovations to solve the problem. In the Iranian context, the study of Keshavarz and Sharafi (2023) found that climate smart regenerative agriculture is a plausible solution to restore agroecosystems, but scaling up was a significant challenge. Along with other socio-economic and institutional attributes, the study suggested technological changes to help wide scale adoption. Precision technologies are suggested to facilitate regenerative agriculture (Green Biz, 2020; Listen Field, 2021; Futures Centre, 2023; Manshanden *et al.*, 2023). For instance, the study of Pearson *et al.* (2022) hypothesized that autonomous systems could help regenerative agriculture. McLennon *et al.* (2021) suggested digital agriculture and sustainable agricultural management using agricultural technologies with artificial intelligence (AI) for regenerative agriculture. ‘Robot one’ a cutting-edge agricultural robot is expected to help regenerative farming practices (Pixel Farming Robotics, 2023). The Kibb autonomous initiative in Sweden is designed to promote regenerative farming (The Pack News, 2022). However, the economics of regenerative agriculture with precision agriculture technology is yet to be explored. In this study, autonomous machines are considered as precision agriculture technology because they have the potential to cost effectively increase the precision of input applications and to collect very detailed data on agricultural production. This economic analysis will guide the regenerative agriculture practices, development of autonomous prototypes and commercialization of autonomous technology and regenerative farming.

The context of the UK was considered because Great Britain is one of the most nature depleted countries which need ecosystem services regeneration. Moreover, the HFH &

HFF was the first whole farm commercial operation conducted at Harper Adams University in the UK (Hands Free Hectare (HFH), 2021). Another underlying reason is associated with the government vision of net zero agriculture. The British government has set an ambitious plan to achieve a net zero target by 2050 (Bank of Scotland, 2021; RASE, 2021). The study of Davies (2022) hypothesized that autonomous machines could facilitate regenerative agriculture that will help decarbonize cereal production in the UK. In British agriculture and policy, regenerative agriculture has received growing attention as part of a soil management strategy (Jaworski, Dicks and Leake, 2023).

Recent research and on-farm regenerative practices experience motivate regenerative farming in Great Britain. Using simulation methods, Jordon *et al.* (2022a) estimated that arable farming in Great Britain could mitigate 16-27% of agricultural emissions without losing crop yield through the adoption of regenerative agriculture. The analysis found that cover cropping, reduced intensity of tillage and incorporation of grass-based ley rotations are effective regenerative practices that increase soil organic carbon. The study mentioned that even though Great Britain farming systems have adoption constraints in the existing farming systems, the adoption of regenerative agriculture could contribute to the net zero target. The Bayesian meta-analysis of Jordon *et al.* (2022b) considering no or reduced tillage, cover crops and ley-arable rotations in Great Britain found that regenerative practices increased soil organic carbon compared to conventional practice. However, these typical regenerative rotations have to yield increasing benefit, while the study suggested future work could think of win-win farming with regenerative practice. Considering the context of the UK, Ken Hill Farms and Estate at Snettisham, Norfolk, found that farming using regenerative agriculture principles has the potential to save fixed costs (Abram, 2020). They also pointed out that regenerative agriculture is an effective strategy when farming practices include intercropping in the farms to reduce substantial amounts of fertilizer and chemical inputs. Based on farmer’s experience it is hypothesized that technology is the key to regenerative farming transition (Abram, 2021). With these backdrops, delving into the profitability of regenerative strip cropping practices under both conventional mechanized farming with human operators and autonomous system will help Great Britain to link with the transitional vision related to productivity and environmental sustainability that is “public money for public goods” subsidization policy.

Chapter 3

Economics of field size and shape for autonomous crop machines

"Arable crop production with autonomous equipment is technically and economically feasible, allowing medium size farms to approach minimum per unit production cost levels. The ability to achieve minimum production costs at relatively modest farm size means that the pressure to "get big or get out" will diminish. … The ability of autonomous equipment to achieve minimum production costs even on small, irregularly shaped fields will improve environmental performance of crop agriculture by reducing pressure to remove hedges, fell infield trees and enlarge fields."

Lowenberg-DeBoer et al. (2021a): 'Precision Agriculture, 22, pp. 1992–2006.

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Note: This chapter writing style is adopted and formatted as submitted to the *'Precision Agriculture'* Journal.

3.1 Introduction

Field size and shape have substantial consequences for environmental management (Bacaro *et al.*, 2015; Clough, Kirchweger and Kantelhardt, 2020; Konvicka, Benes and Polakova, 2016; Marja *et al.*, 2019), technical (Fedrizzi *et al.*, 2019; Griffel *et al.*, 2018; Griffel *et al.*, 2020; Islam, Kabir and Hossain, 2017; Janulevičius *et al.*, 2019; Luck, Zandonadi and Shearer, 2011) and economic feasibility (Batte and Ehsani, 2006; Carslaw, 1930; Larson *et al.*, 2016; Miller, Rodewald and McElroy, 1981; Sturrock, Cathie and Payne, 1977). To facilitate conventional agricultural mechanization, comparatively large rectangular fields are needed and most of the land consolidation around the world in the last decades have been motivated by the desire for larger fields (Kienzle, Ashburner and Sims, 2013; Van den Berg *et al.*, 2007). Field size and shape has been a key factor in determining international crop competitiveness. Since the advent of motorized mechanization countries with relatively large, roughly rectangular fields have had a major economic advantage (e.g., US, Canada, Australia, Brazil, Argentina). In the UK, field size has increased through removing hedgerows and in field trees to allow use of larger machinery and ensure economies of size (MacDonald and Johnson, 2000; Pollard, Hooper and Moore, 1968; Robinson and Sutherland, 2002). On the contrary, small fields are often neglected and considered as non-economic. For instance, in the US many small irregular-shaped fields were abandoned in the 20th Century. The European Union and Switzerland retained small fields in production with subsidies (Lowenberg-DeBoer *et al.*, 2021a; OECD, 2017).

Nevertheless, under the umbrella of landscape management, small fields are promoted by researchers. Research in Canada and the US found higher biodiversity in smaller fields (Fahrig *et al.*, 2015; Flick, Feagan and Fahrig, 2012; Lindsay *et al.*, 2013). Likewise, studies in the UK and the European Union also showed that small fields and more fragmented landscapes have higher biodiversity (Firbank *et al.*, 2008; Gaba *et al.*, 2010; González-Estébanez *et al.*, 2011). Using the context of the agricultural low lands of England, Firbank *et al.* (2008) pointed out that the pressure on biodiversity may be reduced through minimizing habitat loss in agricultural fields. The German case study found that East Germany's large-scale agriculture reduced biodiversity while small-scale agriculture of West Germany had higher biodiversity (Batáry *et al.*, 2017). As the environmental benefits of small fields are well documented in research, it would be interesting to explore the economics of small fields to better identify the win-win scenarios for small fields. Consequently, this study hypothesized that autonomous crop machines would make it possible to farm small, non-rectangular fields profitably, thereby preserving field biodiversity and other environmental benefits.

Autonomous crop machines in this study refer to the mechatronic devices which have autonomy in operation usually through a predetermined field path. More specifically, the autonomous machines are mobile, having decision making capability, and accomplish arable farm operations (i.e., drilling, seeding, spraying fertilizer, fungicide and herbicide, and harvesting) under the supervision of humans, but without the involvement of direct human labour and operator (Lowenberg-DeBoer *et al.*, 2020). Autonomous machines are precision agriculture technology because they have the potential to cost effectively increase the precision of input applications and to collect very detailed data on agricultural production. The autonomous machines, demonstrated by the HFH project used swarm robotics concepts in which multiple smaller robots are used to accomplish farm work usually done by larger conventional machines with human operators. The autonomous swarm robotics of the HFH project are developed by retrofitting conventional diesel operated machines (Hands Free Hectare (HFH), 2021).

Autonomous machines are considered as a game changing technology that could revolutionize precision agriculture (PA) and facilitate the 'fourth agricultural revolution' often labelled ‘Agriculture 4.0’ (Daum, 2021; Klerkx and Rose, 2020; Lowenberg-DeBoer *et al.*, 2021a). Owing to population and economic growth, agricultural labour scarcity, technological advancement, increasing requirements of operational efficiency and productivity, and mitigating environmental footprint, autonomous machines are suggested as a sustainable intensification solution (Duckett *et al.*, 2018; Guevara, Michałek and Cheein, 2020; Santos and Kienzle, 2020). Robotic systems for intensive livestock and for protected environments have been commercialized more rapidly than for arable cropping. Research on autonomous arable crop machines has mostly concentrated on the technical feasibility, not economics (Fountas *et al.*, 2020; Shamshiri *et al.*, 2018). Understanding the economic implications of autonomous machines is key to their long-term adoption. Economic feasibility plays a crucial role in attracting investment, guiding adoption decisions, and further understanding of environmental and social benefits (Grieve *et al.*, 2019; Lowenberg-DeBoer *et al.*, 2020).

Most production economic studies on autonomous machines prior to 2019 focused on horticultural crops and rarely on cereals using prototype testing and experimental data (Edan, Benady and Miles, 1992; Gaus *et al.*, 2017; McCorkle *et al.*, 2016; Pedersen *et al.*, 2017, Pedersen, Fountas and Blackmore, 2008, Pedersen *et al.*, 2006; Sørensen, Madsen and Jacobsen, 2005). Lack of information on economic parameters and machinery specifications has been a bottleneck in economic feasibility assessment because autonomous machines are at an early stage of the development and commercialization processes (Lowenberg-DeBoer *et al.*, 2021a; Shockley *et al.*, 2021).

Most of the earlier economic studies used partial budgeting where only the changes in cost and revenue linked to automation of a single field operation were analysed omitting the economic consequences of farming systems changes (Lowenberg-DeBoer *et al.*, 2020). To date, four studies have considered systems analysis of autonomous machines (Al-Amin *et al.*, 2021; Lowenberg-DeBoer *et al.*, 2021a; Shockley, Dillon and Shearer, 2019; Sørensen, Madsen and Jacobsen, 2005).

Using a Linear Programming (LP) model with data from prototypes at the University of Kentucky, US, Shockley, Dillon and Shearer, (2019) showed that relatively small autonomous machines are likely to have economic advantages for medium and small farms. The most comprehensive study so far was reported by Lowenberg-DeBoer *et al.* (2021a). They assessed the economic feasibility of autonomous machines from seeding to harvesting operations using on-farm demonstration data and estimated equipment times based on methodology from the agricultural engineering textbook of Witney (1988). The study assumed 70% field efficiency from drilling to harvesting operations for both autonomous machines and conventional equipment sets with human operators. They showed that autonomous machines are technically and economically feasible for medium and small sized farms. The study concluded that autonomous machines diminished the pressure of “get big or get out”. The study hypothesized that in the context of the UK, autonomous machines would be economically feasible in small fields. Nonetheless, the study was unable to test the hypothesis because of field efficiency estimates by field size and shape were not available.

To help fill this knowledge gap, the objective of the study is to assess the economics of field size and shape for autonomous machines. Using the experience of the HFH demonstration project, the study developed algorithms to estimate equipment times (h/ha) and field efficiency (%) for different sized rectangular and non-rectangular fields. Historically, in the UK rectangular fields were considered as the most efficient, whereas non-rectangular fields were substantially less efficient to farm (Carslaw, 1930; Sturrock, Cathie and Payne, 1977). Triangular fields were among the least efficient field shape because of the numerous short rounds. To analyse the economic scenarios, the study adopted and re-estimated the Hands Free Hectare-Linear Programming (HFH-LP) model (Lowenberg-DeBoer *et al.*, 2021a) by incorporating equipment times and field efficiency parameters estimated with field size and shape algorithms. The HFH-LP model replicates farm management and machinery selection decisions. It helps researchers understand choices that farmers would make if they had the alternative of using autonomous machine.

3.2 Methods

3.2.1 Field time and efficiency estimation subject to field size and shape

To date the production economics studies on autonomous machines did not consider field size and shape because of lack of data (Lowenberg-DeBoer *et al.*, 2021a; Shockley, Dillon and Shearer, 2019; Sørensen, Madsen and Jacobsen, 2005). Over time, the performance of arable field machinery has received growing attention for farm management and the ability to model field times has accelerated through the development of the technology and modelling approaches (Bochtis *et al.*, 2010; Sørensen, 2003; Sørensen and Nielsen, 2005). Nonetheless, existing studies on arable crop machinery performance lack information of equipment times (h/ha) and field efficiency (%) subject to field size and shape.

Even though logistics software is well developed in trucking and other transportation sectors (Software Advice, 2021), there is no readily available commercial software in the UK to estimate equipment times and field efficiency encompassing field and machine heterogeneity. In the farm equipment path planning research 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). In conventional mechanization and PA literature, few studies estimated field efficiency, but prior studies treated the headlands of the field as non-productive areas, excluded overlap percentage, amalgamated 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 ignored the headland turning patterns.

Studies suggested that future research should separately calculate the headlands turning time, and stoppages time because productive times and non-productive times play a significant role in field efficiency estimation. Keeping these points in consideration, the study developed field time approximation algorithms by field size and shape for 28 kW, 112 kW and 221 kW conventional equipment sets with human operators, and for the HFH sized 28 kW autonomous equipment set. The combine harvesters were assumed to have head widths of 2 m, 4.5 m and 7.5 m respectively. Using the experience of the HFH demonstration project, the algorithms addressed the research gaps identified from the prior studies. 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 as follows:

$E_f = [T_T / (T_{obs} + \mathrm{T_h} + \mathrm{T_{sf}})] * 100 \ \ldots \ \ldots$ (1)

where, E_f is the field efficiency, T_T is the theoretical field time, T_{obs} is the total observed time in the interior field and passes, T_h is the total headland round time, and T_{sf} total stoppage time “within” in the field.

Based on user input of equipment and field measurements, the first step was to calculate field area, number of headlands rounds and other values that were used repeatedly throughout the algorithm. Secondly, headland area and field times were calculated. Afterwards, observed times in the interior field and passes were estimated. Fourthly, the algorithms estimated non-productive times. Fifthly, total field operation times were calculated. The theoretical field times were estimated based on the machine design specifications. For details of the estimation processes of the algorithms see the technical note in Appendix A (i): Supplementary Text (i.e.., STEXTT Supplementary Text, which includes Main Text of the Technical Note).

The algorithms were calibrated for 1 ha, 10 ha, 20 ha, 50 ha, 75 ha, and 100 ha rectangular fields considering the typical farm field sizes of the UK that were assumed to follow the field path of Figure 3.1. To illustrate the impact of field size on technical efficiency, estimates were made for rectangular fields with the length ten times the width of the field, up to one kilometre length. Rectangular field algorithms are detailed in the algorithm’s spreadsheet in Appendix A (ii): Algorithms Spreadsheets (i.e., SM1 Rectangular Field Algorithms).

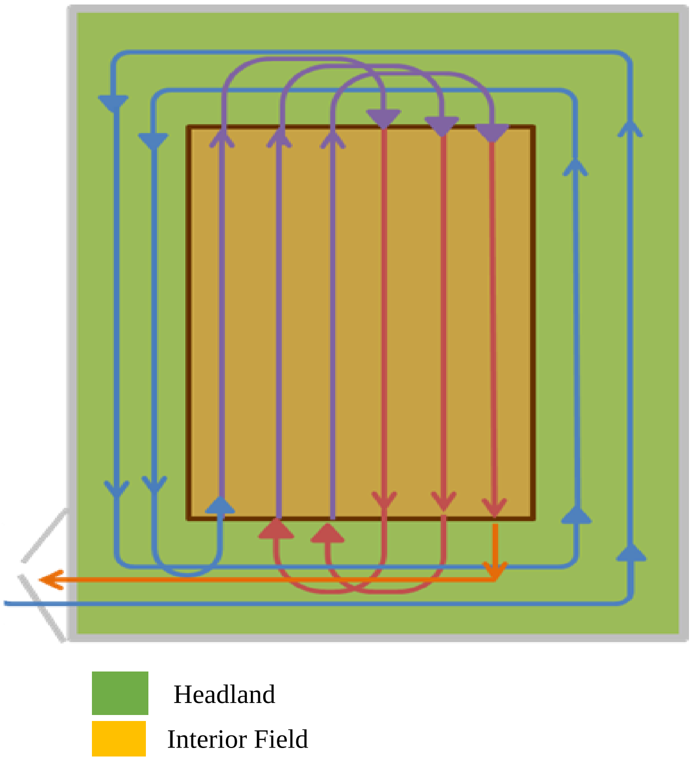

Figure 3.1: Typical field path for rectangular fields considered in the study based on the HFH demonstration project experience.

Similarly, non-rectangular fields algorithms were tested for 1 ha, 10 ha, 20 ha, and 25 ha sized right-angled triangular fields assuming the height equalling twice the base up to a height of one kilometre. The equipment sets were assumed to follow the typical field path given in Figure 3.2. The non-rectangular fields algorithms were estimated with the same equipment sets (for details of the right-angled triangular field algorithms see spreadsheet in Appendix A (ii): Algorithms Spreadsheets (i.e., SM2 Non-Rectangular Field Algorithms (i.e., Right-Angled Triangular Field)).

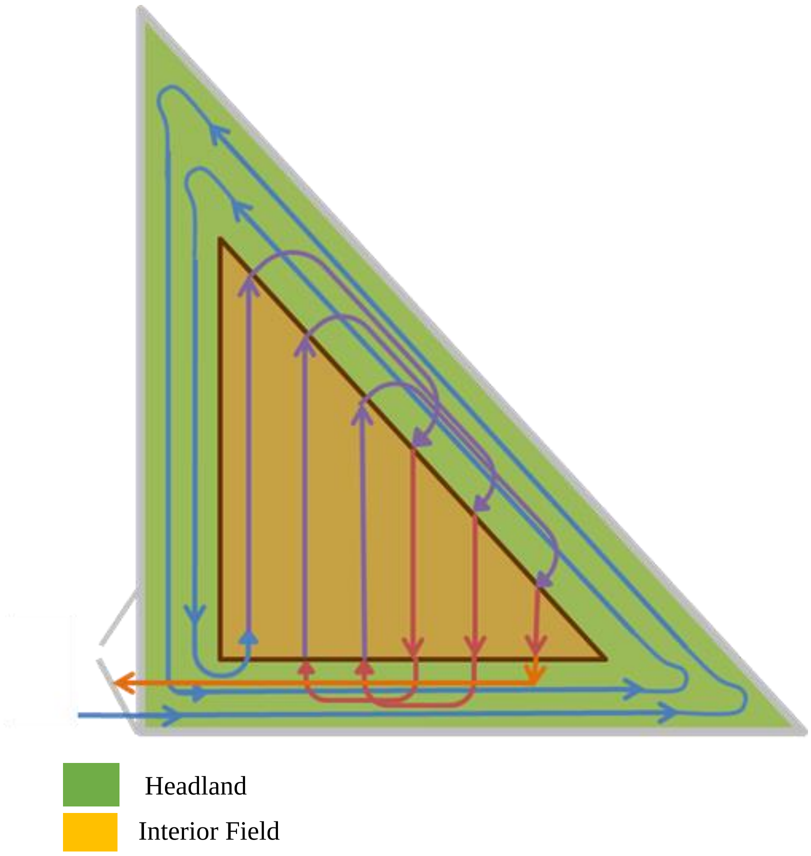

Figure 3.2: Typical field path for non-rectangular (i.e., right-angled triangular) fields considered in the study based on the HFH demonstration project experience.

The study assumed that the equipment enters the field from the lower left corner and completes the headlands first for all field operations (i.e., drilling, spraying, and harvesting). Afterwards, the machine makes a “flat turn” to start the interior passes. Subsequently, follows the “flat turn” to complete the interior headland turns. Finally, the study assumed that the equipment ends on the entry side of the fields as shown in Figure. 3.1 and Figure. 3.2.

3.2.2 Modelling the economics of field size and shape

To understand the whole farm effects of field size and shape with different types of farm equipment, the study adopted and re-estimated the Hands Free Hectare - Linear Programming (HFH-LP) model. The HFH-LP model is a decision-making tool which assesses the economics of autonomous machines compared to conventional equipment sets with human operators. Consistent with typical neoclassical microeconomic farm theory, the objective function of the HFH-LP model was to maximize gross margin (i.e., return over variable costs) subject to primary farm resource constraints in the short-run. In the subsequent stages, using the outcome of the HFH-LP model, the study examined net return to operator labour, management and risk taking (ROLMRT) and evaluated the wheat cost of production to explore the cost economies (i.e., economies of size) (Debertin, 2012; Duffy, 2009; Hallam, 2017; Miller, Rodewald and McElroy, 1981). The HFH-LP model is a one-year "steady state" model for arable grain-oil-seed farm, where the model assumed a monthly time step from January to December. It is steady state in the sense that it is assumed that solutions would be repeated annually long term. The concept of "steady state" was carried over from the Orinoquia model (Fontanilla-Díaz *et al.*, 2021) which used the same software. Following Boehlje and Eidman (1984), the HFH-LP deterministic economic model can be expressed as:

The objective function:

$$Max\ \pi = \sum_{j=1}^{n} c_j X_j \qquad \dots\dots(2)$$

Subject to:

$$\sum_{j=1}^{n} a_{ij} X_j \leq b_i \ for\ i = 1, \dots \dots, m; \qquad \dots\dots(3)$$

$$X_j \geq 0\ for\ j = 1, \dots \dots, n; \qquad \dots\dots(4)$$

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.

The HFH-LP model encompassed limiting constraints i.e., land, human labour, equipment times (i.e., tractor use time for drilling and spraying, and combine use time for harvesting), working capital and cashflow. The equipment scenarios encompassed four farm sizes: 66 ha, 159 ha, 284 ha and 500 ha farms, but did not model field size or shape. This study re-estimated the labour use, tractor use and combine use times for larger fields (10 ha) or smaller fields (1 ha), that were either rectangular or non-rectangular (i.e., right-angled triangular). The assumptions regarding variable costs, crop yields, and land use were same as Lowenberg-DeBoer *et al.* (2021a). The crop variable costs were the same across scenarios, but machinery costs differed. Details of the linear programming (LP) coefficients including machinery investment and operating costs are available from the supplementary materials of Lowenberg-DeBoer *et al.* (2021a). The 10 ha field size was selected for the large fields, because the field efficiency algorithm estimates showed that over 10 ha, field efficiency does not vary much by field size. A 1 ha field size was selected to represent small fields, because relatively few fields in the UK are smaller than 1 ha. The rectangular shape was selected as the shape usually considered most efficient for mechanized farming, and the triangular as the field shape that is among the least efficient (Carslaw, 1930).

The time window is crucial because agricultural operations are sensitive to weather conditions and crop activities. In literature the probability of good field days is considered as primary mechanism to model risk-aversion. The PC/LP model used good field days available in the 17th worst year out of 20 (McCarl *et al.*, 1977) that is 85% of the time. Following Agro Business Consultants (2018) the study assumed that number of good field days available was in 4 years out of 5 years that is 80% of times. Similar to the original HFH-LP model, the conventional machines assumed that field operations of drilling, spraying and harvesting were conducted during daytime that is on an average 10 h/day. The autonomous machines assumed that tractor for drilling and spraying was operated for 22 h/day (2 h for repair, maintenance, and refuelling) while autonomous combine operated for 10 h/day limited for night dew. The LP models of the study were coded using the General Algebraic Modelling System (GAMS) (https://www.gams.com/). Details of other associated assumptions and the programming code is available at Appendix C (GAMS code used) or at the supplementary materials of Lowenberg-DeBoer *et al.* (2021a).

3.2.3 Case study and data sources

Because the Hands Free Hectare (HFH) was a demonstration project, it was difficult to separate on-field stops and down time while the engineers tinkered from those stoppages that would have occurred in normal field operations. Consequently, the model parameters were based on published machine specifications and farm budget information, and guided by the qualitative experience of the HFH project demonstrated at Harper Adams University, Newport, Shropshire, UK (Hands Free Hectare (HFH), 2021). The Lowenberg-DeBoer *et al.* (2021a) HFH-LP model represented the arable grain-oil-seed farm in the West Midlands of the UK, this study re-estimated field times to reflect the range of field sizes and shapes often found in Britain. To calibrate the HFH-LP model, the study used parameters from different sources. The information about commodity produced and the costs estimates were from the Agricultural Budgeting and Costing Book (Agro Business Consultants, 2018) and the Nix Pocketbook (Redman, 2018). To facilitate comparability with the Lowenberg-DeBoer *et al.* (2021a) results, 2018 input and output price levels were retained. Prices were converted following daily average exchange rate of 2018 from Great British Pounds (GBP) to Euro (€) of €1.1305 (Bank of England, 2018). Details of the machine inventory, costs of machines, hardware and software, crop rotations and key baseline assumptions are available at Lowenberg-DeBoer *et al.* (2021a). Field operation timing was adopted from Finch, Samuel and Lane (2014) and Outsider's Guide (1999).

Equipment timeliness (i.e., HFH 28 kW conventional equipment set with human operator and autonomous machine, 112 kW and 221 kW conventional equipment sets with human operators) were estimated through the developed algorithms, where the equipment and field specifications were collected from HFH demonstration experience (https://www.handsfree.farm/) (Hands Free Hectare (HFH), 2021), conventional machine specifications from John Deere (https://www.deere.co.uk/en/index.html) (John Deere, 2022), Arslan *et al.* (2014) and Lowenberg-DeBoer *et al.* (2021a). For more details of the technical parameters used and data sources see Appendix A (ii): Algorithms Spreadsheets (i.e., SM1 Rectangular Field Algorithms and SM2 Non-Rectangular Field Algorithms (i.e., Right-Angled Triangular Field)).

3.3 Results

3.3.1 Field efficiency and times: rectangular fields

The study evaluated the technical feasibility of the HFH 28 kW conventional equipment with human operator and autonomous machines, and 112 kW and 221 kW conventional equipment sets with human operators for all field operations including direct drilling, five spray applications and harvesting operation. The spray application included pre-drill burn down, two nitrogen top dressing and fungicide applications, late season fungicide and pre-harvest desiccant. The human and equipment times were re-estimated subject to field size and shape scenarios. Results show that average whole farm field efficiency for 112 kW and 221 kW equipment sets differed substantially between 1 ha and 10 ha rectangular fields, whereas for rectangular fields a given equipment set the field efficiency was almost the same for 10 ha to 100 ha fields (Figure 3.3). The whole farm field efficiency of HFH equipment sets was relatively high irrespective of different sized rectangular fields, but efficiency for 112 kW and 221 kW conventional equipment sets with human operators dropped for small 1 ha fields. Beyond 10 ha, the field efficiency for a given equipment set was similar for all rectangular field sizes (i.e., 20 ha, 50 ha, 75 ha, and 100 ha).

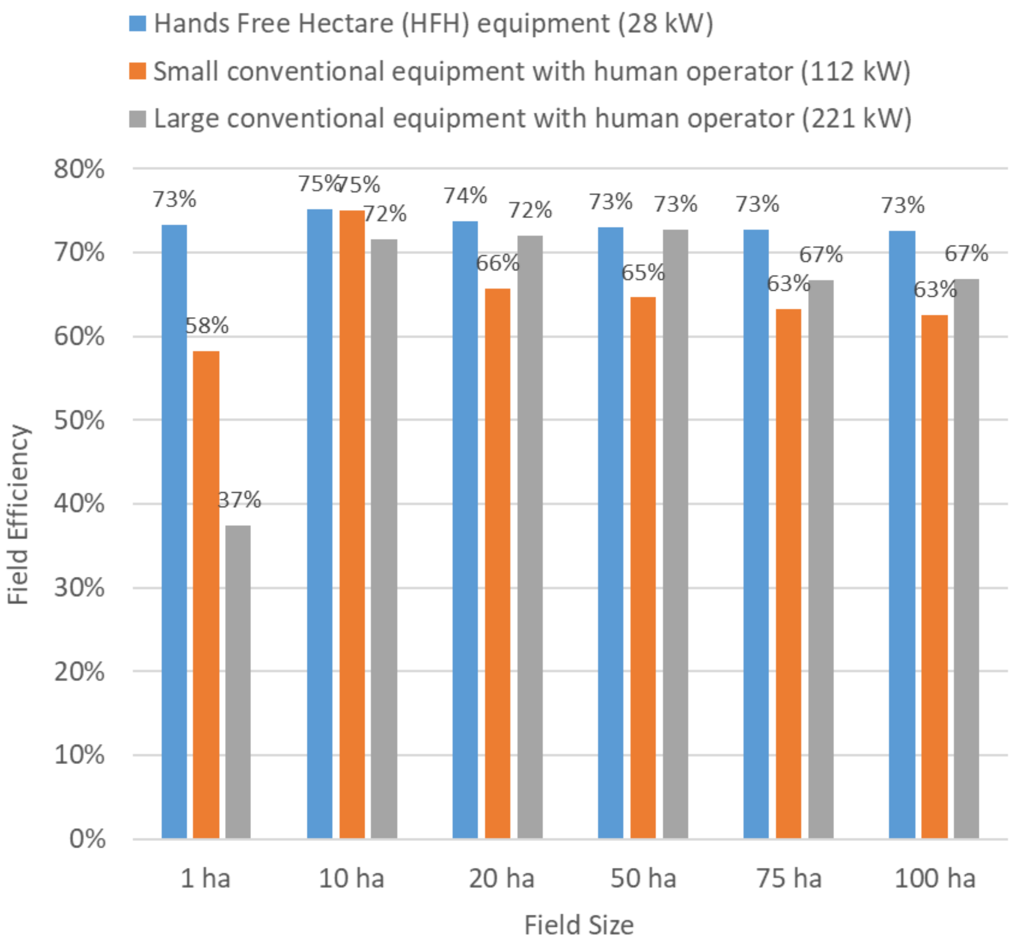

Figure 3.3: Estimated (weighted average) whole farm field efficiency of HFH equipment (i.e., 28 kW conventional equipment with human operator and autonomous machine), large conventional and small conventional machines with human operators in different sized rectangular fields.

Operation specific equipment times (h/ha) and field efficiency (%) results of the rectangular fields show that equipment times for drilling and harvesting operations were longer for small 1 ha fields operated with equipment of all sizes and types, but field sizes had least impact for the HFH equipment sets (Table 3.1). The higher time for small 1 ha fields was largely due to the fact that the full width of the larger equipment could not be used effectively in the smaller fields.

Table 3.1: 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/h)**	Field Efficiency (%)***	Field Times (h/ha)
1 ha Rectangular Field					
HFH equipment set (28 kW):*					
Drill	1.5	10%	3.25	81%	2.81
Sprayer	7	10%	5	71%	0.45
Combine	2	10%	3.25	78%	2.19
Larger conventional set (221 kW):					
Drill	6	10%	5	46%	0.81
Sprayer	36	10%	10	34%	0.09
Combine	7.5	10%	3	44%	1.12
Small conventional set (112 kW):					
Drill	3	10%	5	69%	1.07
Sprayer	24	10%	10	56%	0.08
Combine	4.5	10%	3	59%	1.39
10 ha Rectangular Field					
HFH equipment set (28 kW):*					
Drill	1.5	10%	3.25	89%	2.56
Sprayer	7	10%	5	69%	0.46
Combine	2	10%	3.25	91%	1.88
Larger conventional set (221 kW):					
Drill	6	10%	5	87%	0.43
Sprayer	36	10%	10	65%	0.05
Combine	7.5	10%	3	87%	0.57
Small conventional set (112 kW):					
Drill	3	10%	5	94%	0.79
Sprayer	24	10%	10	70%	0.07
Combine	4.5	10%	3	83%	0.99

Note: ** HFH equipment sets are 28 kW conventional machine with human operator and 28 kW autonomous machine. **The machine specifications and overlap assumptions were collected from the HFH experience and Lowenberg-DeBoer et al. (2021a). *** The authors developed algorithms to estimate the field efficiency of rectangular fields (for details of the estimation procedures and algorithms see the technical note and excel spreadsheet in Appendix A (i): Supplementary Text (i.e.., STEXTT Supplementary Text, which includes Main Text of the Technical Note) and Appendix A (ii): Algorithms Spreadsheets (i.e., SM1 Rectangular Field Algorithms).*

3.3.2 Field efficiency and times: non-rectangular fields

The average whole farm field efficiency for non-rectangular (i.e., right-angled triangular) fields differed substantially between 1 ha and 10 ha fields, but for a given equipment set the average whole farm field efficiency was almost the same for 20 ha and 25 ha fields (Figure 3.4). The technical feasibility (i.e., field times and field efficiency) results show that HFH 28 kW equipment sets were more efficient than larger equipment for all sized non-rectangular fields even in small 1 ha fields.

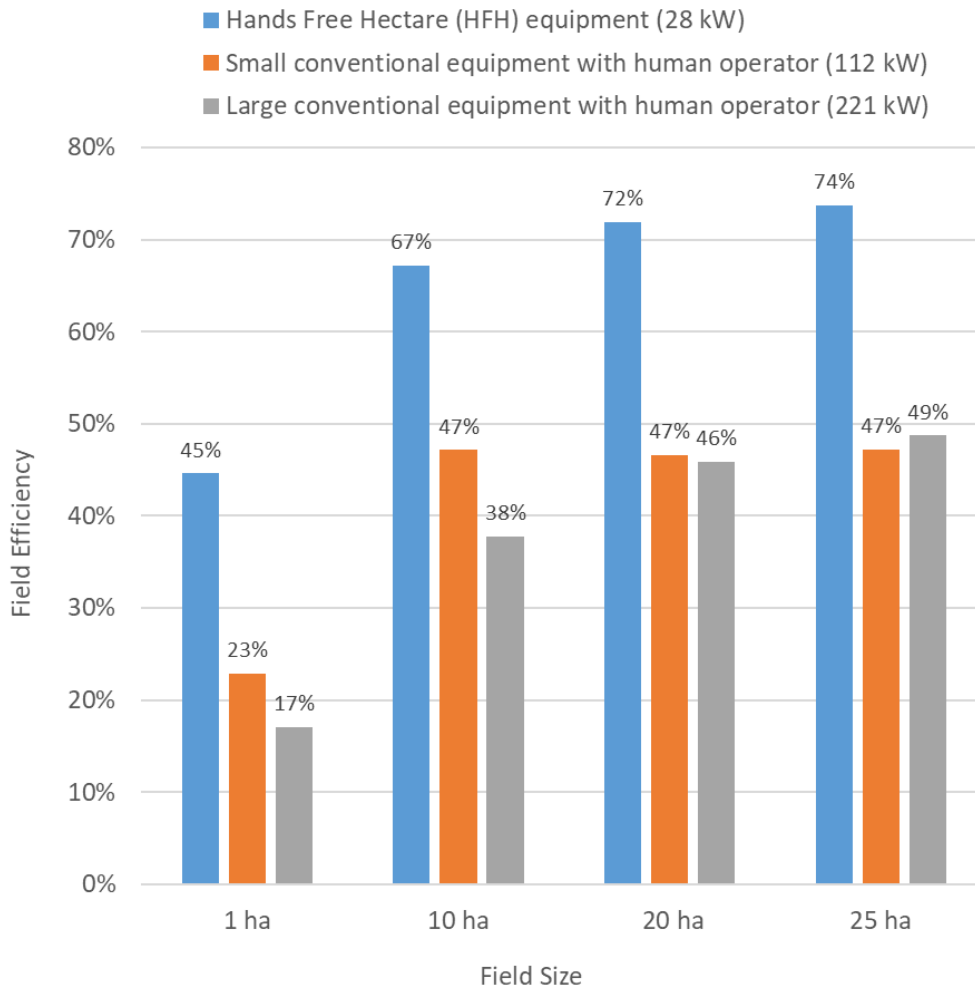

Figure 3.4: Estimated (weighted average) whole farm field efficiency of HFH equipment (i.e., 28 kW conventional equipment with human operator and autonomous machine), large conventional and small conventional machines with human operators in different sized non-rectangular fields.

The equipment times were longer for all operations in small 1 ha non-rectangular fields equipped with equipment of all sizes and types, but field sizes had least impact for the HFH equipment sets (Table 3.2). The higher time for small 1 ha fields was largely due to the fact that the full width of the larger equipment could not be used effectively in the smaller fields. Drilling operations required the highest equipment times and subsequently followed by harvesting and spraying in case of HFH 28 kW equipment sets, whereas for conventional equipment sets with human operators (i.e., 221 kW and 112 kW) irrespective of field sizes, harvesting consumed more time, followed by drilling and spraying. The non-rectangular 1 ha and 10 ha fields had comparatively lower field efficiency and required longer equipment times than rectangular fields with the same area. Small 1 ha non-rectangular fields required more time for field operations than the rectangular fields due to the varying interior length of the passes and higher interior headlands turning time for a given field area. The comparatively lower times for spraying compared to drilling and harvesting operations was associated to the field and equipment specifications of the sprayer because the sprayers were the widest implement. This is also resulted in the lower field efficiency for spraying small fields (detailed estimation of field times for non-rectangular fields are available in Appendix A (ii): Algorithms Spreadsheets (i.e., SM2 Non-Rectangular Field Algorithms (i.e., Right-Angled Triangular Field)).

Table 3.2: Equipment times of the machinery sets for non-rectangular fields of 1 ha and 10 ha.

Equipment	Width of the implement (m)**	Overlap percentage **	Field speed (km/h)**	Field Efficiency (%)***	Field Times (h/ha)
1 ha Non-rectangular Field					
HFH equipment set (28 kW)*:					
Drill	1.5	10%	3.25	47%	4.85
Sprayer	7	10%	5	44%	0.72
Combine	2	10%	3.25	45%	3.80
Larger conventional set (221 kW):					
Drill	6	10%	5	20%	1.85
Sprayer	36	10%	10	16%	0.19
Combine	7.5	10%	3	19%	2.60
Small conventional set (112 kW):					
Drill	3	10%	5	27%	2.74
Sprayer	24	10%	10	22%	0.21
Combine	4.5	10%	3	24%	3.43
10 ha Non-rectangular Field					
HFH equipment set (28 kW)*:					
Drill	1.5	10%	3.25	70%	3.26
Sprayer	7	10%	5	66%	0.48
Combine	2	10%	3.25	71%	2.41
Larger conventional set (221 kW):					
Drill	6	10%	5	43%	0.86
Sprayer	36	10%	10	36%	0.09
Combine	7.5	10%	3	41%	1.20
Small conventional set (112 kW):					
Drill	3	10%	5	54%	1.37
Sprayer	24	10%	10	46%	0.10
Combine	4.5	10%	3	48%	1.71

Note: ** HFH equipment sets are 28 kW conventional machine with human operator and 28 kW autonomous machine. **The machine specifications and overlap assumptions were collected from the HFH experience and Lowenberg-DeBoer et al. (2021a). *** The authors developed algorithms to estimate the field efficiency of a right-angled triangular fields (for details of the estimation procedures and algorithms see the technical note and excel spreadsheet in Appendix A (i): Supplementary Text (i.e.., STEXTT Supplementary Text, which includes Main Text of the Technical Note) and Appendix A (ii): Algorithms Spreadsheets (i.e., SM2 Non-Rectangular Field Algorithms (i.e., Right-Angled Triangular Field)).*

3.3.3 Economics of rectangular fields

The HFH-LP solutions for the farm size, field size and equipment set scenarios for rectangular fields are presented in Table 3.3. For a given farm size gross margins differed only slightly by equipment set and field size. The small differences by field size are due to small changes in cropping plan and the need to hire more labour with smaller fields. Only variable costs are deducted in calculating gross margin, so the costs of different equipment sets are not reflected in that measure of profit. The identical gross margin for 66 ha farms with 1 ha and 10 ha sized rectangular fields is because the smallest farms operated with four equipment scenarios did not face any operator and labour time constraints even with 1 ha fields and consequently planted, maintained and harvested the wheat-oilseed rape (OSR) rotation at optimal times regardless of field size.

For a given farm size, the net return to operator labour, management and risk taking vary more by equipment set, than by field size because of the differences in equipment costs. Except for the smallest farm, the net returns at a given farm size are highest for the autonomous machine scenarios. Net return for the smallest farm was higher when using a 28 kW conventional equipment set with human operator than with autonomous machines mainly because of the cost of retrofitting the equipment set for autonomy, but it is important to note that the conventional scenario required over 3 times more operator time than the autonomous machines. The higher return to operator labour, management and risk taking for the 66 ha farm using conventional equipment is because that measure of profit is a residual after cash costs, but does not deduct for operator compensation. The conventional solution maximizes net return for the smallest farm only if operator labour has a very low opportunity cost.

Table 3.3: HFH-LP outcomes on the economics of technology choice subject to different sized rectangular fields.

Scenario*	Arable area (ha)**	Field size (ha)	Labour hired in the farm (person-days per annum)	Operator time required in the farm (person-days per annum)	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. 28 kW	59.4	10	0	66	53188	17916	181
Conv. 28 kW	59.4	1	0	72	53188	17916	185
Conv. 28 kW[2]	143.1	10	39	119	124670	43937	167
Conv. 28 kW[2]	143.1	1	55	118	123314	42580	168
Conv. 28 kW[3]	255.6	10	138	145	216729	78453	156
Conv. 28 kW[3]	255.6	1	165	144	214348	76072	157
Conv. 28 kW[4]	450.0	10	326	172	374197	144028	147
Conv. 28 kW[4]	450.0	1	371	172	369151	138983	148
Autonomous 28 kW	59.4	10	0	19	53188	13906	154
Autonomous 28 kW	59.4	1	0	22	53188	13906	156
Autonomous 28 kW	143.1	10	0	46	128134	53747	138
Autonomous 28 kW	143.1	1	0	53	1281352	53747	140
Autonomous 28 kW[2]	255.6	10	22	60	226922	90983	137
Autonomous 28 kW[2]	255.6	1	33	61	225961	90022	137
Autonomous 28 kW[3]	450.0	10	72	73	396560	164718	132
Autonomous 28 kW[3]	450.0	1	92	74	394869	163026	132
Conv. 112 kW	59.4	10	0	23	53188	-29394	236
Conv. 112 kW	59.4	1	0	32	53188	-29394	243
Conv. 112 kW	143.1	10	0	56	128134	10448	174
Conv. 112 kW	143.1	1	6	71	127629	9943	180
Conv. 112 kW	255.6	10	19	82	227171	62300	153
Conv. 112 kW	255.6	1	45	92	224916	60045	155
Conv. 112 kW[2]	450.0	10	78	100	396082	92008	153
Conv. 112 kW[2]	450.0	1	139	102	390675	86602	154
Conv. 221 kW	59.4	10	0	14	53188	-80235	323
Conv. 221 kW	59.4	1	0	26	53188	-80235	333
Conv. 221 kW	143.1	10	0	33	128134	-40394	206
Conv. 221 kW	143.1	1	0	63	128134	-40394	216
Conv. 221 kW	255.6	10	0	59	228869	13157	170
Conv. 221 kW	255.6	1	28	86	226438	10725	175
Conv. 221 kW	450.0	10	20	84	401162	103917	148
Conv. 221 kW[2]	450.0	1	95	105	394593	-11163	179

***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 debate about economies of size (i.e., whether increasing economies of size, decreasing economies of size known as diseconomies of size, or constant economies of size) has been carried on largely in terms of cost curves in agricultural production economics (Debertin, 2012; Duffy, 2009, Hallam, 2017). Building on this literature, the study estimated the wheat production cost of mechanized farms with different sized and shaped fields equipped with autonomous machines and conventional equipment sets with human operators. The wheat production cost curves were estimated based on the most profitable farm plans that cultivated all available land with minimum unit production cost for their size. The study hypothesized that irrespective of field size and shape, autonomous machines would have lower wheat production cost and reduced economies of size compared to conventional equipment sets with human operators. The wheat cost of production curves for rectangular fields were similar to those estimated without considering field size, with conventional equipment showing higher production cost. The cost curves for autonomous machines with both field sizes lie below the curves for conventional equipment sets with human operators (Figure 3.5). Autonomous machine wheat production cost scenarios indicating that irrespective of field sizes autonomous systems had lower cost of production and reduced economies of size compared to farms operated with conventional equipment sets. The autonomous machines cost advantage was mainly due to lower labour and machine costs. The reduced economies of size for autonomous machines' cost curves (i.e., 1 ha curve represented by smaller circular marker curve and 10 ha curve with bigger circular marker) can be seen in costs levelling off with a relatively flat bottom at smaller scale compared to the cost curves with conventional equipment sets with human operators. As farm size increases, cost curves for autonomous machines showed similar cost of production irrespective of field sizes. The additional cost curve (i.e., triangular marker curve) above 1 ha and 10 ha rectangular fields represents the wheat production cost curve for autonomous machines without field size consideration estimated by Lowenberg-DeBoer *et al.* (2021a) taken as base category for comparison.

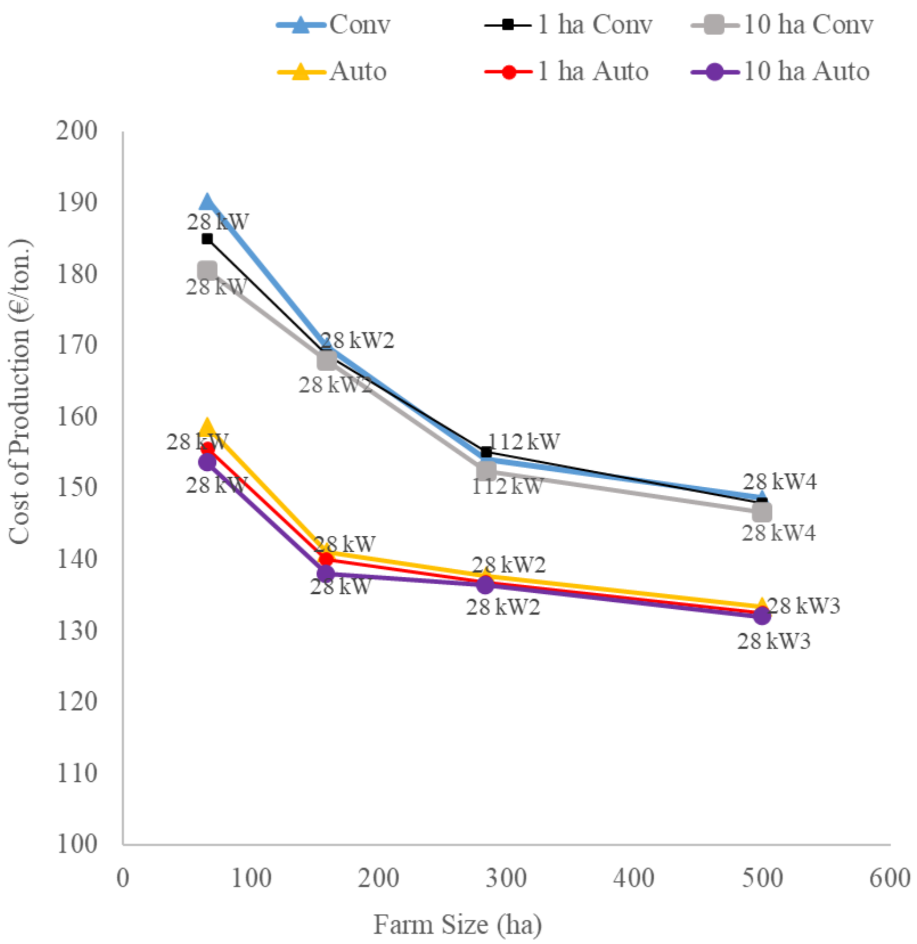

Figure 3.5: Wheat unit cost of production in euro per ton for farms with rectangular fields of different sized farms. The labels on the data points for 1 ha and 10 ha fields are the size of the tractor used and the number of equipment sets. The curves without labels are the baseline analysis which was done without field size and shape modelling.

The wheat cost scenarios by equipment set shows that compared to conventional equipment sets, the autonomous machines reduced wheat cost of production by €15/ton to €29/ton for 1 ha rectangular fields. The wheat cost of production curves with conventional equipment sets (28 kW, 112 kW, and 221 kW) reveal that farms with 1 ha and 10 ha rectangular fields had substantial effect on per unit wheat cost of production. The minimal cost difference between 1 ha and 10 ha sized fields wheat cost of production curves was associated with the lower differences of field times and field efficiency for rectangular fields.

3.3.4 Sensitivity tests: rectangular fields

Because agricultural labour is scarce and difficult to hire in the UK, some of the HFH LP conventional farm solutions may be difficult to implement and consequently the cost curves may not be realistic. For example, for the 500 ha farm the cost curves for conventional machines in both field size scenarios reveal that minimum wheat cost of production was achieved with four 28 kW equipment sets. For that 500 ha conventional farm the 10 ha solution required 326 days of hired labour and the 1 ha solution required 371 days, compared to 72 days and 92 days respectively for the autonomous farm. To test the sensitivity of solutions to the cost of labour, the model was rerun with the wage rate doubled (i.e., €11.02*2*8 = €176/day). With the higher wage rate, the minimum cost for the 500 ha farm with 10 ha fields was achieved at €148/ton with a 221 kW equipment set, but for 1 ha fields minimum cost at €156/ton was still achieved with four units of 28 kW equipment set as earlier. Additional sensitivity tests with triple wage rate (i.e., €11.02*3*8 = €264/day) show that for 500 ha farm with 10 ha fields minimum costs (i.e., €149/ton) achieved as earlier with a 221 kW equipment set, whilst for 500 ha farm with 1 ha fields minimum costs (i.e., €160/ton) achieved with two units of 112 kW equipment set. With higher wage rates the shape of the cost curves for the conventional farms indicated less cost advantage for larger farms irrespective of field sizes (for details see Figure A.1 and Figure A.2 in Appendix A (iii): Supplementary Figures (i.e., SFs Sensitivity Tests Figure, which includes Figures of the Sensitivity Tests).

Further sensitivity scenarios considered hired labour constrained at 50 person days per month with baseline wage rate (€11.02*8 = €88/day), where the optimum solution with minimum cost (€156/ton) for larger 500 ha farm with 1 ha fields, were achieved with two units of 112 kW equipment set and for 10 ha fields minimum costs at (€148/ton) with a 221 kW equipment set (for details see Figure A.3 in Appendix A (iii): Supplementary Figures (i.e., SFs Sensitivity Tests Figure, which includes Figures of the Sensitivity Tests)). Consequently, the use of multiple conventional 28 kW equipment sets with human operators were not feasible solutions with higher wage rates and less labour availability. Moreover, the sensitivity tests with increasing wage rates and reduced labour availability scenarios show a more distinct gap between cost curves for farms with 1 ha and 10 ha fields, because 1 ha fields required substantially more labour.

3.3.5 Economics of non-rectangular fields

For non-rectangular fields, the machinery and field size scenarios show that gross margin and net return to operator labour, management and risk-taking patterns were similar to those of the rectangular fields (Table 3.4). Net returns differed more by equipment set than field size, but the field size effect was more pronounced than for rectangular fields. The identical gross margin for 66 ha farms with 10 ha sized non-rectangular fields is because the smallest farms did not face any operator and labour time constraints, therefore they planted, maintained, and harvested the wheat-OSR rotation at optimal times. On the contrary, gross margins for 66 ha farm with 1 ha non-rectangular fields were higher for autonomous machines and larger conventional equipment compared to 28 kW and 112 kW conventional equipment sets because these two conventional sets faced operator time constraints and required more hired labour for farm operations.

Economic scenarios of non-rectangular fields incorporating fixed costs show that net returns to operator labour, management, and risk taking were higher for autonomous machines irrespective of field sizes, except for the smallest 66 ha farm equipped with 28 kW conventional machine with human operator. As with non-rectangular fields, this is because the autonomous machines required extra cost for retrofitting equipment for autonomy. The higher net return to operator labour, management and risk taking for the conventional 66 ha farm may be an illusion because of the higher labour requirement. For the 66 ha farm with 10 ha fields, no labour was hired in either conventional or autonomous scenarios, but the conventional farm required 3 times more operator labour time than the autonomous farm. For the 66 ha farm with 1 ha fields, the conventional farm required 3 times more operator labour, plus 16 days more hired labour. As discussed above in regard to the rectangular case, a small conventional 28 kW equipment set is not the sustainable solution given the growing labour scarcity in arable farming in the UK.

Table 3.4: HFH-LP outcomes on the economics of technology choice subject to different sized non-rectangular fields.

Scenario*	Arable area (ha)**	Field size (ha)	Labour hired in the farm (person-days per annum)	Operator time required in the farm (person-days per annum)	Whole farm gross margin (€ per annum)	Return to operator labour, manage ment and risk taking (€ per annum)	Wheat cost of production with allocated operator labour (€ per ton)
Conv. 28 kW	59.4	10	0	80	53188	17916	191
Conv. 28 kW	59.4	1	16	106	51796	16525	213
Conv. 28 kW[2]	143.1	10	71	121	121863	41129	171
Conv. 28 kW[2]	143.1	1	144	149	111684	30950	190
Conv. 28 kW[3]	255.6	10	195	147	211630	73354	158
Conv. 28 kW[4]	255.6	1	355	169	197539	48904	173
Conv. 28 kW[4]	450.0	10	415	188	341261	111092	159
Conv. 28 kW[7***]	450.0	1	743	180	337415	76172	164
Autonomous 28 kW	59.4	10	0	24	53188	13906	157
Autonomous 28 kW	59.4	1	0	38	53188	13906	167
Autonomous 28 kW	143.1	10	3	55	127832	53446	141
Autonomous 28 kW[2]	143.1	1	31	60	125421	36666	155

Table 3.4: HFH-LP outcomes on the economics of technology choice subject to different sized non-rectangular fields (Continued).							
Autonomous 28 kW[2]	255.6	10	41	63	225279	89340	138
Autonomous 28 kW[3]	255.6	1	90	72	220972	70664	147
Autonomous 28 kW[3]	450.0	10	105	77	393668	161827	133
Autonomous 28 kW[4]	450.0	1	191	94	386084	139875	140
Conv. 112 kW	59.4	10	0	40	53188	-29394	249
Conv. 112 kW	59.4	1	3	76	52612	-29970	278
Conv. 112 kW	143.1	10	17	78	126621	8934	182
Conv. 112 kW[2]	143.1	1	93	99	119892	-55463	239
Conv. 112 kW	255.6	10	74	96	222323	57452	157
Conv. 112 kW[2]	255.6	1	231	112	208461	-14078	190
Conv. 112 kW[2]	450.0	10	193	107	385913	81840	156
Conv. 112 kW[4***]	450.0	1	470	135	361510	-57900	192
Conv. 221 kW	59.4	10	0	28	53188	-80235	335
Conv. 221 kW	59.4	1	0	60	53188	-80235	358
Conv. 221 kW	143.1	10	0	67	128134	-40394	217
Conv. 221 kW	143.1	1	49	96	123812	-44716	228
Conv. 221 kW	255.6	10	33	87	225987	10275	175
Conv. 221 kW[2]	255.6	1	149	109	215702	-108520	231
Conv. 221 kW[2]	450.0	10	106	105	393552	-12205	179
Conv. 221 kW[3***]	450.0	1	325	130	374258	-140009	213

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 study baseline scenarios assumed a maximum of 100 person-days/month of temporary labour available, but in the sensitivity testing that was raised to 200 person-days/month.*

The wheat cost of production curves with non-rectangular fields shows that irrespective of field sizes, farms with autonomous machines had cost advantages (i.e., lower cost of production) and reduced economies of size compared to farms with conventional equipment sets with human operators (Figure 3.6), but the field size effect is more evident than rectangular fields.

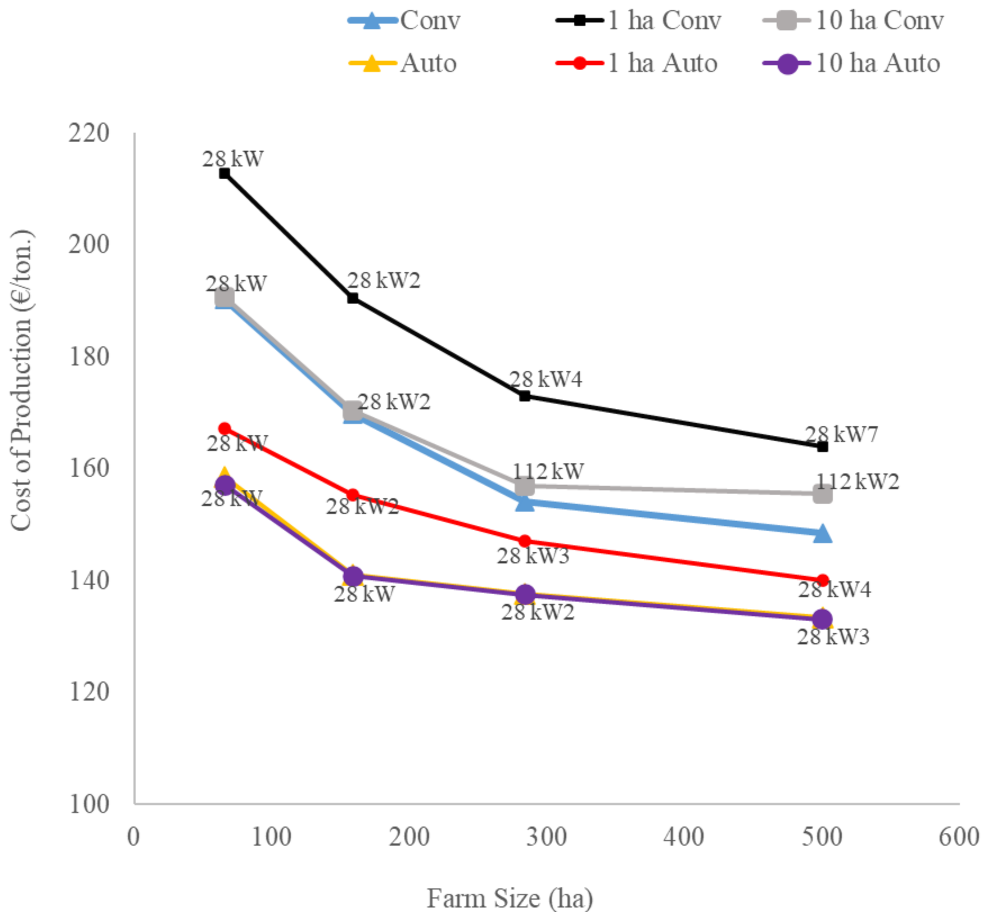

Figure 3.6: Wheat unit cost of production in euro per ton for farms with non-rectangular fields of different sized farms. The labels on the data points for 1 ha and 10 ha fields are the size of the tractor used and the number of equipment sets. The curves without labels are the baseline analysis which was done without field size and shape modelling.

More specifically, the autonomous cost curves scenarios reveal that small 1 ha non-rectangular fields entailed higher wheat cost of production compared to 10 ha fields, which was associated with comparatively higher hired labour, operator time and equipment scenarios (i.e., number of equipment required). The equipment scenarios show that small non-rectangular fields required more autonomous equipment sets to optimally operate the same farm, except for the smallest farm. Likewise, for conventional equipment sets, small 1 ha fields had substantially higher wheat production costs compared to 10 ha fields. For larger 500 ha farms equipped with conventional sets, the minimum unit cost of production was achieved with seven-units of 28 kW equipment set for 1 ha fields, whereas 10 ha fields had minimum unit cost scenarios with two units of 112 kW equipment sets. The wheat cost scenarios by equipment set shows that autonomous machines reduced wheat cost of production by €24/ton to €46/ton in 1 ha non-rectangular fields, indicating that autonomous equipment has cost advantage (i.e., lower cost of production) and reduce economies of size compared to conventional equipment sets with human operators.

3.3.6 Sensitivity tests: non-rectangular fields

The sensitivity tests with wage rate double and triple for mechanized non-rectangular fields reveal that all farms irrespective of field sizes were able to operate profitably with minimum wheat cost of production using the same equipment scenarios as with the baseline wage rate (i.e., €11.02*8 = €88/ton) equipment scenarios. However, with the increasing wage rates, the profitable farms had to incur more per unit production cost for all conventional and autonomous equipment sets. Small 1 ha fields operated with conventional equipment sets with human operators had to take more cost burden. For instance, 500 ha farms with small 1 ha fields had to incur €16/ton and €32/ton more costs with double and triple wage rates scenarios. Interestingly, even with double and triple wage rates, the autonomous machines had the lower cost of production and reduced economies of size compared to the conventional mechanized farms (for details see Figure A.4 and Figure A.5 in Appendix A (iii): Supplementary Figures (i.e., SFs Sensitivity Tests Figure, which includes Figures of the Sensitivity Tests).

Further sensitivity test with reduced labour availability at 50 person days per months reveal that multiple conventional equipment scenarios with human operators were not an economically feasible solution (Figure A.6). For example, with the base wage rate scenario, 500 ha farms with 10 ha fields achieved minimum costs at €156/ton operated with two units of 112 kW equipment sets with human operators, whilst in case of reduced labour availability, the minimum cost was achieved at €167/ton with the same equipment scenarios, indicating diseconomies of size. Moreover, the reduced labour availability made larger conventional mechanized farms plans (i.e., 284 ha and 500 ha) with small 1 ha fields non-economical and unrealistic because the existing conventional equipment sets with human operators (i.e., 28 kW, 112 kW and 221 kW) were unable to cultivate the optimum land with the available resources of the farms. The 500 ha farm with small 1 fields equipped with four units of autonomous machines were unable to operate the optimum land, that was 53 (450 - 397.41 = 52.59 ha), 1 ha fields were left unutilized with the available resources of the farms.

3.4 Discussion

The economic implications of field size and shape, contributes to the cost economies literature as prior production economies studies did not include the economics of field size and shape for autonomous machinery. The present study filled the research gap with the findings that irrespective of field size and shape, autonomous machines had lower wheat production cost and reduced economies of size compared to conventional equipment sets with human operators.

Throughout the world agricultural labour is difficult to hire and wage rate is increasing. In addition, the Covid-19 pandemic sparked the labour scarcity. These real-world crises spurred the study to further investigate the sensitivity scenarios with increasing wage rates and reduced labour availability. Considering the context of the UK, the sensitivity scenarios of double and triple wage rates and reduced labour availability reveal that irrespective of field size and shape, multiple conventional equipment sets with human operators were not a good solution for small fields. Autonomous machines (i.e., autonomous swarm robotics) were an economically feasible alternative in the face of rising wage rates ensuring the lower cost of production and more competitiveness for medium and small farms. Under the reduced labour availability scenario, autonomous machines allowed available labour to farm more land with lower cost of wheat production than the conventional equipment scenario, but with small, non-rectangular fields even the autonomous machines faced binding labour constraints. This is primarily due to the continued need for some human supervision and for human operators on public roads (i.e., assumption of 10% human supervision time during field operations and 100% human operators driving in the public road for hauling grain from the field to farmstead or market during harvest based on the study of Lowenberg-DeBoer *et al.* (2021a)).

The results support the hypothesis of the study that autonomous machines offer the possibility of farming small fields profitably, implying the potentials of biodiversity enhancement and environmental performance of such small fields as a side effect (Fahrig *et al.*, 2015; Firbank *et al.*, 2008; Konvicka, Benes and Polakova, 2016). The autonomous arable crop farms could support the UK's agricultural transition plan for sustainable farming. The economic feasibility of small autonomous farms facilitates implementation of the UK government Environmental Land Management (ELM) Scheme focused on encouraging agriculture to provide environmental public goods including improved soil health, greater field biodiversity and carbon sequestration (DEFRA, 2020; DEFRA, 2021). Likewise, the study supports agri-environment schemes (AES) to encourage small fields for biodiversity in the European Union and elsewhere (Geppert *et al.*, 2020).

The findings of the study also provide information to guide decision making by farmers, agribusinesses, technology developers, and policymakers. More specifically, the study guides "*farm size and shape policy*" generally associated with *"agricultural mechanization policy"* and *"biodiversity conservation policy"* of large (i.e., Brazil, Argentina, US, Australia, and Mexico) and medium (i.e., UK and Europe) scale farming to develop policies considering environmental performance in arable farming. The profitability of autonomous farms with small fields irrespective of field size and shape, indicate that the rule of thumb

of conventional mechanized agriculture (i.e., “get big, or get out” and promoting “structural change of arable landscapes”) will be superseded with autonomous machines.
However, this study has some limitations in the development of algorithms and existing economic modelling scenarios. Because of data deficiencies, the algorithms assumed zero down time due to machine problems (e.g., seed tines blocked with crop residue, plugged sprayer nozzles, damp straw wrapping a combine harvester drum). Hands Free Hectare (HFH) was a demonstration project, so it was difficult to separate stops for research purposes and those that would have occurred on any farm. Future research could reinvestigate this assumption based on farm experience. In terms of technical and economic modelling scenarios, the study only considered four equipment sets (28 kW, 112 kW and 221 kW conventional equipment set with human operators and 28 kW autonomous machines retrofitted for autonomy); there may be other equipment sizes that may better fit the given circumstances, especially for small 1 ha rectangular and non-rectangular fields. The study assumed same field times and efficiency for 28kW machines whether autonomous or human operated. In the future autonomous machines may be equipped with improved technology that reduce field times and increase efficiency beyond even the best human operator, but the conservative assumption for this study was that they were the same for the 28kW machines whether conventional or autonomous. In addition to the large and medium scale farming, future research should consider the context of small-scale farming (i.e., most of Asia and Africa), with field sizes tiny, fragmented fields of less than 1 ha. Some observers have hypothesized that autonomous machines would be technically and economically feasible solution for labour scarcity problems on small farms, especially in peak production seasons (Al-Amin and Lowenberg-DeBoer, 2021; HLPE, 2013; Lowder, Skoet and Raney, 2016).

The economic implications of field size and shape considered here different sized rectangular fields and right angled triangular fields, with the latter being least efficient to operate under whole farm mechanized cropping systems (Carslaw, 1930). However, the developed algorithms associated with field specifications (i.e., base area, headland area, and interior field area calculation) need modifications to apply to other field shapes (e .g., circular, trapezium, square, parallelogram, etc). The equipment specifications, other assumptions and estimation processes will be same as used for rectangular and right-angled triangular fields, while modification of right field shape geometry will be needed for other field shapes.

This study focused tightly on the implications of field size and shape for the economics of autonomous machines in the UK. Because high and medium income countries and even in many cases the low income countries throughout the world face labour scarcity in agriculture (Lowenberg-Deboer, 2022b; World Bank, 2021a, 2021b), the methodology could be adapted to estimate the economic implications of autonomous equipment in other cropping systems with different challenges. Future economic research could address other associated benefits of autonomous machines such as reduced fuel use or alternative renewable fuel use, potentials of mixed cropping like pixel, patch, strip, relay cropping and regenerative agriculture (Davies, 2022; Ditzler and Driessen, 2022; Hein, 2022; Ward, Roe and Batte, 2016). Even though, the technical and economic feasibility of autonomous machines in small, non-rectangular fields show potential for improving environmental management, future research should incorporate field inclusions, such as in field trees and wetlands. These inclusions may address field topography issues like grass waterways of Batte and Ehsani (2006) and/or encourage aboveground environmental diversification with intercropping and non-crop habitat such as flower strips, hedgerows and seminatural habitats within the field or around the field (Bellon-Maurel and Huyghe, 2017; Boeraeve *et al.*, 2020; Tamburini *et al.*, 2020). Similarly, the economic implications of soil compaction with low weight autonomous machines random trafficking fields could be compared to larger/heavier machines conventional or autonomous machines working in a controlled traffic setting (Berli *et al.*, 2004; Keller *et al.*, 2019; Keller and Or, 2022; Shockley *et al.*, 2021).

3.5 Conclusions

The study contributed to the cost economies literature with the findings that irrespective of field size and shape, autonomous machines had lower wheat production cost and reduced economies of size compared to conventional equipment sets with human operators. This study hypothesized that autonomous crop machines would make it possible to farm small, non-rectangular fields profitably, thereby preserving field biodiversity and other environmental benefits. To test the hypothesis, the study developed algorithms to estimate field efficiency (%) and equipment times (h/ha) for different sized rectangular and non-rectangular (i.e., right angled triangular) fields. Algorithm results show that the smallest equipment considered (i.e., HFH 28 kW conventional equipment set with human operator and retrofitted autonomous machines) required more time per hectare, but had higher field efficiency irrespective of field size and shape, compared to the conventional equipment sets with human operators (i.e., 221 kW and 112 kW). This was true for both rectangular and non-rectangular fields. Economic scenarios (i.e., return over variable costs and net return to operator labour, management, and risk taking) examined with mathematical programming (i.e., HFH-LP models) show that autonomous machines were a profitable solution for arable farms with small fields. The wheat production cost curves comparison reveal that autonomous machines reduced cost of production by €15/ton to €29/ton for farms with small 1 ha rectangular fields. For farms with 1 ha non-rectangular fields per unit wheat production cost was reduced by €24/ton to €46/ton. The ability of autonomous crop machines to profitably farm small, irregularly shaped fields, even with increasing wage rates (i.e., double and triple) and reduced labour availability (i.e., 50 person days per month), make them potentially useful in achieving the goals of the Environmental Land Management (ELM) Scheme in the UK and agri-environment schemes (AES) in the European Union and elsewhere.

Chapter 4

Economics of strip cropping with autonomous machines

"The advent of radical new technologies, for instance, small supervised autonomous (robotic) equipment, might greatly alter the cost calculus for farming small strips, allowing capture of yield advantages of very narrow strips without the much higher machine and labour costs …"

Ward, Roe and Batte (2016): Journal of American Society of Farm Managers and Rural Appraisers (ASFMRA), pp. 149-166.

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4.1 Introduction

Autonomous machines are expected to be a game changer for open-field arable crop farming (Klerkx and Rose, 2020; Gackstetter *et al.*, 2023) which would facilitate more diverse, agroecological and ecosystem services restoring farming practices (Daum, 2021; Pearson *et al.*, 2022). Research suggests that within field heterogeneous, small-scale and spatio-temporal mixed cropping systems such as strip cropping (Ghaffarzadeh, Préchac and Cruse, 1994; Smith and Carter, 1998; Verdelli, Acciaresi and Leguizam´on, 2012), pixel cropping (Ditzler and Driessen, 2022), patch cropping (Grahmann *et al.*, 2021; Donat *et al.*, 2022), and relay cropping (Tanveer *et al.*, 2017; Patel, 2020) enable more diverse cropping practices. However, more complex mixed cropping practices constrain autonomous farm management due to the technical difficulty of automating management with different plant heights and growth patterns (Ditzler and Driessen, 2022). Among different mixed cropping systems, strip cropping is the simplest and most technically feasible with conventional mechanization (Exner *et al.*, 1999; van Apeldoorn *et al.*, 2020; Alarcón-Segura *et al.*, 2022).

Strip cropping refers to a farming practice of simultaneously growing two or more crops in adjacent strips, where the strips are wide enough for independent cultivation, whilst narrow enough for facilitating crop interaction (Vandermeer, 1989; Brooker *et al.*, 2015; Hernández-Ochoa, Gaiser and Kersebaum, 2022). Strip cropping is considered as a means of sustainable intensification because this cropping system can improve utilization of on-farm resources through managing spatio-temporal heterogeneity, increasing land productivity, and enabling multifunctionality of agricultural landscapes (Gao *et al.*, 2009; Li *et al.*, 2011; Raseduzzaman and Jensen, 2017; Juventia *et al.*, 2022). Here spatial heterogeneity refers to portions of the field cultivated with different crops and site-specific management using mechanized systems. Temporal heterogeneity is reflected in different planting and harvesting time frames (i.e., early and/or late), yearly crop rotations, and field operations at different stages of plant growth.

Agronomic research on strip cropping with varying height plants has demonstrated the edge effects that increase yields of the taller species and often lead to a yield penalty for shorter crop plants (Jurik and Van, 2004). These studies were conducted in large scale farming in the US (West and Griffith, 1992; Ward, Roe and Batte, 2016) and Argentina (Bravo and Silenzi, 2002; Verdelli, Acciaresi and Leguizam´on, 2012), medium scale farming in Germany (Munz *et al.*, 2014a), and small-scale farming of China (Munz *et al.*, 2014c; DU *et al.*, 2018; Liu *et al.*, 2022), as well as in Africa (Rahman *et al.*, 2021; Kermah *et al.*, 2017). Research on corn (*Zea mays* L.), grain sorghum [*Sorghum bicolor* (L.) Moench], and soybean [*Glycine max* (L.) Merr.] in the Corn Belt of eastern Nebraska, US

(Lesoing and Francis, 1999), and corn and bush bean (*Phaseolus vulgaris* L. var. nana) research in China and Germany (Munz *et al.*, 2014a), showed that outside border rows of the taller corn plant had increased yield due to the extra sunlight advantage, whilst smaller subordinate plant yields decreased in border rows because of competition for solar radiation, soil water and nutrients. Agronomic studies also showed that strip width and orientation have yield impacts (Tan *et al.*, 2020; van Oort *et al.*, 2020; Liu *et al.*, 2022; West and Griffith, 1992). The review of corn and soybean strip cropping experiments based in Eastern and Midwest US showed that narrow corn strips increased the yield advantage over wider strips (Francis *et al.*, 1986). Studies in Africa also showed that with increasing strip width the yield advantage of the taller crop decreased (Agyare *et al.*, 2006; Konlan, 2013). The potential economic benefits of strips arise when the value of yield decreases from the shorter crop are less than the value of yield gains from the larger crop.

The ecological benefits of strip cropping include biodiversity enhancement as each small strip is considered as a small field (Alignier *et al.*, 2019; van Apeldoorn, 2020). Recent research using similar height plants in the context of medium scale farming in Germany, showed that wheat (*Triticum aestivum* L.) and oilseed rape (*Brassica napus* L.) strip cropping enhanced biodiversity, ecosystem services and reduced pest densities (Alarcón-Segura *et al.*, 2022). Research in China by Cong *et al.* (2015) showed that wheat-corn, wheat-faba bean (*Vicia faba* L.) and corn-faba bean strip cropping had agroecosystem benefits such as carbon sequestration and improvement of soil health. A wheat-alfalfa (*Medicago sativa* L.) strip cropping study in China found biological pest control advantages over sole cropping (Ma *et al.*, 2007). Corn and peanut (*Arachis hypogaea* L.) strip cropping research in China showed that it suppressed pests, indicating the practice is an effective conservation and biological control measure (Ju *et al.*, 2019). Similarly, in the Chinese context, corn-pea (*Pisum sativum* L.) and corn-wheat strip cropping showed reduced soil respiration and lower emission of carbon (Qin *et al.*, 2013). Although agronomic and ecological (i.e., agroecological) synergies of strip cropping are relatively well-understood, capturing the economic benefits of strip cropping are constrained by higher labor requirements in conventional mechanized systems (Ward, Roe and Batte, 2016).

Mixed cropping is often evident in manual agriculture because it is overall more productive compared to whole field sole cropping (Francis *et al.*, 1986), but the practice usually disappears with conventional mechanization (Qian *et al.*, 2018). Research in the Midwest US found that higher labor requirements and associated fixed costs of conventional strip cropping systems offset the economic benefits (Ward, Roe and Batte, 2016; West and

Griffith, 1992). Even in the smallholders' context of China labor shortages, increasing wage rate and off-farm employment preferences constrained the labor intensive strip cropping practices (Feike *et al.*, 2012). Over the last few decades, strip cropping researchers have hypothesized that economically feasible agricultural intensification would be possible with new planting equipment (Lesoing and Francis, 1999), precision management (Exner *et al.*, 1999) and autonomous small swarm robotic field operations (Slaughter, Giles and Downey, 2008; Ward, Roe and Batte, 2016; van Oort *et al.*, 2020). Unfortunately, production economics research on precision agriculture has concentrated on whole field sole cropping economics (Shockley, Dillon and Shearer, 2019; Lowenberg-DeBoer *et al.*, 2021; Al-Amin *et al.*, 2023).

Existing strip cropping literature has lacked systems analysis by not considering the whole farm economics of operations from planting to harvesting. Strip cropping research has often measured economic payoffs by using partial indicators such as Land Equivalent Ratio (LER), Gross Margin Ratio (GMR), Monetary Equivalent Ratio (MER) and/or harvested yields (Francis *et al.*, 1986; Smith and Carter, 1998; Lesoing and Francis, 1999; Yu *et al.*, 2015; van Oort *et al.*, 2020; Rahman *et al.*, 2021) and/or partial budgeting (West and Griffith, 1992; Exner *et al.*, 1999; Ward, Roe and Batte, 2016). The most up-to-date economic analysis of strip cropping was conducted by Ward, Roe and Batte (2016), but they were unable to test the hypothesis of strip cropping profitability with autonomous machines due to a lack of autonomous whole farm operations experience and data.

Noting this research gap, the overall objective of this study was to determine if the use of autonomous machines could enable corn and soybean strip cropping to be more profitable than whole field sole cropping. It is hypothesized that autonomous machines (i.e., crop robots) make strip cropping profitable, thereby allowing farmers to gain additional agroecological benefits. The economic potential of strip cropping with autonomous machines would open the door for further research to optimize strip cropping systems (i.e., strip width, hybrid and variety choice, pest management, machine size and soil fertility).

4.2 Materials and methods

4.2.1 Approach and data

The ex-ante study used a whole farm economic linear programming (LP) approach to examine the economics of strip cropping with autonomous machines for corn and soybean farming in central Indiana of the Corn Belt of the US. Indiana is one of the higher corn and soybean yielding states in the Midwest (Egli, 2008; Mishra and Cherkauer, 2010; USDA, 2023), with both crops being of major importance and widely cultivated (Suyker and Verma, 2012; Green *et al.*, 2018; Capehart and Proper, 2021). Yearly rotations of corn and soybean were considered for the economic modelling of whole field sole cropping, conventional strip cropping and autonomous strip cropping practices. An additional reason for analyzing corn and soybean strip cropping was the availability of agronomic data on edge effects (i.e., yield benefits of corn and penalty of soybean) (Francis *et al.*, 1986; Verdelli, Acciaresi and Leguizamón, 2012; Feng *et al.*, 2022). Soybean, a C3 legume, and corn, a C4 cereal, have different plant heights, utilize inputs at different times, acquire nutrients from different sources or in different forms (e.g., soybean uses soil and atmospheric N_2 and corn uses reduced soil nitrogen), and both have high photosynthetic and carbon gain activities (Echarte *et al.*, 2011; Omoto, Taniguchi and Miyake, 2012; Yang *et al.*, 2015).

The modelling of the whole field sole cropping and strip cropping practices relied on the basic assumptions of Ward, Roe and Batte (2016). Following their farm size, the present study modelled a 2156.97 ha non-irrigated corn and soybean farm. The agronomic practices, yields and prices used in this study were based on the 2022 Purdue Crop Cost and Return Guide for rotational corn and soybean in high productivity soil (Langemeier *et al.*, 2022), and converted to a per ha basis. The corn seed cost assumed a genetically modified hybrid having multiple traits and the soybean seed cost assumed Round-Up Ready® varieties. The application rates of fertilizers such as phosphate, potash and lime were based on the Tri-State Fertilizer Recommendations (Langemeier *et al.*, 2022). The study assumed N, P_2O_5, K_2O and lime application rates stated in the 2022 Purdue Crop Cost and Return Guide for rotational corn and soybean. The study assumed that the soil tests for potassium, phosphorus and pH were in the maintenance and recommended range. In whole field sole crop farming, following the 2022 Purdue Crop Cost and Return Guide and Ward, Roe and Batte (2016), the study considered anhydrous ammonia (NH_3) application with custom hire service instead of owner operated machine application, because custom hire service was common for NH_3 applications in central Indiana. The custom application fee was based on prices cited in Arnall (2017). The study assumed that genetically modified rootworm resistant hybrid corn is an adequate corn rootworm management strategy. The pesticide costs encompassed insecticides and herbicides. The study did not consider a fungicide application for corn (Langemeier *et al.*, 2022).

The corn and soybean yield for high productivity soil was 20% higher than the yield on average soils. The yields assumed average farm management and weather conditions and timely planting and harvesting dates. The yields were based on long-run trends reported by National Agricultural Statistics Services (Langemeier *et al.*, 2022). The yield adjustments for planting and harvest dates were estimated based on the Purdue

Crop/Livestock Linear Program (PC/LP) Farm Plan B-21 Crop Input Form (Doster *et al.*, 2006, P. 43-44). To be consistent with the HFH-LP model (Lowenberg-DeBoer *et al.*, 2021a) the time periods were combined in monthly time periods as: *April:* April 22-May 2; *May:* May 3-May 30; *June:* May 31-June 13; *Sept.*: Sept. 20-26; *Oct.*: Sept. 27-Oct. 31, *Nov.*: Nov. 1-Dec. 5 (Doster *et al.*, 2006, P. 43-44). In strip cropping yield scenarios, in addition to the yield adjustment from the PC/LP Farm Plan, the study incorporated the edge effects following the field trials under normal conditions in Illinois (Ward, Roe and Batte, 2016). The corn yield percentage change using 6 row strips was 115% and the soybean yield percentage change in 6 row strips was 92% (for details see Appendix B (ii) Supplementary Text). The headlands (representing 5% of the field) yield for continuous soybean was considered 80% of estimated yield due to the penalty of continuous soybean production. Soybeans must be used for headlands year after year to facilitate in-season access to corn rows for field operations.

The corn and soybean harvest prices were based on opening prices from 21 March 2022 CME Group futures prices, assuming a $0.25 basis adjustment for corn and $0.35 for soybean (Langemeier *et al.*, 2022). To check the sensitivity of results to soybean/corn (i.e., s/c) price ratios, the historical corn and soybean marketing year prices were based on the USDA NASS Quick Stats data set from 1973 to 2021 (USDA NASS, 2023). The period from 1973 to 2021 was selected to capture the two most recent crop price periods (i.e., 1973 to 2006; 2007 to present) (Irwin and Good, 2011) with higher average s/c price ratios of 2.49 and minimum s/c price ratios of 1.99.

Dryer fuel costs for corn, interest and insurance costs for corn and soybean were based on the 2022 Purdue Crop Cost and Return Guide (Langemeier *et al.*, 2022). The guide did not consider temporary hired labor costs, so the study used the hourly wage rate of the US Corn Belt from the USDA 2021 database for economic class of farm regions and states (USDA NASS, 2021).

The machinery specifications for whole field sole cropping and strip cropping practices followed the assumptions made by Ward, Roe and Batte (2016). The whole field sole cropping was assumed to be operated with larger conventional equipment sets represented by 228 kW tractors. Strip cropping with smaller conventional equipment sets were represented by 37.4 kW tractors with human operators, and autonomous strip cropping represented by 37.4 kW tractors retrofitted for autonomy. The modelling of autonomous machines (i.e., crop robots or swarm robots) was based on the experience of the Hands Free Hectare (HFH) demonstration project at Harper Adams University in the UK (Hands Free Hectare (HFH), 2021). The initial investment costs of larger and smaller conventional machines were priced from different equipment manufacturers sites having available list prices for the US. If new equipment list prices were not available, prices for recent used equipment were considered. The retrofit costs were converted using the exchange rate of Great British Pound (GBP) to United States Dollar (USD) (Board of Governors of the Federal Reserve System (U.S.)., 2022) and inflation adjustment (FRED, 2022).

However, small combines needed for strip cropping (i.e., 6 row corn head 4.57 m wide) are no longer manufactured in the US and are not newly marketed there. Prices that are available in the US for the used combines of that size are mostly very old and near the end of their useful life span. Therefore, a price estimate was needed to approximate the cost of a new combine of that size in the Corn Belt region of Indiana. Small combines are manufactured in Asia, but the reliability, maintenance cost and salvage value of those machines under the US conditions is unknown. Thus, prices were sought for the CLAAS AVERO (151 kW) which is sold and used in Europe and the UK under conditions that are similar to those in the US. The study hypothesized that if strip cropping were shown to be profitable and it became common in the US, some manufacturer would either resume making combines that size in North America or arrange to import them from a subsidiary or partner in Europe or Asia. The price of the AVERO 240 model was estimated based on the price quote for a new machine provided by a CLAAS representative in the UK. The price of used AVERO 240 model combines was checked in Agriaffaires (https://www.agriaffaires.co.uk/). With some allowance for depreciation the price of the used AVERO 240 combines was consistent with the list price. Further details of the equipment and prices are available in Appendix B (ii) Supplementary Text.

Field operations and field efficiency (%) were based on Ward, Roe and Batte (2016) and 2022 Purdue Crop Cost and Return Guide (Langemeier *et al.*, 2022). The study used working days (i.e., good field days) data for Indiana from the Ag Manager (https://www.agmanager.info/) developed by the Agricultural Economics Department of Kansas State University (AgManager.info., 2022).

The strip crop scenarios assumed that urea or other granulated N would be used for nitrogen because regulatory approval of autonomous NH_3 application may be problematic. The list price of a fertilizer applicator (Urea and other granulated N) was obtained from 1st products.com (https://1stproducts.com/) by requesting a quote. Further details of the fertilizer applicator and price are available in Appendix B (ii) Supplementary Text. As overhead costs were not included in the 2022 Purdue Crop Cost and Return Guide, the study used fixed costs from ‘Crop Budgets, Illinois, 2022’ for systematic corn and soybean rotations on high productivity farmland developed by the Department of Agricultural and Consumer Economics of the University of Illinois (Schnitkey and Swanson, 2022). The fixed costs, such as opportunity cost of capital, fuel and lubricant, and land rent, were taken from Langemeier *et al.* (2022), Agro Business Consultants (2018) and Kuethe (2021). Details of the fixed costs assumed in this study are available in Appendix B (ii) Supplementary Text.

4.2.2 Base economic model

The economic analysis undertaken here goes beyond Ward, Roe and Batte (2016) because they did not consider systems analysis. Instead, they used partial budgeting where only the change in costs and revenues were considered with all other things remaining the same assumption.

The study adopted the Hands Free Hectare - Linear Programming (HFH-LP) ‘steady-state’ profit maximization models (Lowenberg-DeBoer *et al.*, 2021a). The concept of ‘steady-state’ was adopted from the Orinoquia model and assumed that solutions would be repeated annually over time (Fontanilla-Díaz *et al.*, 2021). The HFH-LP was developed based on the Purdue Crop/Livestock Linear Program (PC/LP) model (Dobbins *et al.*, 1994).

The HFH-LP optimization model for corn and soybean farms of central Indiana estimated the gross margin measure of profitability for human operated larger conventional mechanized whole field sole cropping, human operated smaller conventional mechanized strip cropping, and autonomous strip cropping system. The maximization model was estimated subject to the binding constraints of land, operator time, tractor time for field preparation, planting and spraying, combine time for harvesting, good field days, and working capital and cash flow.

The study estimated return to operator labor, management and risk-taking by subtracting fixed costs from farm gross margin. The fixed costs included annual machine cost, rent of land, repair of farm property and buildings, professional fees and subscriptions, fixed utilities, depreciation of buildings and other miscellaneous fixed expenses.

Using standard notation of Boehlje and Eidman (1984), the economic model can be mathematically expressed with an objective function as:

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

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:

$\prod$ = gross margin,

X_j = the level of *j*th production activities,

c_j = the gross margin per unit over fixed farm resources (b_i) for the *j*th production activities,

a_{ij} = the amount of *i*th resource required per unit of *j*th activities, and
b_i = the amount of available *i*th resource.

The study modelled 2156.97 ha of non-irrigated land in roughly rectangular fields with length assumed longer than the width. The conventional whole field sole cropping practice was assumed to plant half in corn and half in soybean following an annual corn and soybean rotation.

The strip cropping practices (i.e., conventional, and autonomous strip cropping scenarios) assumed headlands on the two ends cultivated with continuous soybean to allow equipment access to the interior field strips (i.e., interior field refers to the field except the headlands) as repeated access would be needed for farm operations. Following Ward, Roe and Batte (2016), the headlands were assumed to be 18.29 m wide because the sprayer width required enough space to turn the sprayer. The interior strips were assumed to be 4.57 m width (Figure 4.1). The corn and soybean strips were assumed to be rotated annually. Consequently 47.50% of each interior field was cultivated with corn, 47.50% with soybean and 5% in headlands with continuous soybean.

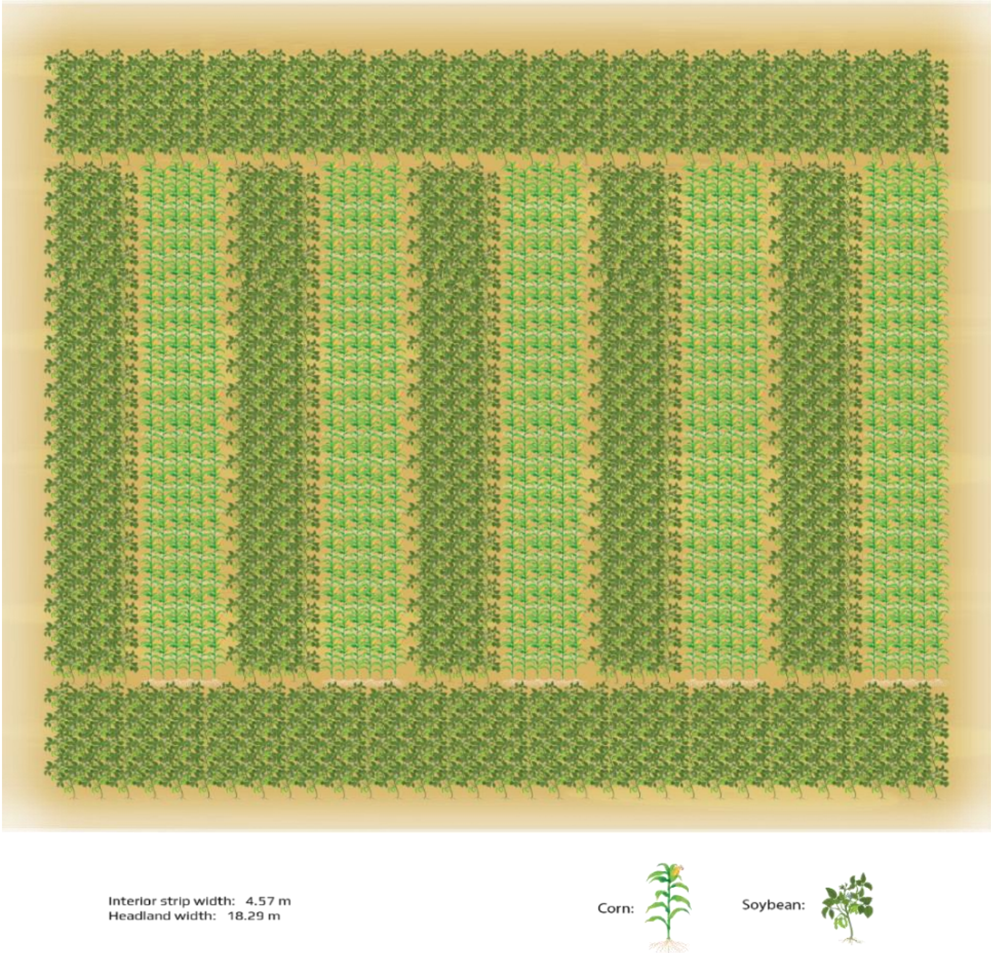

Figure 4.1: Corn-soybean strip cropping field layout planted in six, 0.76 m row strips based on Ward, Roe and Batte (2016).

The study assumed available labor included a full-time farm operator and temporary hired labor for 800 h per month per farm. The operator time, tractor time and combine time were estimated for the three equipment sets. The study considered field transition times following the assumption of Ward, Roe and Batte (2016) that all fields were 2.01 km apart for transport with road speed between fields 19.96 km/h except for the combine at 14.97 km/h. Because the field time parameters in the model were given on a per hectare basis, the travel time was proportional over the area of the field operation at each visit: 53.82 ha for the whole field sole crop farming and 26.95 ha for the strip cropping scenarios. The incorporation of field-to-field logistics time goes beyond the original HFH-LP analysis by Lowenberg-DeBoer *et al.* (2021a).

The cash needed for field operations covers the direct costs of seed, fertilizer, pesticide, dryer fuel, interest and insurance for rotational corn and soybean production. Costs of machinery fuel, machinery repairs and hauling were included in annual machinery cost estimation as fixed costs following Lowenberg-DeBoer *et al.* (2021a).

As the field work time window is an important source of risk for the farmers, the study used good field days estimate of Indiana, US for 80th (more) percentile following the AgManager (https://www.agmanager.info/) 'Days Suitable for Fieldwork' estimates (AgManager.info., 2022). The PC/LP model assumed 17th worst year out of 20 (McCarl *et al.*, 1977). The HFH-LP assumed 4 years out of five (i.e., 80%) based on the Agro Business Consultants (2018). Following Lowenberg-DeBoer *et al.* (2021a), the study considered 22 h operation time on good field days for autonomous tractors (2 h for repair and refuelling/refilling) and 10 h operation time for a combine. The conventional larger and smaller equipment sets assumed 10 h operation time daily, similar to the HFH-LP model assumptions.

Further details of the constraints and associated scalar and parameter assumptions considered in modelling this study are available in Appendix B (ii) Supplementary Text and Excel spreadsheets of coefficients estimation in Appendix B (iii) Coefficients Estimation Spreadsheets (i.e., Estimating Coefficients_AJ_VFF.xlsx).

The linear programming model was coded using the General Algebraic Modelling System (GAMS) (https://www.gams.com/) (GAMS Development Corporation, 2020). The programming code used in this study is available at Appendix C (GAMS code used) or at the supplementary materials of Lowenberg-DeBoer *et al.* (2021a).

4.2.3 Modelling sensitivity scenarios

The sensitivity scenarios examined the impacts of different output prices and human supervision on gross margin and return to operator labor, management and risk-taking. The first sensitivity testing used soybean/corn price ratios. The second sensitivity testing addressed the economic impacts of different human supervision levels as suggested in the study of Lowenberg-DeBoer *et al.* (2021b).

The first sensitivity scenario considered the historical marketing year (i.e., begins at current year harvest time and continues until the following year harvest time) prices of soybean and corn from 1973 to 2021 to estimate soybean/corn price ratios (Leibold, Hofstrand and Wisner, 2022; USDA NASS, 2023). The marketing year soybean/corn price ratio was estimated by dividing each marketing year soybean price with respective marketing year corn price.

The base price considered in this study was the rotational corn and soybean price in the 2022 Purdue Crop Cost and Return Guide (Langemeier *et al.*, 2022). The 2022 soybean/corn price ratio is 2.14, only slightly lower than the historical average of 2.49, and thus modestly favorable for corn production. Because strip cropping benefits corn yields more than soybean yields, the hypothesis is that strip cropping will be most profitable when the soybean/corn price ratio is low (i.e., when corn price is comparatively high) and least profitable when the price ratio is high (i.e., when soybean price is comparatively high). Consequently, the price sensitivity test looked at the maximum, average and minimum soybean/corn prices ratios. To anchor this comparison in reality, corn prices were estimated using the 2022 soybean price at the historical maximum, average and minimum price ratios, and soybean prices were estimated using the 2022 corn price at the historical maximum, average and minimum price ratios. Overall, six-price corn and soybean price combinations were tested.

The second sensitivity scenario investigated the economics of different levels of human supervision as autonomous machines required by law or because the technology is troublesome. The study by Lowenberg-DeBoer *et al.* (2021b) suggested 10%, 50% and 100% supervision time. Maritan *et al.* (2023) found economically optimal supervision between 13% to 85% of machine field times depending on the frequency of human intervention required and the supervisor location (i.e., remote, on-site). Using whole field sole cropping context of the US, Shockley *et al.* (2021) found that field speed restriction and on-site supervision regulation reduces the profitability of arable crop farming. The economic implications of human supervision in arable farming with alternative crop geometries are not clear. The present study examined the economic implications of different human supervision scenarios for autonomous strip cropping following 10%, 50% and 100% supervision assumptions. The base autonomous strip cropping model considered 10% of machine field times following the production economics study of Lowenberg-DeBoer *et al.* (2021a).

4.3 Results

4.3.1 Baseline results

The baseline optimal economic solutions show that the autonomous corn and soybean strip cropping system had higher economic benefits compared to the whole field sole cropping and conventional strip cropping systems (Table 4.1). The whole field sole cropping and autonomous strip cropping was feasible with the baseline assumptions of labor available for full-time farm operator and temporary hired labor for 800 h per month per farm. However, the conventional strip cropping practice was infeasible with this assumption as the system needed temporary hired labor of 1200 h per month to operate the whole farm.

Table 4.1: Comparative labor requirements and profitability of whole field sole cropping and strip cropping practices under conventional and autonomous machine (crop robot) scenarios in the Corn Belt of central Indiana, US.

Equipment scenario*	Hired labor time (h /ha/yr)	Operator time (h /ha/yr)	Gross margin ($/ha/yr)	Return to operator labor, management and risk-taking ($/ha/yr)
Whole field sole cropping: Conventional 228 kW[2]	0.65	0.57	1503.63	185.27
Strip cropping: Conventional 37.4 kW[5**]	2.06	0.66	1694.70	590.88
Strip cropping: Crop Robot 37.4 kW[3]	0.49	0.53	1769.50	753.46

Note: **The superscript indicates the number of equipment sets needed for timely operation of the 2156.974 ha farm. ** In the baseline modelling, the study assumed 800 h per month temporary hired labor for the whole farm, whereas the conventional strip cropping scenario required 1200 h per month temporary hired labor to optimally operate the whole farm.*

The optimization model of autonomous strip cropping reveals that three sets of autonomous machines (also known as swarm robots) were required to operate the whole farm (i.e., 2156.97 ha) in a timely way. The autonomous machine scenario finds that per annum 0.49 h/ha of hired temporary labor time and 0.53 h/ha of operator time were needed for optimal operations, whilst conventional whole field sole cropping required 0.65 h/ha and 0.57 h/ha temporary labor time and operator time. In comparison, conventional strip cropping required 2.06 h/ha hired temporary labor and 0.66 h/ha operator time. The conventional strip cropping would not be an economically attractive farming solution in Indiana where farm labor can be scarce. The study shows that conventional strip cropping practice required five sets of smaller conventional machines. The conventional strip cropping system faced severe labor constraints. The farm had binding operator time constraints in April to July, October, and November. In addition, tractor time was binding in April.

The findings show that at the 2022 grain prices and input costs the gross margin was $265.87/ha (i.e., $1769.50-$1503.63) higher for autonomous strip cropping compared to whole field sole cropping (Table 4.1). Conventional strip cropping with human equipment operators shows a slightly lower gross margin ($74.80/ha) than the autonomous scenario mainly because of the additional hired labor. The higher gross margin for strip cropping occurs because the value of additional corn from the edge effects in the strips more than offsets the reductions in soybean yields.

Similarly, return to operator labor, management and risk-taking was $568.19/ha (i.e., $753.46-$185.27) higher for autonomous strip cropping than whole field sole cropping. The main factors in this difference are higher value of grain production with strip cropping, lower machinery costs with swarm robots and slightly less labor hired. Return to operator labor, management and risk-taking is somewhat lower (i.e., $753.46-$590.88=$162.58/ha) for conventional strip cropping than for autonomous strip cropping because of the higher labor and machine costs in the conventional scenario.

The profitability of conventional strip cropping is not strictly comparable to whole field sole cropping and autonomous strip cropping because conventional strip cropping could not farm 2156.97 ha with the initial assumption of 800 h per month of temporary hired labor for the whole farm. With 800 h per month of temporary hired labor, the most profitable solutions for the conventional strip cropping scenario were to leave 45.4 ha farmland uncultivated because labor was a binding constraint in peak production months of April, May, October and November. Moreover, operator time was binding in April to June and September to November. The optimal solutions for conventional strip cropping finds that 1200 h per month of temporary hired labor was required to optimally operate the whole farm. As previous research has suggested conventional strip cropping is only possible with ample labor availability (Ward, Roe and Batte, 2016). However, worldwide agricultural labor is in short supply. The COVID 19 pandemic, travel restrictions and the political impasse over immigration reform have made the situation even more critical in the US (Charlton and Castillo, 2021; Hamilton *et al.*, 2022).

4.3.2 Equipment investment costs

The whole field sole cropping equipment inventory and investment costs show that timely field operations required at least two units of the larger conventional equipment set with an initial equipment investment cost of $4,806,278.00 and an annual cost of $988,963.02 (Table 4.2). The optimal equipment needed to operate the whole farm was selected based on the linear programming gross margin maximization model. The larger conventional equipment inventory included two sets of: 228 kW tractors, 12.19 m planters, 36.57 m self-propelled sprayers, 292 kW combines with 6.09 m corn heads and 10.67 m grain heads, and 27.94 t grain carts. Grain carts were included in whole field sole cropping because harvest unloaded on-the-go was assumed. Usually corn and soybean growers have many options for machinery selection. In this study, the equipment choice was based on Ward, Roe and Batte (2016) to represent the typical farming scenarios of the Midwest US. Farmers may choose to use their own equipment and/or use a custom hire service. This study used mixed systems for whole field sole cropping, where the corn and soybean production assumed a mostly farmer owned equipment set, except for use of custom hire for NH_3 application which is common on central Indiana farms.

The depreciation costs of machinery are associated with equipment age. Consequently, the study used straight line depreciation assuming 7 years for combine and planter, and 10 years for other equipment sets based on Langemeier *et al.* (2022) and Lowenberg-DeBoer *et al.* (2021a). Further details of the assumptions together with the costs of insurance as percentage of investment, repair and maintenance as percentage of initial investment, fuel and lubricant assumptions are available in Appendix B (ii)Supplementary Text.

Table 4.2: Conventional larger machine inventory and costs for whole field sole cropping in US$.

Inventory items	Width of the implement (m)	Initial investment	Useful life	Opportunity cost of capital	Annual depreciation	Ins.	Repair and maintenance	Annual cost (Whole farm)	Annual cost (Per ha)
Tractor (228 kW)		468183	10	23409	46818	4682	9364	93636.67	43.41
Tractor (184 kW)		366677	10	18334	36668	3667	7334	73335.40	34.00
Chisel plow	7.01	97315	10	4866	9732	243	1946	16786.84	7.78
Field cultivator	14.326	52500	10	2625	5250	131	1050	9056.25	4.20
Self-propelled sprayer (4542.49 L tank)	36.576	279591	10	13980	27959	699	5592	48229.45	22.36
Water tank (9084.99 L portable)		4720	10	236	472	12	94	814.20	0.38
Planter (16 Row)	12.192	190341	7	9517	27192	476	3807	40991.22	19.00
Combine, (292 kW)		577680	7	28884	82526	5777	11554	140293.71	65.04
Corn head (8 Row)	6.096	94336	10	4717	9434	236	1887	16272.96	7.54
Grain head	10.668	100296	10	5015	10030	251	2006	17301.06	8.02
Grain semi		100000	10	5000	10000	3000	3000	24000.00	11.13
Grain cart (27.94 t)		71500	10	3575	7150	179	1430	13763.75	6.38
Total		2403139						494481.51	229.25
Whole farm total*		4806278						988963.02	458.50

Note: **The study found that two sets of conventional larger machines allowed for timely operation of the whole farm (2156.974 ha).*

In strip cropping, the LP solutions show that five sets of human operated smaller conventional machines were able to optimally operate the whole farm (Table 4.3). The initial investment costs were $2,456,236.00 for five units of smaller conventional equipment sets, which included 37.4 kW tractors, 18.29 m trailed sprayers, 4.57 m fertilizer applicators, and planters, 151 kW combines with 4.57 m corn heads and grain heads. The strip cropping systems machinery inventory did not include a grain cart because the strips were not wide enough to run a combine and grain cart side-by-side. Considering harvesting efficiency, the study assumed that the combine unloads directly into the grain semi at the end of the field. The annual cost of the conventional equipment was estimated as $526,208.48.

Table 4.3: Conventional smaller machine inventory and costs for strip cropping in US$.

Inventory items	Width of the implement (m)	Initial investment	Useful life	Opportunity cost of capital	Annual depreciation	Ins.	Repair and maintenance	Annual cost (Whole farm)	Annual cost (Per ha)
Tractor (37.4 kW)		29207	10	1460	2921	292	584	5841.33	2.71
Chisel plow	2.438	7334	10	367	733	18	147	1265.03	0.59
Field cultivator	3.658	14404	10	720	1440	36	288	2484.69	1.15
Trailed sprayer (Attached with 4542.49 L tank)	18.288	6894	10	345	689	17	138	1189.17	0.55
In Cab controller (4 Boom control sections)		4291	10	215	429	11	86	740.23	0.34
Solenoid valves (36 for 4 Boom)		4356	10	218	436	11	87	751.41	0.35
Wiring and harness		622	10	31	62	2	12	107.31	0.05
Water tank (9084.99 L portable)		4720	10	236	472	12	94	814.20	0.38
Fertilizer applicator (Urea and other granulated N)	4.572	19180	10	959	1918	48	384	3308.55	1.53
Planter (6 Row)	4.572	39462	7	1973	5637	99	789	8498.42	3.94
Combine (Equivalent model to AVERO 240, 151 kW)		160000	7	8000	22857	1600	3200	38857.14	18.01
Corn head (6 Row)	4.572	70582	10	3529	7058	176	1412	12175.40	5.64
Grain head	4.572	30196	10	1510	3020	75	604	5208.81	2.41
Grain semi		100000	10	5000	10000	3000	3000	24000.00	11.13
Total		491247						105241.70	48.79
Whole farm total*		2456236						526208.48	243.96

Note: **The study found that five sets of conventional smaller machines allowed for timely operation of the whole farm (2156.974 ha).*

The modelling of autonomous machine scenario shows that three autonomous equipment sets were able to farm 2156.97 ha in a timely way. The autonomous strip cropping system used the same smaller conventional machinery but retrofitted for autonomy for field operations. Apart from conventional equipment inventory, the autonomous machines inventory required additional hardware and software to retrofit for autonomy that needed initial investment costs of $40,871 (Table 4.4). The initial investment needed to equip the autonomous strip cropping farm was $859,882 (i.e., $2,456,236-(($491,247+$40,871)*3)) less than for the conventional strip cropping.

Table 4.4: Hardware and software needed to retrofit for autonomous system.

Equipment Type	Item	HFH Equipment Cost* (GBP 2016)	US ($) 2022**
	Tractor and combine		
Safety equipment	Laser	3282	5767
	Remote Emergency Stop	75	132
	Stop Buttons - system	63	111
Control System	GPS Systems	2300	4042
	Autopilot	112	197
Control Adaptations	Steering Motor	768	1350
	Driver Control	860	1511
	Linkage Control	430	756
Camera Feedback	CCTC cams	340	597
Communications	WiFi	100	176
	RC System	413	726
Consumables	Boxes/connectors etc.	600	1054
	Total for Tractor and combine	9343	16418
	Combine only		
Safety Equipment	Extra laser	3282	5767
	Three actuators	1290	2267
	Total for Combine only	13915	24453
Total for Equipment Set		23258	40871

Note: **Adopted from Lowenberg-DeBoer et al. (2021a). **Exchange rate - GBP to USD - (Board of Governors of the Federal Reserve System (U.S.)., 2020) with inflation adjustment - (FRED, 2022).*

4.3.3 Allocation of farm expenses

Comparison of the returns and expenses of whole field sole cropping and strip cropping practices shows that total revenue was higher (i.e., $3025-$2800 = $225/ha) for autonomous strip cropping compared to whole field sole cropping (Figure 4.2), as the total value of grain produced was higher. Similarly, return to operator labor, management and risk-taking was also substantially higher (i.e., $568/ha) for strip cropping with crop robots because of higher grain value, lower machinery costs and less hired labor. Annual machinery costs and total costs were $302/ha (i.e., $458 - $156) and $343/ha (i.e., $2615

- $2272) lower for the autonomous scenario compared to whole field sole cropping operated with human drivers because of differences in the number of equipment units required. The whole field sole cropping required two units of 228 kW larger equipment sets and the autonomous strip cropping required three units of 37.4 kW retrofitted autonomous equipment sets. On the contrary, the conventional strip cropping scenarios required five units of 37.4 kW conventional equipment sets operated with human drivers making conventional strip cropping non-economical in labor scarce scenarios as compared to autonomous strip cropping. This is because the conventional strip cropping optimal solution was only feasible if hired labor availability raised to 1200 h per month per farm, where the base assumptions was 800 h per month per farm. The costing of the HFH based machineries were used here because of the lack of market price information for autonomy retrofits. The electronic components market structure is a relatively open market, consequently, the prices are broadly similar for those retrofit kits between the UK and the US. Moreover, prior research also considered the HFH retrofit kits cost for the US case study (Shockley *et al.*, 2021). Therefore, the machinery costing is applicable for commercial owner operated farm operations. The initial investment costs, retrofitting costs, and per annum machinery costs were based on the commercial machinery estimation processes following the pricing available at Agro Business Consultants (2018) and HFH retrofitting costs of open source software (Hands Free Hectare (HFH), 2021). Further details of the annual machinery costs estimation processes are available in the supplementary material of Lowenberg-DeBoer et al. (2021a): Supplementary file6 (DOCX 52 kb) at: https://link.springer.com/article/10.1007/s11119-021-09822-x#:~:text=By%20using%20smaller%20equipment%20more,equipment%20on%20the%20smallest%20farm.

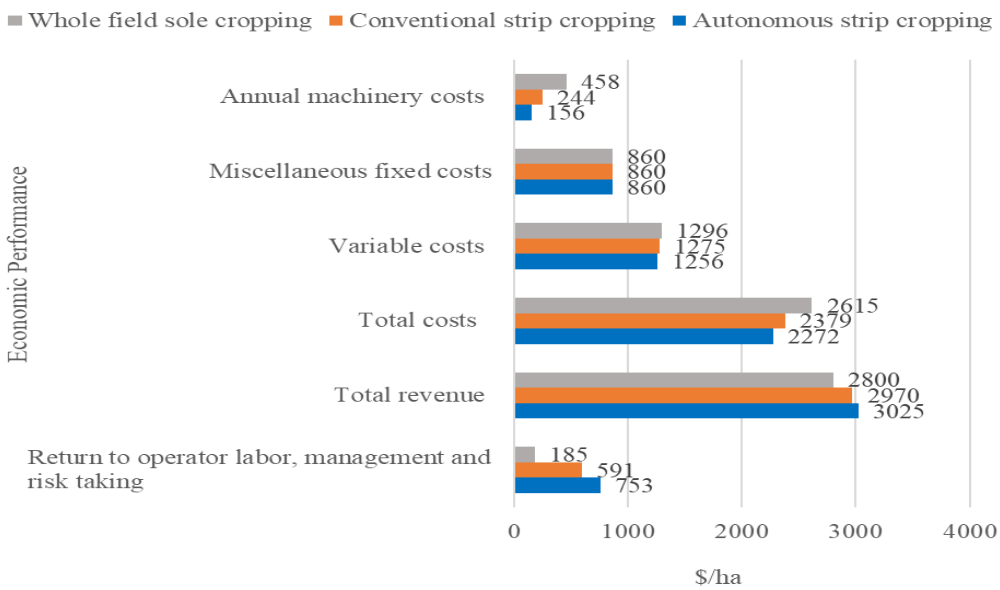

Figure 4.2: Comparative returns and expenses of whole field sole cropping and strip cropping practices.

The breakdown of costs as a percentage of total costs for the three cropping systems indicate that machine costs encompassed 18.00% of the total costs for whole field sole cropping practice operated by humans with larger conventional machines, whilst the share was significantly lower for autonomous strip cropping (i.e., only 7.00%) (Figure 4.3). The conventional strip cropping practice required more hired temporary labor (1.47% of total costs) that made conventional strip cropping infeasible for labor scarce arable crop sectors. The autonomous strip cropping had the advantage of reducing labor costs. In total cost percentage shares, the variable costs (seed, fertilizer and pesticide) occupied the majority. Subsequently, fixed costs other than machinery costs (i.e., rent for farm; property and building repair; professional fees and subscriptions; water, electricity, etc., building depreciation and miscellaneous fixed costs) encompassed the second highest share as a percentage of total costs.

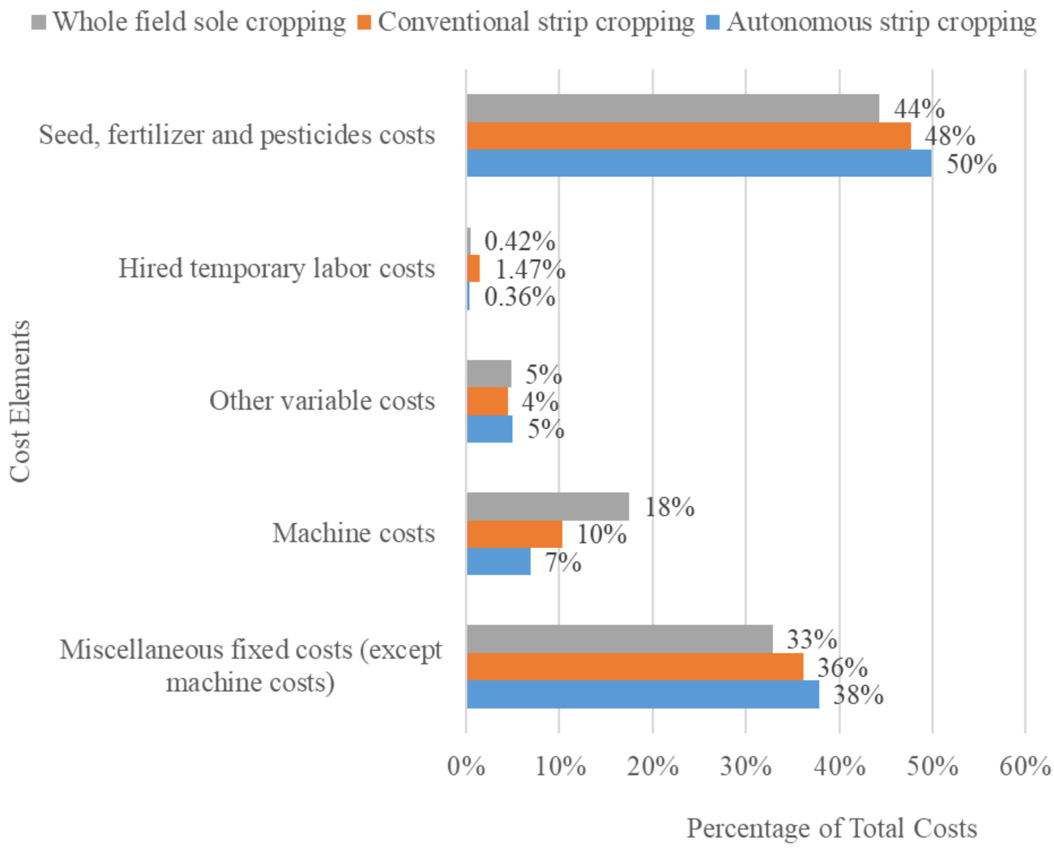

Figure 4.3: Cost elements as percentage of total costs.

4.3.4 Impacts of soybean/corn price ratios and increasing demand for human supervision

Sensitivity testing over historical maximum and minimum soybean/corn price ratios showed that autonomous strip cropping had a higher return to operator labor, management and risk-taking than conventional whole field sole cropping in each scenario.

The strip cropping advantage was reduced when the price ratio was high (i.e., favored soybean production), but economics favored autonomous strip cropping in all scenarios. Detailed price sensitivity test results are given in Appendix B (i) Supplementary Tables (i.e., Supplementary Table B.1).

The study finds that increasing supervision requirements during field operation (i.e., 50% and 100% of machine time) reduced the economic gains of strip cropping as gross margin and return to operator labor, management and risk-taking was lower compared to the baseline at 10% of machine time (Appendix B (i) Supplementary Tables: Supplementary Table B.2). However, even with supervision at 50% and 100%, the gross margin was higher than for the whole field sole cropping. Similarly, return to operator labor management and risk-taking was \$552.97/ha (i.e., \$738.24-\$185.27) higher at 50% supervision and \$516.24/ha higher (i.e., \$701.51-\$185.27) at 100% supervision. Sensitivity tests of increasing field-to-field transition distance (i.e., 4.02 km, whereas the baseline was 2.01 km) found that autonomous strip cropping was more profitable than whole field sole cropping and conventional strip cropping (Appendix B (i) Supplementary Tables: Supplementary Table B.3) even though economic gains (i.e., gross margin and return to operator labor, management and risk-taking) were reduced. The findings show that with double field-to-field transition distance strip cropping required another additional equipment set, that is the conventional strip cropping required 6 units of smaller conventional machines and the autonomous strip cropping required 4 units of crop robots to optimally operate the whole farm.

4.4 Discussion

The results of this study indicate an opportunity for research to optimize strip cropping with autonomous machines and enable commercialization of the practice. Widespread use of strip cropping techniques in commercial agriculture has been constrained by the high labor requirements. The results of this study support the hypothesis stated by Ward, Roe and Batte (2016) that corn and soybean strip cropping could be profitable with autonomous crop machines. Sensitivity testing suggested that autonomous strip cropping was more profitable than whole field sole cropping over a wide range of soybean/corn price ratios, and even when 100% human supervision is required (e.g., as crop robots required by law or because the technology is troublesome). Autonomous strip cropping also remained more profitable than whole field sole cropping with field-to-field distances over the baseline 2.01 km.

The results indicate that at the historically high 2022 grain prices, conventional strip cropping with human drivers on small equipment would be less profitable than autonomous strip cropping, but more profitable than whole field sole cropping if temporary hired labor is reliably available. This differed from the Ward, Roe and Batte (2016) results which showed that strip cropping with conventional equipment was unprofitable at 2015-2016 prices.

This study showed that strip cropping was more profitable than whole field sole farming even when using agronomic practices that are optimized for whole field production. It is quite possible that the optimal choice of hybrids and varieties, pest management, soil fertility management and other agronomic practices might be somewhat different for strip cropping.

Field layout might also be optimized for strip cropping. Depending on the cost of the autonomous tractor and trailed sprayer (or autonomous sprayer unit), the time window for spray applications and other factors, it might be more profitable to use a narrow spray boom (to match strip width) and reduce headland width. Given the added machine traffic on the strip cropping headlands, grass headlands would be worth consideration.

The cost-effective choice of small, retrofitted machines would help farmers, engineers and agribusinesses move towards autonomous agroecological strip cropping. Small crop robots may invigorate smaller equipment manufacturers of the US and/or open the import opportunities and/or promote an autonomy retrofit kit market (Karsten, 2019a; Koerhuis, 2021b).

One of the major uncertainties in this study is the cost of retrofitting conventional equipment for autonomy. None of the companies that now offer autonomy retrofit kits for conventional equipment published price lists. The HFH economics study (Lowenberg-DeBoer *et al.*, 2021a) only provided estimates of the parts and software needed for retrofitting, but did not estimate a value for the labor and expertise required. In addition, HFH adapted open-source drone software to guide its equipment. That was an inexpensive solution, but not a perfect one. The HFH tramlines were a bit “wobbly.” Wavey tram lines were not a major problem for the broadacre crops grown on HFH, but might be more of a problem for row crops. For Hands Free Farm (HFF), the 35 ha follow-on project from HFH that tests autonomy on a farm scale, autonomous machines drive straight lines with the help of commercial auto-guidance. Consequently, the retrofitting cost might be substantially more than listed in this study. However, the gain with autonomous strip cropping seems to be enough to cover the cost several multiples of the HFH estimate. The autonomous strip cropping scenario requires three crop robot units. With a useful life of 10 years, each robot unit adds $4,087.10 in depreciation to whole farm costs or $1.89/ha. If three units are needed that is $5.68/ha. Doubling that would be $11.37/ha. Quadrupling the baseline estimate would be $22.74/ha. With a margin of $568.19/ha gain with autonomous strip cropping, the autonomous option would remain the most profitable scenario even with higher retrofit costs.

Apart from the strip cropping yield advantage, the agroecological mixed farming system has the potential of reducing input use (Chen *et al.*, 2017; Tian *et al.*, 2022), lower pest densities and less disease infestation (Trenbath, 1993), and increasing soil carbon and nitrogen (Cong *et al.*, 2015). The opportunity costs of reduced fertilizer and pesticide use would increase the autonomous strip cropping payoffs. Optimizing spatio-temporal heterogeneity with strip cropping (Juventia *et al.*, 2022) and site-specific localized input application, a potential of autonomous machines (Lowenberg-DeBoer, 2022b) may reduce the variable costs of farming. These advantages were out of the scope of the study due to a lack of data. Further research to optimize autonomous strip cropping should consider input use, pest management and soil health impacts.

Some critics have viewed autonomous machines as a blueprint of replacing human labor. But the study found that autonomous strip cropping did not substantially reduce operator labor. The whole field sole cropping required 0.57 h/ha operator time, whilst autonomous strip cropping needed 0.53 h/ha. Interestingly, autonomous machines reduced the problem of temporary hired labor scarcity by only requiring 0.49 h/ha temporary hired labor. Contrary to this, whole field farming needed 0.65 h/ha and conventional strip cropping needed 2.06 h/ha temporary hired labor.

Autonomous strip cropping was even profitable with the human supervision regulations that are imposed in the European Union and the US state of California. Sensitivity tests found that with 50% and 100% supervision the economic returns were higher for autonomous strip cropping than whole field farming and conventional strip cropping. The findings suggest favorable legislation would increase economic payoffs, whereas rigid regulation provides a barrier to the viability of autonomous farming (Groeneveld, 2023; Maritan *et al.*, 2023; Shockley *et al.*, 2021).

The economic benefits of autonomous machines over whole field sole cropping and conventional strip cropping signal an opportunity for the broader adoption of autonomous mixed farming. This study makes a contribution to the state of the art of strip cropping and precision agriculture, although there are some limitations to the economic modelling. The study only considered edge effects in strip cropping owing to empirical data availability. The input saving potentials and biodiversity benefits were also not modelled due to lack of data. Future on-field autonomous strip cropping trials may evaluate the economics of strip cropping incorporating agronomic and environmental (i.e., agroecological) benefits. The study modelled 4.57 m width strip (i.e., 6 rows strip of corn or soybean), whereas economics of varying row widths with autonomous machines is not examined. Future economic research could address the sensitivity of outcomes to different row widths. The yield penalty of continuous soybean in the headlands could be better defined with on-field trials. The study calculated field times based on the assumptions of Ward, Roe and Batte (2016) following the estimation processes of Lowenberg-DeBoer *et al.* (2021a). However, use of algorithms to calculate field time as followed in Al-Amin *et al.* (2023) or by using on-field farm operations time may provide more real economic scenarios in systems analysis. The study only considered corn and soybean row crops and could be expanded to include a broader diversity of available land use options. Inclusion of “Beetle Banks” (e.g., prairie strips) in the North American context may increase biodiversity and provide a yield advantages, which would add to the concept of precision conservation (Swinton, 2022) and agricultural regeneration (i.e., regenerative agriculture).

4.5 Conclusions

Corn and soybean strip cropping are well known to have yield and agroecological advantages, but implementation of the practice has been limited by cost disadvantages resulting from higher labor requirements in conventional human-driven mechanized systems. Noting the economic and agroecological trade-offs, this study hypothesized that autonomous machines (i.e., crop robots) might make strip cropping profitable, thereby allowing farmers to gain additional agroecological benefits. The HFH-LP optimization model adapted to the Corn Belt of central Indiana, US, showed that corn and soybean strip cropping practice was more profitable with autonomous crop machines than whole field sole cropping and strip cropping systems using conventional machines. Sensitivity tests found that autonomous strip cropping remained more profitable over a wide range of soybean/corn price ratios, human supervision requirements, and increased field-to-field transition distance. The profitability of autonomous strip cropping reveals that autonomous machines could be a game changer with win-win farming potential, reconciling economic, agronomic, and environmental goals of arable crop farming.

Chapter 5

Economics of autonomous machines for regenerative agriculture

"Agri-robotic systems provide multiple emerging opportunities that facilitate the transition towards net zero agriculture. ... Robotics could impact sustainable food production systems to ... deliver regenerative agriculture."

Pearson et al. (2022): Current Robotics Reports, 3, pp. 57–64.

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5.1 Introduction

Robotics and autonomous systems (RAS) are expected to facilitate regenerative practices (Pearson et al., 2022). Regenerative agriculture is a sustainable alternative to transform food production and agroecosystems that has been degraded with whole field sole cropping systems (Gordon, Davila and Riedy, 2023; Soto, de Vente and Cuéllar, 2021). Worldwide, different scales of farming (Lowder, Skoet and Raney, 2016) initiated regenerative practices. For instance, large scale farming in North America (LaCanne and Lundgren, 2018), Australia (Gosnell, Gill and Voyer, 2019) and New Zealand (Grelet et al., 2021); medium scale farming of the UK (Jaworski, Dicks and Leake, 2023) and Europe (Dougherty, 2019; Schreefel et al., 2020; Schreefel et al., 2022b); and small scale farming of Asia and Africa (Bunch, 2022; Jat et al., 2022) have applied regenerative farming practices. Apart from academia and research, considering agronomic and ecological grounds, civil society, government, NGOs, media, and multinational food companies supported regenerative practices (Gosnell, Gill and Voyer, 2019; Giller et al., 2021; Umantseva, 2022; Sharma, Lara, and Lee, 2022; Levine, 2023; DEFRA, 2020).

However, the production economics literature on regenerative agriculture found mixed profitability (Bennett, 2021; Boston Consulting Group, 2023; WBCSD, 2023; Schreefel et al., 2022a; Constantin et al., 2022) and that low profitability would constrain wide scale adoption and scaling up of regenerative practices. Research indicates that the choice of regenerative agriculture practices is sensitive to enterprises, farming systems, technologies, and the regional context of farming (Schreefel et al., 2022b; Lal, 2023). To manage spatial and temporal heterogeneity of crop species within the same field farmers, agribusinesses, agri-tech innovators, ecology innovators, and researchers have suggested multiple cropping systems such as pixel, relay and strip cropping as alternative approaches of whole field sole cropping (i.e., monoculture crops) (Ditzler and Driessen, 2022; Juventia *et al.,* 2022).

Multiple cropping is well known in manual agriculture, but usually disappears when farming is mechanized with a focus on whole field sole cropping practices for labour productivity (Francis et al., 1986; Brooker et al., 2015). To reduce human labour requirements of multiple cropping, autonomous machines have been proposed (Pearson *et al.,* 2022; The Futures Centre, 2022; Ward, Roe and Batte, 2016), but differences in plant height and growth pattern are proving to be an engineering challenge for more complex cropping patterns (Ditzler and Driessen, 2022). Strip cropping is the simplest mixed cropping system. It is technically feasible with conventional mechanization, but rare because of labour and management requirements. Researchers have long hypothesized that autonomous machines might make strip cropping economically feasible (Ward, Roe and Batte, , 2016). Al-Amin *et al.* (2022a) presented preliminary results indicating that autonomous strip cropping maize and soybeans would be more profitable than whole field sole cropping in the US. They also pointed out that an autonomous strip cropping system has the potential of achieving the techno-economic and environmental feasibility which may facilitate regenerative practices through the inclusion of buffer strips for precision conservation and/or grass ley for production of livestock. Strip cropping should be considered precision agriculture (PA) because it affects the spatial and temporal management of agriculture (ISPA, 2019).

Regenerative agriculture in this study is considered with regenerative strip cropping practices that are expected to promote the five soil health principles (Jaworski, Dicks and Leake, 2023; Manshanden et al., 2023). The state of the knowledge reveals that the scientific definition of regenerative agriculture is not yet clear (Schreefel *et al.*, 2020) because the existing definitions are based on processes (i.e., incorporating cover crops, livestock and tillage reduction or elimination) or outcomes (i.e., improvement of soil health, carbon sequestration and biodiversity enhancement) and/or combination of both (Newton et al., 2020; Manshanden *et al.*, 2023). This study adopted the definition of regenerative agriculture considering both the processes and outcomes where regenerative strip cropping refers to a year-round sustainable farm management strategy that addresses the spatio-temporal variability with diversifying crop production within the same field in strips to minimize soil disturbance, improve resource use efficiency of the farm through reducing synthetic chemical input use, boosting soil health, biodiversity, and farm productivity.

Considering the technical, economic, and environmental feasibility of regenerative agriculture, precision agriculture (PA) technologies are suggested (Green Biz, 2020; Listen Field, 2021; Futures Centre, 2023; Manshanden *et al.*, 2023; Pixel Farming Robotics, 2023; Davies, 2022; Keshavarz and Sharafi, 2023; Pearson et al., 2022; McLennon et al., 2021; Pearson, 2007). This study hypothesized that autonomous machines could make regenerative strip cropping profitable, thereby supporting the agricultural transition plan of the UK to improve soil health, biodiversity and achieve carbon net zero target. In this study, the context of the UK was considered as a case study because British agriculture is intensified through crops, inputs use and agricultural mechanization since 1945. The intensification approaches entail a loss of biodiversity, soil fertility, ecosystems services and increase greenhouse gas (GHG) emissions (Robinson and Sutherland, 2002; Agrospecials, 2023). To help achieve food security, restore, and enhance the environment for the next generation, the UK government has set a broad vision. The British government has initiated an ambitious plan to achieve a net zero target by 2050 through a wide range of resource efficient and nature friendly land management measures in agriculture (Bank of Scotland, 2021; RASE, 2021; DEFRA, 2020; Agrospecials, 2023).

In the UK research suggests regenerative agriculture as a means of reinvigorating natural systems interactions (Cusworth, Garnett, and Lorimer, 2021). As farmers are the pivotal player to tackle the challenges of climate change and biodiversity loss, the public goods subsidization policy (i.e., "public money for public goods") is encouraged in recent times (DEFRA, 2020; Lowenberg-DeBoer et al., 2022c). A growing number of farmers have started considering long term changes of their farms through regenerative practices. The input price inflations, record heat, prolonged dry spells, and wet winters push farmers to consider risk-reducing and less external inputs dependent regenerative practices to improve farm profitability and resilience against climate change (Agrospecials, 2023; Abram, 2020; Abram, 2021).

In Great Britain, regenerative agriculture is hypothesized to help decarbonize cereal intensive farming practices where autonomous machines could facilitate this goal (Davies, 2022). Nevertheless, the cost-effective regenerative farming practices are not yet guided with policy suggestions. To guide future regenerative practices and promote scaling up, this study used an ex-ante analysis built on the Hands Free Hectare - Linear Programming (HFH-LP) model developed by Lowenberg-DeBoer et al. (2021a). This study modelled a five-year winter wheat-winter barley-nectar flower mix-winter wheat-spring bean yearly rotations because for same height plants typical in the UK optimizing positive edge effects through strip orientation and timing of field operations could be the best alternative available. In the UK, most crop plants are of a similar height (e.g., wheat, barley and field bean are all about one meter tall) and no yield information is available from experimental trials to estimate strip cropping edge effects. This study assumed that strip crop yield benefits are possible even when crop height is similar because of temporal differences in crop growth. For instance, winter wheat and barley largely stop growth by late June and in July are maturing and drying down, while field beans continue active photosynthesis in July and early August. This cereal intensive rotation is proposed assuming that in the UK this could help achieve food security, transitional agricultural target and build resilience against climate change and biodiversity loss as envisaged by the British government (Agro Business Consultants, 2018; DEFRA, 2020; Agrospecials, 2023). This five-year rotation is the shortest one including all the different aspects of the crop only system. Apart from cereals, the nectar flower mix (NFM) was modelled in the interior field and two-sided headlands because equipment needed frequent access to the interior field strips at different stages for farm operations. The NFM here represented the mid-tier Countryside Stewardship Scheme (CSS) scheme.

Considering five soil health principles of regenerative agriculture, including grass ley strips in interior field and headlands would be best combined with ruminant livestock raising (Lal, 2023; Jaworski, Dicks and Leake, 2023). However, due to the complexity of adding livestock (e.g., impractical to graze narrow strips, logistical challenges in harvesting forage from strips and transporting it to animals over public roads, challenges in transporting and returning manure to the strips) and the lack of data from autonomous mixed crop and livestock farms, this study considered the NFM under the UK government's CSS programmes. The nectar flower seed mix contains both shorter-lived legumes and longer-lived wildflower species to provide an extended supply of pollen and nectar from late spring through to the autumn for beneficial insects such as bees, butterflies and moths (United Kingdom Rural Payments Agency, 2022). The NFM is subsidized by the British government to promote diversity of flora and fauna in crop fields (Agro Business Consultants, 2018; Redman, 2018) which is relevant because this study used 2018 input and output prices and government CSS programme to make comparison with the base modelling scenarios of Lowenberg-DeBoer *et al.* (2021a) conducted for whole field sole cropping. During 2018 the Environmental Land Management Scheme (ELMs) of the UK was in pipelines. This study assumed that the ELMs will be allied with the CSS programme.

This ex-ante economic analysis is expected to guide the regenerative practices. Start-ups and commercial manufacturers could benefit from a clearer understanding of profitable autonomous regenerative agriculture practices to guide prototype development, adoption and further scaling up. Finally, the British transitional agriculture sector will get insights about cost-effective practices that improve soil health, biodiversity and help achieve the carbon net zero target by 2050 while linking with the public money for public goods policy.

5.2 Materials and methods

5.2.1 Case study and data

The study considered the context of the United Kingdom to model 500 ha farm as followed in the study of Lowenberg-DeBoer et al. (2021a). The 2018 input and output prices and government programme data were used to avoid the volatility of current farm prices due to supply and demand shock of COVID-19 pandemic, Russian invasion of Ukraine, and the policy uncertainty of post-BREXIT Britain. The use of 2018 prices also facilitated the comparisons with the baseline HFH economics study of Lowenberg-DeBoer *et al.* (2021a). The data of yield, output prices, operating costs, and CSS grant payment (i.e., mid-tier scheme of nectar flower mix (NFM)) and costs were taken from Agro Business Consultants (2018) and the Nix Pocketbook (Redman, 2018).

The per ha subsidy payment of the CSS that assumed to be received in December was based on the Agro Business Consultants (2018). The costs per ha for predrill herbicide & drilling the NFM (i.e., Bumble bird mixture) assumed to be incurred in March was collected from the Nix Pocketbook (Redman, 2018).

The equipment specifications and costs information of 221 kW conventional machines with human operators, 28 kW smaller conventional machines with human operators and 28 kW smaller conventional machines retrofitted for autonomy were collected from Agro Business Consultants (2018), Lowenberg-DeBoer et al. (2021a) and Hands Free Hectare (HFH) (2021). The hardware and software needed for retrofitting the 28 kW conventional machines included the safety equipment, control system, control adaptations, camera feedback, communications, consumables. The list of inventory and associated costs are adopted from Lowenberg-DeBoer et al. (2021a). The driver's seats and steering wheels are retained on the autonomous machines to allow a human driver to move the equipment on public roads. Implying that the HFH type autonomous machines considered in this study are assumed to be conducted farm operations autonomously, while public road driving was conducted by a driver. For further details of the retrofitting costs see the following supplementary material of Lowenberg-DeBoer et al. (2021a): Supplementary file6 (DOCX 52 kb) at: https://link.springer.com/article/10.1007/s11119-021-09822-x#:~:text=By%20using%20smaller%20equipment%20more,equipment%20on%20the%20smallest%20farm

Field operation timing was adopted from Finch, Samuel and Lane (2014) and Outsider's Guide (1999). The yield penalties for non-optimum planting and harvesting operations were based on Witney (1988).

5.2.2 Base modelling

The study used long-term 'steady state' optimization models that were based on the Hands Free Hectare – Linear Programming (HFH-LP) model. The concept of steady state implies that the annual solutions of the model would be repeated indefinitely (Lowenberg-DeBoer *et al.,* 2021a). The ex-ante model assumed monthly time steps from January to December. The HFH-LP model was coded in the General Algebraic Modelling Systems (GAMS) software (GAMS Development Corporation, 2020).

The gross margin maximization model is mathematically expressed as:

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

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 = gross margin, X_j = the level of *j*th production activities, c_j = the gross margin per unit over fixed farm resources, a_{ij} = the amount of *i*th resource required per unit of *j*th activities, b_i = the amount of *i*th resource available.

The objective of the study was to maximize gross margin subject to land, operator labour time, tractor time for drilling and spraying, and combine time for harvesting. The study estimated return to operator labour, management and risk taking (ROLMRT) by subtracting fixed costs from the gross margin. The fixed costs included land rent, property and building repairs, professional fees and subscriptions, water, electricity, etc, building depreciation and miscellaneous fixed costs (for details see Lowenberg-DeBoer *et al.,* 2021a).

Three machine sets were evaluated. The conventional whole field sole cropping was assumed to operate with 221 kW conventional equipment sets with human operators. The conventional strip cropping was assumed to operate with 28 kW smaller conventional equipment with human operators and autonomous strip cropping operated with 28 kW smaller conventional equipment set that was assumed to be retrofitted for autonomy. The 28kW equipment sets modelled the potential of swarm robotics. The 28 kW size is not necessarily the optimal swarm robot size, but it was selected because that is the size used on the HFH. The equipment times were estimated following the algorithms of Lowenberg-DeBoer *et al.* (2021a), but zero overlap was assumed instead of 10% overlap assumption based on the recent HFF experience (Harper Adams University (HAU), 2023).

This study modelled 500 ha farm assumed to have roughly 10 ha sized rectangular fields with the length of the field about 10 times the width as assumed in the study of Al-Amin *et al.* (2023) for sole field sole cropping grain-oil-seed farm in the UK. The farm was assumed to be 90% tillable, where the remaining 10% was occupied for ecologically focused areas such as lanes, hedgerows, drainage ditches and farmstead (Lowenberg-DeBoer *et al.,* 2021a).

A five-year winter wheat-winter barley-nectar flower mix-winter wheat-spring bean yearly rotations were considered. The optimum planting and harvesting dates are based on Finch, Samuel and Lane (2014), Outsider's Guide (1999) and Agro Business Consultants (2018). The optimum planting and harvesting dates modelled in this study were: winter wheat planted in October and harvested August, winter barley planted in October and harvested in August, nectar flower mix planted in March and subsidy grant received in December, and spring bean planted in March and harvested in September.

In whole field sole cropping each crop was assumed to be planted on 90 ha out of the total 450 tillage ha. Given that managing strip cropping requires repeated access to the field interior (i.e., field except the headlands) for different crops, the strip crop headlands (i.e., 0.14 ha, 1% of the fields) were assumed to be sown to nectar flower mix. The interior of the strip crop fields (i.e., 9.86 ha) were cultivated with 2 m strips of winter wheat-winter barley-nectar flower mix-winter wheat-spring bean annual rotations. In the interior field, each enterprise encompassed 1.972 ha, i.e., 20% of the field interior.

The groups of the five strips were assumed to be repeated across the whole interior field (Figure 5.1). In the subsequent years annual rotations were followed keeping the objective of maximizing edge effects. The edge effects are usually predominant for larger and smaller plants growing in strips, e.g., maize and soybean (Ward, Roe and Batte, 2016). However, this study assumed that for similar height plants typical in the UK that don't differ much in height like soybean and maize, they do differ in growth pattern. For example, winter wheat achieved maximum biomass and photosynthesis in midsummer (usually June-July) and was harvested in August, field beans achieved maximum growth in late summer and usually harvested in September. From this crop layout as shown in Figure 5.1, this would create synergies among the crops. For instance, in the first-year winter wheat in strip 2 could capture more sunlight in early summer when the field beans are small. Field beans could capture more sunlight in late summer after the wheat is mature and has been harvested. Similarly, in strip 4, winter wheat was assumed to benefit from both sides of spring bean and nectar flower mix. In second year, winter barley in strip 2 was assumed to be benefited from both sides, for being next to nectar flower mix and being before winter wheat.

	Year 1	Year 2	Year 3	Year 4	Year 5
Strip 1*	Winter Barley	Nectar Flower Mix	Winter Wheat	Spring Bean	Winter Wheat
Strip 2	Winter Wheat	Winter Barley	Nectar Flower Mix	Winter Wheat	Spring Bean
Strip 3	Spring Bean	Winter Wheat	Winter Barley	Nectar Flower Mix	Winter Wheat
Strip 4	Winter Wheat	Spring Bean	Winter Wheat	Winter Barley	Nectar Flower Mix
Strip 5	Nectar Flower Mix	Winter Wheat	Spring Bean	Winter Wheat	Winter Barley

positive edge effects both sides

positive edge effects one side

Note: Headlands on both ends of the field were assumed planted with Nectar Flower Mix. Headland: 7 m wide.
* Strips were 2m wide and the length of the field was assumed 10 times the width. The sequence of the five strips in this chart were repeated over the whole field.

Figure 5.1: Five-year rotational layout of regenerative strip cropping to maximize edge effects.

This study modelled risk aversion considering the probability assumed for good field days. The original Purdue Crop Livestock Linear programming (PC/LP) model assumed good field days data available for the 17th worst year out of 20 (McCarl et al. 1977) which is the food field days available at 85% of the time. The Agro Business Consultants (2018) followed in this study considered good field days available for 4 years out of 5 which is 80% of the time as followed in the study of Lowenberg-DeBoer *et al.* (2021a) and Al-Amin et al. (2023) for the Great Britain.

This study assumed that conventional machines operated during daytime which is about 10 h/day. The autonomous machine scenarios assumed that the machines operated for 22 h/day, while remaining 2 h/day for repair, maintenance, and refuelling. However, for grain harvesting, the autonomous machines assumed 10 h/day which is limited considering the UK weather, especially for night dew as assumed in the study of Lowenberg-DeBoer *et al.* (2021a) and Al-Amin et al. (2023). Further details of the base modelling assumptions are available in the study of Lowenberg-DeBoer *et al.* (2021a) as presented in the Supplementary file6 (DOCX 52 kb) available at: https://link.springer.com/article/10.1007/s11119-021-09822-x#:~:text=By%20using%20smaller%20equipment%20more,equipment%20on%20the%20smallest%20farm.

5.2.3 Sensitivity scenarios

The reduced external inputs dependency, costs related to inputs use, increasing ecosystem services, and yield benefits of regenerative practices are well known (Pearson et al., 2022; McLennon et al., 2021; Eckberg and Rosenzweig, 2020; Rehberger, West and Spillane, 2023; Soto, de Vente and Cuellar, 2023; Rhodes, 2017; Bartley et al., 2023; Jordon et al., 2022b) but not well studied and quantified. Similarly, strip cropping agronomic (i.e., edge effects that is yield benefits of taller plant and penalty for shorter plant) and ecological benefits are evident by research in small, medium, and large-scale farming context all over the world (Ward, Roe and Batte, 2016; Verdelli et al., 2012; Munz et al., 2014; Liu et al., 2022; Rahman et al., 2021; van Apeldoorn, 2020; Qin et al., 2013). But strip cropping edge effects and ecological benefits are not quantified by research for the same height plants typical in the UK.

Based on the state of the knowledge, this study assumed that regenerative strip cropping practices could ensure agronomic and biodiversity benefits. However, due to the lack of data on agronomic and ecological benefits for the same height cereals typical in the UK, this study modelled 10% yield benefits and 10% inputs saving premiums. This study hypothesized that selection of appropriate enterprises, addressing spatial heterogeneity through strips rotation and temporal heterogeneity through early and late planting and harvesting, and farm operations at different times will help to optimize the edge effects and ecological benefits of regenerative strip cropping practices in both conventional farm management with human operated machines and autonomous farm management with retrofitted machines. The longer-term vision is that if autonomous strip cropping were found profitable, on-field trials could be worthwhile for maximizing agronomic and ecological benefits. This autonomous regenerative strip cropping practices will in-turn help to achieve simultaneously the production goals of productivity and profitability and environmental goal of limiting environmental footprints of arable farming.

5.3 Results

5.3.1 Baseline results

The baseline optimum solutions with all 450 ha of arable land planted models are presented in Table 5.1. Compared to the whole field sole cropping more intensive winter wheat, oilseed rape (OSR) and spring barley rotations in the baseline HFH study conducted by Lowenberg-DeBoer *et al.* (2021a), the gross margins with the regenerative rotations (i.e., a five-year winter wheat-winter barley-nectar flower mix-winter wheat-spring bean) considered in this present study were substantially lower. For example, the gross margin for the 450 ha baseline conventional farm in the HFH study of Lowenberg-DeBoer *et al.* (2021a) was £353,677. Gross margin for that more intensive rotation of Lowenberg-DeBoer *et al.* (2021a) was £76,530 (i.e., £353,677-£277,147) higher than for the whole field sole cropping of this regenerative rotation with conventional machines (i.e., 221 kW machines for whole field sole cropping). This is because a smaller portion of the land was devoted to the higher return crops (i.e., winter wheat and OSR). In this study, gross margin for the strip cropping with conventional equipment (i.e., 28 kW smaller conventional machines with human operators) are somewhat lower than the whole field scenario because 13 times more labour was required, and the labour constraint was binding in August. The operator time was binding in March, April, May, August, September, and October. Labour hired in the autonomous strip crop scenario is more (i.e., 66 person days per year per farm) than in the conventional whole field case (i.e., 21 person days per year per farm), but still much less than in the conventional strip crop scenario (i.e., 280 person days per year per farm).

Results of the baseline models reveal that return to operator labour, management and risk taking (ROLMRT) was £71,974 for autonomous regenerative strip cropping. This is £57,760 higher than whole field sole cropping and £25,596 higher than conventional regenerative strip cropping. The autonomous strip cropping ROLMRT advantage is larger because two units of retrofitted 28 kW autonomous machines (i.e., swarm robots) were able to operate the 450 ha regenerative farm profitably while the conventional strip crop unit required four 28 kW machines and the much higher investment cost of machines for the whole field conventional farm scenario. These two units of autonomous machines requirement for strip cropping can be compared to three 28 kW autonomous machines required for the 450 ha farm in the HFH study conducted by Lowenberg-DeBoer *et al.* (2021a). Fewer autonomous machines were required for the regenerative rotation because the nectar flower mix (NFM) required very little machine time during predrill herbicide & drilling operations and the field beans were planted and harvested during periods when machine time was not in high demand. Even with four units of 28kW conventional machines in the conventional regenerative strip cropping scenario, operator time was binding in March to May and August to October, and temporary labour was binding in the peak harvesting period (i.e., August) of winter wheat and winter barley. Although gross margin was higher for whole field sole cropping with conventional equipment, this mono-cultural system required more operator time (i.e., 73 person days per year per farm) than the autonomous regenerative strip cropping (i.e., 63 person days per year per farm) and had much higher equipment costs. In the UK, hiring agricultural labour is difficult at the best of times and has become even more problematic in the post-BREXIT period, so the higher labour requirement is problematic.

Table 5.1: Optimization models outcomes for five-year winter wheat-winter barley-nectar flower mix-winter wheat-spring bean rotations in the UK arable farm.

Equipment scenario*	Labour hired (Person-days per year per farm)	Operator time (Person-days per year per farm)	Gross margin (£ per year per farm)	Return to operator labour, management and risk taking (£ per year per farm)
Baseline				
Conv. 221 kW: Whole farm sole cropping	21	73	277147	14213
Conv. 28 kW^{4}: Regenerative strip cropping	280	135	249976	46377
Autonomous 28 kW^{2}: Regenerative strip cropping	66	63	264343	71974
Yield Advantage Sensitivity Test				
Conv. 28 kW^{4}: Regenerative strip cropping	280	135	290497	86898
Autonomous 28 kW^{2}: Regenerative strip cropping	66	63	304633	112264
Cost Reduction Sensitivity Test				
Conv. 28 kW^{4}: Regenerative strip cropping	280	135	265852	62253
Autonomous 28 kW^{2}: Regenerative strip cropping	66	63	280219	87849

Note: **The superscript indicates the number of equipment sets needed.*

5.3.2 Sensitivity results

Empirical research in small scale farming (i.e., China) and large-scale farming (i.e., North America) shows that strip cropping with plants that differ in height show the edge effects (Qin *et al.,* 2013; Van Oort *et al.,* 2020; Ward, Roe and Batte, 2016). In particular, in maize-soybean systems, the maize yields tend to be higher in strip cropping because outside rows next to the shorter soybeans can capture more light. However, in the UK, most crop plants are of a similar height (e.g., wheat, barley and field bean are all about one meter tall) and no yield information is available from experimental trials to estimate strip cropping effects. It is hypothesized that strip crop yield benefits are possible even when crop height is similar because of temporal differences in crop growth. For example, winter wheat and barley largely stop growth by late June and in July are maturing and drying down, while field beans continue active photosynthesis in July and early August. Optimizing the yield impact of strip cropping would probably depend on the crop varieties and agronomic practices. This assumption was the basis for a sensitivity test considering a 10% yield increase.

A scenario with 10% yield premiums for winter wheat, winter barley and spring field beans show that with swarm robots, the per annum gross margin per farm was £40,290 (i.e., £304,633-£264,343) higher compared to without autonomous strip cropping yield advantage considered in the baseline scenario (Table 5.1). As the equipment use was the same for this yield advantage scenario, the ROLMRT increased by the same amount as the gross margin (i.e., £40,290). The conventional strip cropping gross margin was £40521 (i.e., £290,497-£249,976) higher with 10% yield premiums as compared to the conventional strip cropping base scenario without any yield advantage for regenerative strip cropping practices.

Similarly, there is a hypothesis that improved soil health and more robust field ecosystems could reduce pest management costs in strip cropping. There is some evidence of greater insect diversity in strip crop fields (Alarcón-Segura *et al.,* 2022). This hypothesis was the basis for a scenario which assumed a 10% reduction in variable costs. In the 10% variable costs reduction scenario, the per annum gross margin per farm was increased £15,876 (i.e., £280,219 - £264,343) more compared to the autonomous strip cropping scenarios considered in baseline modelling (Table 5.1). With 10% inputs saving advantage conventional regenerative strip cropping ROLMRT was £15876 (£62253 - £46377) higher than conventional regenerative strip cropping in baseline scenario without any input savings through regenerative strip cropping practice.

5.4 Discussion

Many British farmers chose agricultural careers to continue family traditions and because they want an active, outdoor lifestyle, but to retain enough farmers in the sector to achieve the UK's food security and land management goals, the earnings must be comparable to other options, including conventional industrial mono-crop farming and non-farm careers. The relevant benchmark earnings needed to make regenerative practices attractive is not clear, but this study shows that autonomous regenerative strip cropping ROLMRT of £71,974 is almost £19,000 less than that of conventional farming with the more intensive winter wheat/OSR rotation in the HFH study conducted by Lowenberg-DeBoer et al. (2021a), but slightly more than the £64,768 average farm manager compensation from the 2016 Farm Manager Survey (Redman, 2018). The baseline results without any yield benefits and inputs savings premiums shows that autonomous regenerative strip cropping was profitable intensification solutions as compared to mechanized conventional regenerative strip cropping and whole field sole cropping operated with human drivers.

The yield and variable cost sensitivity testing show that only small yield increases or variable cost reductions linked to regenerative strip cropping would be enough to make it competitive with the intensive crop rotation (i.e., wheat-OSR rotational whole field sole cropping considered in the HFH study) (Lowenberg-DeBoer *et al.,* 2021a). This study assumed whole field agronomic practices for the strip cropping, but those practices may need to be modified for strip cropping. Agronomic history suggests that such modest yield increases and/or cost savings might be achieved through optimizing the strip width, crop genetics, field operation timing, soil management and other aspects of the farming system (Ward, Rose and Batte, 2016).

The main limitation of this preliminary study of regenerative strip cropping is lack of livestock integrated into the rotational system. Due to the lack of information of precision livestock management supported by autonomous forage production, this study assumed a nectar flower strip produced entirely for environmental benefits and compensated through a government subsidy. Instead of autonomous forage production for supporting livestock this study assumed that the inclusion of the CSS (i.e., mid-tier scheme of nectar flower mix (NFM)) was more relevant because the study used 2018 input and output prices and government programme to make comparison with the base modelling scenarios of Lowenberg-DeBoer *et al.* (2021a).

A more complete analysis is planned which will include livestock grazing, forage harvesting, and manure returned to the soil. Because livestock integration is one of the five important components of soil health principles of regenerative agriculture. Future research could include autonomous grass ley production to support winter finishing suckled calves in the modelling which will help achieve the five soil health principles of regenerative agriculture. Another important limitation is the lack of experimental data on yield and pest management effects of regenerative strip cropping for the same height plants typical in the UK. It is hypothesized that autonomous regenerative strip cropping and associated intensive data collection may result in several other benefits such as improve plant health, early detection of disease, better scouting of crops, improvement of soil health and restoration of in-field biodiversity, etc. In North America, there is a long history of strip cropping experimental trials in corn-based systems and a similarly long history of farmers and agribusinesses trying to find mechanization systems that would allow them to reap the benefits of strip cropping without adding too much additional labour and management cost. British (and other European) farmers and agribusinesses will probably need similarly robust evidence of yield increases and/or cost savings to motivate them to explore strip cropping farming systems that would help in regenerative practices as strip cropping is the simplest mixed cropping system.

5.5 Conclusion

The study shows that regenerative strip cropping with autonomous machines was more profitable than conventional strip cropping and whole field sole cropping farm with the same crop rotations. The modest increases in yield or reductions in variable costs due to lower crop protection expenses could make autonomous regenerative strip cropping economically competitive compared to more intensive wheat-OSR rotations without regenerative practices. Regenerative strip cropping with autonomous machines could provide a profitable approach to restore and improve within-field biodiversity and ecosystem services.

Chapter 6

General discussion and conclusions

"We are entering at the age of robot farmers…"

Daum (2021): Trends in Ecology and Evolution, 36(9), pp. 774-777.

6.1 General discussion

Production economics research on autonomous machines hypothesized that autonomous arable farming operations in small, irregularly shaped fields and mixed cropping systems will improve environmental performance as well as maintain farm profitability (Ward, Roe and Batte, 2016; Lowenberg-DeBoer *et al.*, 2021a). To contribute to the existing state of the knowledge, this study assessed the opportunity costs of autonomous farming operations as compared to conventional mechanized farming with human operators. This study examined three research hypotheses related to field size and shape implications of autonomous machines, autonomous strip cropping to facilitate mixed cropping and autonomous regenerative agriculture.

To assess the hypotheses this study used linear programming (LP) to simulate farmer decision making. The LP model outcomes are relevant because autonomous machines are in the commercial pipeline and farmers will soon need to make investment decisions about them (Lowenberg *et al.*, 2021a; Shockley *et al.*, 2021). Research pointed out that the world is entering a robotic farming era owing to the advancement of technology and increasing labour scarcity (Klerkx and Rose, 2020; Lowenberg-DeBoer *et al.*, 2020; Daum, 2021; Shockley *et al.*, 2021). The use of econometric methodology was not feasible for this ex-ante study because there is no track record of autonomous machine use in arable agriculture. Consequently, 'steady state' LP optimization model was used to assess the gross margin measure of profitability. The concept of 'steady state' here refers to the solutions that would be repeated annually over time (Lowenberg-DeBoer *et al.*, 2021a). The findings of this study have farm management implications, suggesting arable commodity crop producers to consider seriously the cropping options and profit opportunities available with autonomous machines.

The profitability of autonomous machines irrespective of field size and shape indicates that the rule of thumb of conventional machines related to field enlargement and structural change through removing biodiversity and hedgerows (i.e., 'get big, or get out') will be superseded with autonomous machines. The optimization model shows that autonomous machines were more profitable solutions for farms with small 1 ha rectangular and non-rectangular fields compared to farming with conventional machines with human operators. This economic potential of autonomous machines in small, non-rectangular fields imply that autonomous machines could help in biodiverse farming as research shows that small fields are rich in biodiversity.

The research on automating mixed cropping to date has focused on technical aspects of farm management (Ditzler and Driessen, 2022). Strip cropping is the simplest form of mixed cropping and thus an appropriate place to start economic analysis. Autonomous machines are hypothesized for a profitable strip cropping system because substantial labour requirements and fixed costs associated with conventional mechanized farming constrained the practice in conventional mechanized system (Ward, Roe and Batte, 2016). The LP optimization model found that autonomous strip cropping system was more profitable than conventional strip cropping and conventional whole field sole cropping, implying the adoption and scale up potential. The profitability of autonomous strip cropping even under different on-farm resource constraints (field to field transition, negative edge effect on smaller plant), market shocks (commodity price ratios) and regulatory obligations (human supervision), implying that autonomous machines could expand the options for arable open field farming beyond whole field monocultures. Autonomous strip cropping will potentially maximize the production goals of productivity and profitability. Simultaneously, an autonomous strip cropping system will help achieve the environmental goal of limiting environmental footprint of crop agriculture through best utilizing within field spatio-temporal heterogeneity.

The profitability of regenerative strip cropping practice with autonomous machines compared to conventional regenerative practice and conventional whole field sole cropping indicate that autonomous machines could bring a paradigm shift in arable farming. The regenerative strip cropping practice could help to improve soil health, biodiversity and achieve net zero targets. The findings reveal that autonomous machines could facilitate sustainable intensification solutions because autonomous regenerative practices will integrate multifaceted objectives of arable farming that farmers and society as a whole envisaged.

Overall, the findings of the study have implications to guide arable sole cropping systems and mixed cropping systems. The profitability of autonomous machines irrespective of field size and shape, even with labour scarcity are expected to help in biodiverse smart farming for which labour is the prime constraint (Daum *et al.*, 2023). The ex-ante economic analyses of autonomous agroecological strip cropping and autonomous regenerative strip cropping practices already helped motivate the new HFF strip cropping demonstration trials at Harper Adams University in the UK (Figure 6.1) (Harper Adams University (HAU), 2023).

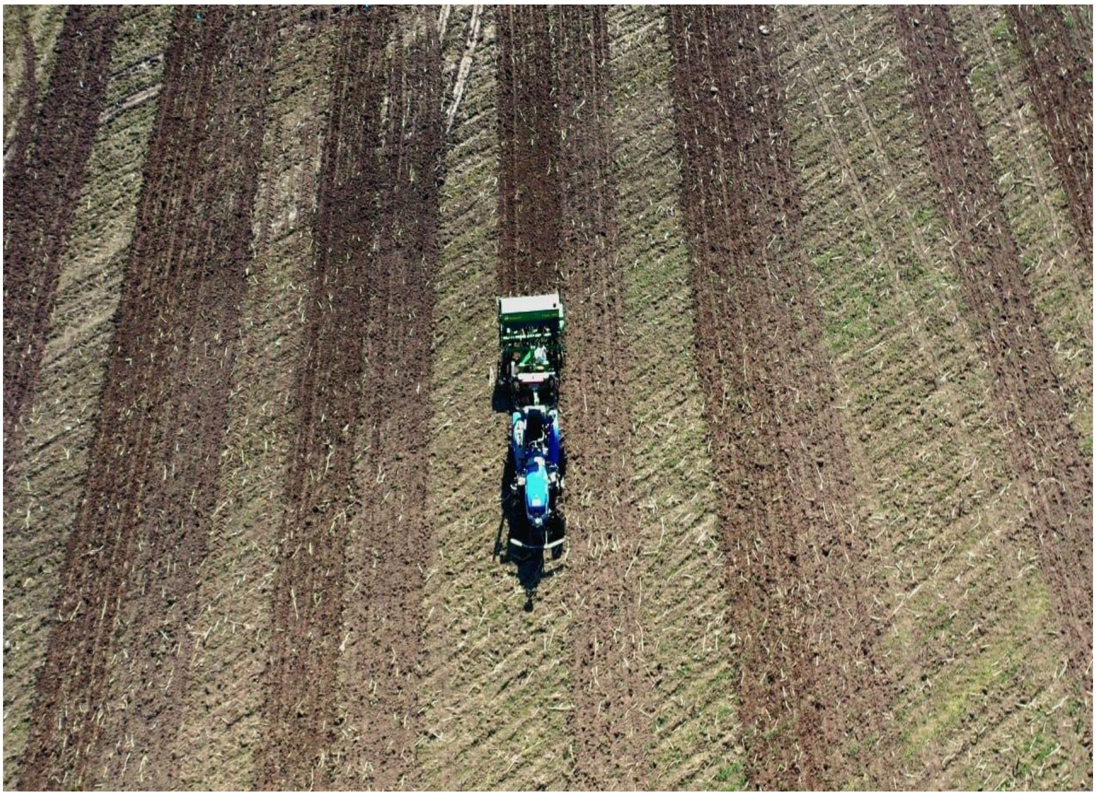

Figure 6.1: New Hands Free Farm demonstration research of autonomous strip cropping.

Source: *https://www.harper-adams.ac.uk/news/207994/new-hands-free-research-set-to-take-root-this-spring?utm_source=Twitter&utm_medium=Social+Post&utm_campaign=HAU+Social+Media*

Although this study considered the context of medium scale farming of the UK (in objective 1 and objective 3) and large-scale farming of the US (in objective 2) as case study due to the technical, agronomic and economic data availability, this study has implications for small scale farming of Asia and Africa having less than two ha average farm size (High Level Panel of Experts (HLPE), 2013; Lowder, Skoet and Raney, 2016). The small fields and machines considered in this study are similar to those used in the smallholder's context, e.g., in Bangladesh (Al-Amin, Lowenberg-DeBoer and Mandal, 2023).

6.2 Limitations and future research

This study contributed to the scientific knowledge through economic evaluation of autonomous machines for commodity crops production. However, the study has limitations in economic modelling and associated scenarios analyses. The limitations of this study and future research directions are as follows:

- This study did not quantify the biodiversity benefits. What implications the biodiversity benefits have for agricultural policy is yet to be explored. Although this research implies that autonomous machines profitability in small, irregularly shaped fields will allow greater integration of biodiversity into farming systems, future research could address biodiversity benefits and policy implications, incorporating hedgerows, in-field trees and wetlands.

- The field time estimation algorithm did not adequately reflect downtime due to machine problems. What will be the impact of using autonomous machines on downtime? With swarm robotics (i.e., fleet of robots) a breakdown of one machine does not stop the field operations, because the other swarm robots continue. With large conventional equipment, the failure of one part will often stop all machine work. This research has limited scope to work on non-productive stoppage time calculation as HFH was a demonstration project. Future research could reinvestigate the associated downtime with real time data from the Global Positioning System (GPS) log file of autonomous machines.

- The field geometry algorithms used in this study is applicable for rectangular and right-angled triangular fields. Future research interested to replicate these algorithms of machines times should modify the field specifications algorithms (i.e., base area, headland area, and interior field area calculation) to apply for other field shapes (e.g., circular, trapezium, square, parallelogram, irregular, etc). The equipment specifications, other assumptions, and estimation processes would be same as used for rectangular and right-angled triangular fields.

- The economic modelling of this study was unable to answer the questions about the optimal size of swarm robots. This study considered 28 kW, 112 kW and 221 kW conventional equipment sets with human operators and 28 kW autonomous machines retrofitted for autonomy. There may be other equipment sets that may better fit, especially in small 1 ha fields. Moreover, considering smallholders farming of Asia and Africa, a range of small equipment less than 100 kW should be examined because smallholders are producing one-third of the global food (Ritchie, 2021) and confronting on-farm resource constraints (Al-Amin and

Lowenberg-DeBoer, 2021; HLPE, 2013; Lowder, Skoet and Raney, 2016) like medium and large scale farming.

- The strip cropping analysis is a preliminary approximation. To capture the within field spatio-temporal variability, economic analysis needs field trial data of yield estimates considering edge effects, machines time and inputs saving. This study only considered taller plant (corn) yield premium and small subordinate plant (soybean) yield penalty based on field data to represent edge effects. This study modelled six row strips. Future research should model row width variations and orientation effects based on field trial data.

- The yield impacts of biodiversity inclusion such as prairie strips in strip cropping systems are not available. Future research could guide precision conservation incorporating biodiverse inclusions within the fields.

- This study focused on the efficiency aspects among ten elements of agroecological farming. Other elements should be considered within a multi-objective analysis. Future research could extend the focus on rigorous agroecological mixed cropping economic modelling including agroecological principles.

- The autonomous machines costs for the US context in strip cropping system assumed that conventional machines were retrofitted for autonomy following the HFH & HFF demonstration experiences (Hands Free Hectare (HFH), 2021) as used in the study of Lowenberg-DeBoer et al. (2021). HFH&HFF costs were used because there is a lack of data on the market price autonomous systems for farm machines. Prior US study conducted by Shockley et al. (2021) also used HFH autonomous experience for their research. This study hypothesized that if this type of retrofit kit became common there would be commercially available package for any given tractor. It is assumed that when the technology is mature these retrofit kits will be "plug and play". Future research could conduct sensitivity tests considering the costs of newly developed commercial autonomous machines.

- The autonomous regenerative strip cropping practices lack livestock integration on rotational systems. A more nuanced regenerative practice must include livestock grazing and/or forage harvest for livestock feed and manure returned to the soil to achieve the five soil health principles of regenerative agriculture.

- The preliminary regenerative strip cropping research lacks recent data and Environmental Land Management (ELM) scheme details. The initial analysis considered nectar flower mix as an environmental management strategy as suggested in the Country Stewardship Scheme (CSS) and added government support as a benefit in the modelling. This subsidy benefit and other datasets only considered 2018 data to enable comparison with the whole field sole cropping study conducted by Lowenberg-DeBoer *et al.* (2021a). Future research could take the advantage of recent data and consider the requirements and subsidy of the ELM scheme that will better represent the present scenarios of Great Britain.

- What will be the impact of regenerative strip cropping practices with autonomous machines on yield patterns of plants of the same height? Some regenerative agriculture argues that with greater soil health crops are more resilient and yield less variable. This study was mainly based on ex-ante scenarios analyses due to lack of on-farm data of regenerative strip cropping practices. Future research could analyse a variety of demonstrate regenerative mixed cropping practices to better guide the agricultural transition to achieve the production and environmental goals of arable farming.

- This study did not deal with the transitional pathways from conventional equipment to autonomous machines. It is unlikely that most farmers will completely get rid of all conventional equipment in one go and start over with autonomous machines. Future research could explore the transitional period during which they maintain both conventional and autonomous machines. Similarly, the likely transition path should be investigated.

- The opportunity costs of farmers time are not considered in this study. Availability of autonomous technology will probably mean reorganization of farm enterprises. If farmers are spending less time driving machines, what will be the optimal use of that time? Will they add or expand other farm enterprises (e.g., livestock production, controlled environment horticulture, etc.)? Will they start or expand on-farm value added enterprises? Is it optimal in some cases for the farmer to seek off-farm employment?

6.3 Conclusions

Multiple emerging opportunities are hypothesized with the use of autonomous machines in open-field arable farming operations with whole field sole cropping, mixed cropping, and regenerative agriculture practices. Autonomous machines are expected to help simultaneously reconcile the production goals of productivity and profitability, and environmental goal of limiting environmental footprints of arable crop farming. Research envisaged that autonomous machines would facilitate biodiverse farming through making small, irregular fields economically profitable, that will supersede the ‘‘get big or get out’’ rule of thumb of conventional mechanization operated with human drivers.

Apart from the economies of size in small, irregular fields (i.e., irrespective of field size and shape) in whole field sole cropping system, profitable mixed cropping system to encourage agroecological farming and regenerative agriculture practice are also hypothesized with the advent of autonomous machines. However, prior economic research was unable to answer the economics implications of field size and shape, mixed cropping, and regenerative practices economics with autonomous machines. In addition to the choice of cropping systems in farm management decisions, farmers have to make farming decisions under multiple on-farm resources constraint which is really a challenge for the resource poor farmers. Challenges like labour scarcity, equipment operations timing (tractor time and combine time), climatic challenges that disrupt farming operations (i.e., good field days), cashflow, and yield penalty and premiums related to the cropping systems selection and/or timing of farm operations are among the prime drivers that constraint farm profitability. Considering the context of the UK and the US due to the availability of agronomic, economic, and technical parameters, this study provided insights on farm management decisions. This study assessed farm profitability under farm machinery alternatives such as whether to select conventional mechanization with human operators or autonomous machines in specific field and production system conditions.

To guide farm management decisions subject to binding constraints, this study used whole farm linear programming (LP) model. The selection of HFH-LP type model was rational considering the context of the UK and US because this analytical tool help farmers to maximize the gross margin measure of profit with their available on-farm resource constraints that is ignored in traditional partial budgeting. Prior research both in the UK and the US context also used HFH-LP type optimization model to answer farm management decisions.

This study contributed to the state of the arton the implications of field size and shape for the economics of autonomous machines. The study found that autonomous machines were profitable on small, irregularly shaped fields, implying the potential of preserving biodiversity and other environmental benefits. Because research already found that small, irregular fields are rich in biodiversity. The wheat production cost curves of autonomous machines and conventional machines in British context shows that autonomous machines reduced cost of production by €15/ton to €29/ton for farms with small 1 ha rectangular fields and €24/ton to €46/ton for farms with 1 ha non-rectangular fields respectively. The study also found that even with on-farm resource constraints, such as increasing wage rates and reduced labour availability, autonomous machines were a potentially profitable alternative of conventional machines with human operators.

The economic implications of this study go beyond whole field sole cropping system, to guide mixed cropping decisions. Strip cropping is considered as an example of within field mixed cropping system because strip cropping is the simplest mixed cropping even feasible with conventional mechanization with human operators, but substantial labour requirement making uneconomic to farm. This study contributed to the strip cropping literature considering the North American Corn Belt context. Results found that per annum return to operator labour, management and risk-taking (ROLMRT) was \$568.19/ha and \$162.58/ha higher for autonomous corn-soybean strip crop farms compared to whole field sole crop and conventional strip crop farm respectively. The conventional strip cropping was only profitable with a substantial amount of labour availability because the base scenario with 800 h per month labour available was unable to operate the whole farm. The optimum solution was only achieved with 1200 h per month labour availability. The findings reveal that autonomous machines have the potential to make mixed cropping within the fields economically feasible. The sensitivity scenarios of market shocks (soybean/corn price ratios), regulatory obligation (human supervision requirements) and logistics (increased field-to-field transition distance) show that autonomous strip cropping remained more profitable compared to conventional strip cropping and typical whole field sole cropping.

The strip cropping economic study was also extended considering regenerative practices to assess regenerative agriculture with similar height crop combinations typical of the UK and EU. Results of the regenerative strip cropping practices in the context of the Great Britain show that without considering any yield increases and input savings, the ROLMRT was £71,974 for autonomous regenerative strip cropping practice which is £57,760 higher than whole field sole cropping and £25,596 higher than conventional regenerative strip cropping. The modest increases in yield or reductions in variable costs due to lower crop protection expenses would make the autonomous regenerative practice even more economically competitive compared to conventional farming practices.

The profitability of autonomous machines for commodity crop production, irrespective of field size and shape, within field strip cropping system, and regenerative strip cropping practices implies that autonomous machines could provide win-win farming solutions. Autonomous machines could ensure a profitable approach to restore and improve within-field biodiversity, and to increase ecosystem services that may facilitate the net zero target and precision conservation in arable crop farming.

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Appendix A

Supplementary materials for: Economics of field size and shape for autonomous crop machines

Supplementary Materials Encompass:

(i) Supplementary Text (i.e.., STEXTT Supplementary Text, which includes Main Text of the Technical Note).

(ii) Algorithms Spreadsheets (i.e., SM1 Rectangular Field Algorithms and SM2 Non-Rectangular Field Algorithms (i.e., Right-Angled Triangular Field))

(iii) Supplementary Figures (i.e., SFs Sensitivity Tests Figure, which includes Figures of the Sensitivity Tests).

Appendix A (i): Supplementary Text (i.e.., STEXTT Supplementary Text, which includes Main Text of the Technical Note)

A TECHNICAL NOTE ON AN ALGORITHM TO ESTIMATE FIELD TIMES AND FIELD EFFICIENCY

Farm machinery performance evaluation has received substantial attention for the management of the arable crop farm and improvement of crop equipment operations (Bochtis *et al.*, 2010; Sørensen and Nielsen, 2005). The development of Information and Communication Technology (ICT) systems accelerates the interest of maximizing operational efficiency (Grisso *et al.*, 2002b; Grisso *et al.*, 2004; Bochtis *et al.*, 2010) and studies have suggested the shift from large conventional technology to autonomous machines for better performance, management and economic feasibility (Blackmore *et al.*, 2005; Lowenberg-DeBoer *et al.*, 2021a; Shockley, Dillon and Shearer, 2019). To date, most of the research on autonomous machines concentrated on the technical feasibility of robotic systems (Duckett *et al.*, 2018; Shamshiri *et al.*, 2018). Very few production economics studies in arable robotic operations mentioned the significance of field performance, for instance, in automated (i.e., still required human operator) field operations, Clary *et al.* (2007) and Cembali *et al.* (2008) commented on the operational efficiency. Likewise, Sørensen, Madsen and Jacobsen (2005) mentioned that efficiency is the critical prerequisite for improved profitability and assumed 80% efficiency for autonomous robotic weeding. Using the experience of the Hands Free Hectare (HFH) demonstration project at Harper Adams University, UK, Lowenberg-DeBoer *et al.* (2021a) hypothesized that autonomous machines are more economical on small fields. They assumed constant 70% field efficiency for all operations and equipment sets based on the discussion of Witney (1988). However, the economic viability of autonomous crop machines over the range of field sizes and shapes has not been tested.

The existing conventional equipment and precision agriculture literature mainly developed models for predicting machinery performance (Sørensen, 2003; Sørensen and Nielsen, 2005; Jin and Tang, 2010; Fedrizzi *et al.*, 2019) and evaluated the field efficiency in farm operation (Taylor, Schrock and Staggenborg, 2001; Grisso, Jasa and Rolofson, 2002a; Taylor, Schrock and Staggenborg, 2002; Grisso *et al.*, 2004; Bochtis *et al.*, 2010; Spekken and de Bruin, 2013). Nevertheless, the evaluation of field efficiency and field times of autonomous machines and the economic implications of field size and shape are still unexplored. To fill this research gap, the present study investigated the economic viability of autonomous machines in commodity crop production through the lens of machinery performance with a reference to different sized and shaped fields.

Considering the experiences of the HFH demonstration project, the study developed algorithms to estimate field times (h/ha) and field efficiency (%) for different sized rectangular and non-rectangular fields (i.e., right-angled triangular fields). The algorithms were adopted and modified following the study of Bochtis *et al.* (2010), Jin and Tang (2010), Shamshiri *et al.* (2013), Fedrizzi *et al.* (2019), Lowenberg-DeBoer *et al.* (2021a) and the discussion of Witney (1988). The developed algorithms went beyond the existing studies as the present study used systems analysis from planting to harvesting that incorporated HFH on-field level demonstration experiences, field sizes and shapes, machine specifications, overlap consideration, headlands timing, interior passes timing, inputs refill timing, fuel refill timing, and field entry and exit time estimation.

The algorithms were developed considering the flexibility of future implications that would be applicable for any kinds of arable machines operated in different sized rectangular and non-rectangular fields. Keeping the research gaps in mind, the present study gave emphasis in the headlands and interior field time calculation as prior studies considered headlands passes and headlands turning as non-productive areas (Gónzalez, Marey and Álvarez, 2007; Bochtis *et al.*, 2010). However, based on the experience of the HFH project, despite having lower yields compared to the rest of the field due to the compaction of soil and damage from machines turning, the headland is considered as a productive area. In addition, previous studies missed out pass to pass overlap (i.e., overlap percentage) in field efficiency estimation (Lowenberg-DeBoer *et al.*, 2019). The study of Lowenberg-DeBoer (1999); Griffin, Lambert and Lowenberg-DeBoer, (2005) and Ortiz *et al.* (2013) assumed 10% overlap as the benchmark.

Another contribution of the algorithms is that the present study addressed the limitations of earlier studies and incorporated their suggestions. Prior studies suggested that in field efficiency estimation, future studies should separately calculate the headlands turning time, and stoppages time (Taylor, Schrock and Staggenborg, 2001; Taylor, Schrock and Staggenborg, 2002; Bochtis *et al.*, 2010; Shamshiri *et al.*, 2013) 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). Considering the significance of headlands turning types, field size and shape (for details see Jin and Tang, 2010 and Fedrizzi *et al.*, 2019), the study incorporated the headlands turning pattern of the HFH demonstration project. In summary, in developing the algorithms, the present study incorporated field and machine specifications, overlap percentage, productive times (i.e., field passes time, headlands turning time, and headlands passes time) and non-productive times (i.e., replenish inputs, refuelling, and

blockages) for calculating the field efficiency of autonomous machines and conventional technologies with human operators for different sized and shaped fields.
Although logistics software is well developed in trucking and other transportation sectors (Software Advice, 2021), there is no readily available commercial software in the UK to estimate equipment times and field efficiency encompassing field and machine heterogeneity. Field times were sometimes generated as a by-product in the farm equipment path planning research literature (Hameed, 2014; Jensen *et al.*, 2012; Oksanen and Visala, 2007; Spekken and de Bruin, 2013). The agri-tech economic studies often rely on text book (Lowenberg-DeBoer *et al.* 2021a). For easy use of the algorithms by the students and researchers, especially those who are involved in the Agri-Tech Economics, the study developed algorithms in Excel spreadsheets. These algorithms could be further use for developing software and mobile app.

The technical note is organized with one section on the algorithms for the rectangular field and another section focused on the non-rectangular (i.e., right-angled triangular) field. The common assumptions and parameters used are as follows:

Assumptions and parameters used

The study assumed that the equipment enters the field from the entry side and completed the headlands first, after which the machine made usual flat turn to start the interior passes. The equipment ends on the entry side of the field, even if it is operating a partial swath or not at all on the return.

The field and HFH equipment specifications were collected from the experience of the HFH demonstration project at Harper Adams University, Newport, Shropshire, UK. HFH conventional machine with human operator and HFH autonomous machines are identical except for the autonomy hardware and software. The specifications of conventional machines were collected from Lowenberg-DeBoer *et al.* (2021a), John Deere (https://www.deere.co.uk/en/index.html), Arslan *et al.* (2014), and Witney (1988). The parameters used and parameter definitions to calibrate the algorithms are presented in Table A.1 and Table A.2.

ALGORITHMS TO ESTIMATE FIELD TIMES AND FIELD EFFICIENCY FOR RECTANGULAR FIELD

Estimation of field times and field efficiency

The algorithms used for estimating field times (h/ha) and field efficiency (%) for different sized rectangular fields are sub divided in the following sections:

1) The first section incorporated the main parameters and base calculations, which encompassed field and equipment specifications (for details see Table A.1 and algorithms presented in excel spreadsheet in Supplementary Material i.e., SM1 Rectangular Field Algorithms).
2) Secondly, the algorithms incorporated the headland area and field time calculation.
3) Thirdly, interior field and passes time were estimated.
4) Fourthly, non-productive time calculations were performed that incorporated headland and interior field input refill time, fuel refill time, and blockages times. By summing the input and fuel refilling time and blockages the total non-productive time (i.e., total stoppages times) were calculated.
5) Fifthly, the algorithms estimated the total field operation time.
6) Sixthly, the theoretical field time was calculated based on the machine design specifications, and
7) Finally, field efficiency was estimated as the ratio of theoretical field time based on machine design specifications like the estimates of theoretical field time to its actual field productivity.

1. Main parameters and base calculations

Field attributes calculation

The study tested the algorithms for 1ha, 10ha, 20ha, 50ha, 75ha, and 100ha rectangular fields (where, 1 ha = 10,000 m^2) equipped with 28 kW conventional machines with human operator and autonomous machines, and 112 kW and 221 kW conventional machines with human operators. Details of the field specifications are given in Table A.1 and Supplementary Material (i.e., SM1 Rectangular Field Algorithms). The study assumed that length of the field is ten times the width of the field. Following this assumption, the width of the rectangular field was estimated as the square root of the area divided by ten:

$$W_f = Sqrt\ (A/10) \ldots \ \ldots (1)$$

where, W_f is the width of the field, and A is the area of the field.

Subsequently, the length of the rectangular field was calculated as:

$L_f = 10 * W_f \ldots \ \ldots$ (2)

where, L_f is the length of the field.

The equipment specifications are evident in the Table A.1 (for further details see the algorithms in the excel spreadsheet in Supplementary Material i.e., SM1 Rectangular Field Algorithms). The effective swath width of the implement was calculated as the width of the implement multiplied by one hundred minus overlap percentage:

$W_s = W_m * ((100 - Overlap\ percentage)/100) \ldots \ \ldots$ (3)

where, W_s is the effective swath width, and W_m is the width of the implement. For all operations and equipment sets this study assumed a 10% overlap percentage following Lowenberg-DeBoer *et al.* (2021a).

The total number of passes around the headlands for a rectangular field was calculated as the width of the headland divided by the effective swath width of the implement:

$N_{hp} = \lceil W_h/W_S \rceil \ \ldots \ \ldots$ (4)

where, N_{hp} is the total number of passes around the headland to the nearest positive integer.

This algorithm ensures that the headland width allows operation of all equipment sets, and W_h is the width of the headland (i.e., the study assumed headland width equals the effective swath width of the sprayer as the sprayer width was the largest implement among drilling, spraying, and harvesting operations).

2. Headlands area and field time calculation

Time for the headland round was calculated as the sum of the length and width of the field, minus the width of the previous headland rounds in four sides of the field, minus the square corner distance of four corners of the rectangular field, which is divided by the implement running speed in the passes, and plus the four corners distances that is divided by the turning speed of the implement. The turning speed of the implement was one third of the implement running speed in the passes. Thousands were used to convert speed from km/h to m/h. The study used the following algorithm to calculate headlands round time:

$$\mathrm{T_{hi}} = \begin{cases} (((L_f + Wf) - (n_{hi} - 1) * 4 * \mathrm{W_S}) - ((2 * \mathrm{r}) + (0.5 * 2 * \mathrm{W_s})) * 2) * 2/(1000 * v_p) \\ \qquad + (\mathrm{r} * \pi/2) * 4/(1000 * v_t)\ ; n_{hi} \le N_{hp} \\ 0;\ n_{hi} > N_{hp} \end{cases}$$

… … (5)

where, T_{hi} is the time required for the headland round (i = 1, 2, … …, 9), n_{hi} is the number of rounds required for the headland operation (i. e., n_{hi} =1, 2, … …, 9), *r* is the turning radius of the implement, v_p is the implement running speed in the passes, and v_t is the implement turning speed. When the number of passes is less than or equal to the total number of headlands passes, the first term is half the perimeter of the field. It is multiplied by 2 (the 2 just before the first slash) to give the whole perimeter. In the first headland round the machine travels a path that is half a swath width inside the perimeter; this is why $(0.5 * 2 * \mathrm{W_s})$ is deducted. For each headland round after the first another four swath widths are deducted in each half perimeter (i.e., $(n_{hi} - 1) * 4 * \mathrm{W_S}$); one on each side of the field width and one on each side of the field length. The corner turn distance is as the turning speed and in estimated in the second term which is four quarter turns in a half field perimeter $(i.e., (\mathrm{r} * \pi/2) * 4)$. To avoid double counting two radius lengths are deducted from the first term at pass speed (i.e., 2*r). To allow for deceleration and acceleration before and after the corner a second swath width is deducted $(0.5 * 2 * \mathrm{W_s})$.

After completing the headlands first, the machine entered the interior field (i.e., refers to the field excluding width of the headlands on all four-sides). The time from headland to the first interior pass was calculated following the experience of the HFH demonstration project and the study adopted and modified the typical "Flat" turn of Jin and Tang (2010) as follows:

$$\mathrm{T_{hturn}} = (\mathrm{W_s} * (1 + \mathrm{n} + \mathrm{Cot}\delta)) + (\mathrm{r} * (\pi - 2)) / (1000 * v_t) \ldots \ldots (6)$$

where, T_{hturn} is the turning time from headland to first interior pass, *n* is the number of swaths skipped during turning, and δ is the swath direction in radians. The Jin and Tang (2010) equation is modified by including the "n" which is the linear distance along the headland when swaths are skipped before resuming the next pass. Skipping swaths is required for flat turns when the turning radius exceeds the swath width. The $\mathrm{W_s}$*Cot δ term is used to estimate the extra distance travelled when the headlands are not exactly perpendicular to the passes.

The total time in the headlands rounds was estimated as the summation of all headlands round times and the turning time from headland to first interior pass as follows:

$T_h == \sum_i^9 T_{hi} + T_{hturn} \dots \dots (7)$

where, T_h is the total time in the headland rounds.

The area of the headland of the field was calculated as follows:

$A_{hf} = A - (L_{if} * W_{if}) \dots \dots (8)$

where, A_{hf} is the area of the headland, L_{if} is the length of the interior field, and W_{if} is the width of the interior field.

3. Interior field and passes time calculation

Interior field refers to the field excluding the four-sided widths of the headland. The length of the interior field was calculated as the length of the field minus the two sides headlands width of the field:

$$L_{if} = \begin{cases} (L_f - 2 * W_h);\ W_{if} \geq W_s \\ 0;\ W_{if} < W_s \end{cases} \dots \dots (9)$$

The width of the interior field was calculated as the width of the field minus the two sides headlands width of the field as follows:

$$W_{if} = \begin{cases} \left(W_f - 2 * W_h\right);\ (W_f - 2 * W_h) > 0 \\ 0; \left(W_f - 2 * W_h\right) \leq 0 \end{cases} \dots \dots (10)$$

The area of the interior field was estimated as the length of the interior field multiplied by the width of the interior field:

$A_{if} = L_{if} * W_{if} \dots \dots (11)$

where, A_{if} is the area of the interior field.

For rectangular field, the number of interior headland turn was estimated by dividing the width of the interior field parallel to which the interior turns take place by the effective swath width as follows:

$$N = \begin{cases} \lceil W_{if}/W_s \rceil;\ \lceil W_{if}/W_s \rceil > 0 \\ 0;\ \lceil W_{if}/W_s \rceil \leq 0 \end{cases} \dots \dots (12)$$

where, N is the total number of interior headlands turn. This algorithm ensures that the headland width allows operation of all equipment sets.

The total number of interior passes of the field must be even to bring the machine back to the entry side of the field. Consequently, it was estimated as the total number of interior headlands if even and total number plus one if odd.

$$N_P = \begin{cases} N+1; N = ODD \\ N; N = EVEN \end{cases} \ldots \ \ldots (13)$$

where, N_P is the total number of interior passes. The conditional algorithm is used to ensure field entry and exit in the same path.

The total time in the interior field passes was calculated by multiplying the length of an interior field pass with the total number of interior field passes which is divided by the running speed of the implement in the passes and one thousand is divided to reach in the unitary of the units used:

$$T_p = (N_P * L_{if}) \,/\, (1000 * v_p) \ldots \ \ldots (14)$$

where, T_p is the total time in the interior field passes.

In field efficiency calculation, the headland turning time is considered with greater importance (Witney, 1988; Grisso *et al.*, 2002b; Gónzalez, Marey and Álvarez, 2007; Bochtis *et al.*, 2010; Jin and Tang, 2010). Even though, prior studies considered headlands as non-productive area (Witney, 1988; Gonzalez, Alvarez and Crecente, 2004; Gónzalez, Marey and Álvarez, 2007; Bochtis *et al.*, 2010), the study treated headland as useful area based on the HFH demonstration experience. The methodology of headland turning time was adopted and modified from the study of Jin and Tang (2010) and Fedrizzi *et al.* (2019). The study of Jin and Tang (2010) considered several turning types (i.e., “Flat” turn, “U” turn, “Bulb” turn, “Hook” turn). The study modified their algorithm following the HFH demonstration project, which always follow the “Flat” turn, unlike the “Flat” turn of Jin and Tang (2010) as HFH equipment skipped swaths. The autonomous machinery operations of HFH followed the “Flat” turn with skipping of swaths (i.e., during headlands turning the machine skipped two swaths nearer and enter the field after skipping those swaths) (for typical “flat turn” see Jin and Tang 2010 and for HFH “flat turn” see Figure 3.1 and Figure 3.2 in the main manuscript). With the experience of the HFH demonstration project, the turning time for “flat” turn goes beyond the calculation of Jin and Tang (2010) and was calculated as:

$$\mathrm{T_{turn}} = ((\mathrm{W_s} * (1 + \mathrm{n} + \mathrm{Cot}\delta)) + (\mathrm{r} * (\pi - 2)) \,/\, (1000 * v_h) \ \ldots \ \ldots (15)$$

where, T_{turn} is the interior headland turning time.

The total interior headlands turning time of the field was estimated by multiplying the number of interior headlands turn with the interior headlands turning time as follows:

$T_r = \mathrm{N} * T_{turn}$ … … (16)

where, T_r is the total interior headlands turning time.

The distance to field entry and exit assumes that after the last pass (and returning to the entry side of the field if the number of passes in odd) the machine ends up at the far side of the interior field relative to the entry. The distance from the far side is assumed to be a diagonal line across the headland to the entry in the corner. Using the Pythagorean theorem that distance is the square root of the square of the headland width plus the square of the field width minus the headland width. To calculate the total time for field entry and exit passes these square distances of field entry and exit were divided by the implement turning speed. The algorithm of the total time for field entry and exit passes was as follows:

$T_{fe} = \sqrt{((W_h)^2 + (W_f - W_h)^2)} / (1000 * v_t)$ … … (17)

where, T_{fe} is the total time for field entry and exit passes.

The total observed time in the interior field and passes (T_{obs}) incorporated the total time in the interior field passes (T_p), the total time in the interior headlands turning (T_r), and total time for field entry and exit passes (T_{fe}) as follows:

$T_{obs} = T_p + T_r + T_{fe}$ … … (18)

4. Non-productive times calculation

The non-productive time is another important factor associated with field times and field efficiency estimation. In this study, non-productive time encompassed replenishing inputs, blockage, and refueling. The algorithms for estimating non-productive times are as follows:

Headland and interior field input refill time calculation

Input required for the interior field was calculated as multiplication of the seeding rate per ha to the area of the interior field as follows:

$IR_{if} = (Q_s * A_{if})/10000$ … … (19)

where, IR_{if} is the input required for the interior field, and Q_s is the seeding rate per ha.

Input required for the headlands was calculated as multiplication of the seeding rate per ha to the area of the headland of the field:

$IR_h = (Q_s * A_{hf})/10000 \ldots \quad \ldots$ (20)

where, IR_h is the input required for the headland.

Input required for the headland and interior fields was calculated by summing the input required for the interior field and input required for the headland as follows:

$IR_{hif} = IR_{if} + IR_{hf} \ldots \quad \ldots$ (21)

where, IR_{hif} is the input required for the headland and interior field.

Number of refills needed within the field was estimated as dividing the input required for the headland and interior field to the capacity of the bin minus one. Because the study assumed that the equipment entered the field and started operation with a full bin of seed, consequently, the number of refills needed "within" the field would be less than the total number of refills needed to complete the field operation.

$NRN_f = \lceil \lfloor ((IR_{hif}/C_b) - 1) \rfloor \rceil \ldots \quad \ldots$ (22)

where, NRN_f is the number of refills needed "within" the field, C_b is the capacity of the bin. This algorithm used $\mathrm{ROUNDDOWN}$ or $\mathrm{ROUNDUP}$ represented with $\lceil\lfloor \quad \rfloor\rceil$, which allows all operations with all equipment sets. ROUNDDOWN is used based on the consideration of the capacity of the bin (i.e., if the sum of the input requirement is less than the bin capacity). However, if the sum of the input requirement is greater than the capacity of the bin, the study used ROUNDUP to avoid equipment running with empty bin and ensure seed in the bin.

Total stoppage time for input refill was estimated by multiplying the number of refills needed "within" the field with the stoppage time for a single input refill which is divided by 60 considering unitary of the units used in hour:

$T_{sir} = (T_{ssir}/60) * NRN_f \ldots \quad \ldots$ (23)

where, T_{sir} is the total stoppage time for input refill, T_{ssir} is the stoppage time for a single input refill.

Headland and interior field fuel refill time calculation

The headland and interior field fuel refill time followed the same estimation procedures mentioned in the above equation (19), (20), (21), (22), and (23). In this case, for estimating the fuel required for the interior field and headland, the fuel consumption rate per ha (Q_f) was used. Likewise, to calculate the number of refills needed "within" the field the capacity of the fuel tank (C_t) was considered. Finally, using the same algorithms of stoppage time calculation the total stoppages time for fuel refill (T_{sfr}) was calculated, where the stoppage time for single fuel refill (T_{ssfr}) was considered.

Blockages time calculation

They study assumed zero blockage time because of lack of clear data from the HFH demonstration project.

Total stoppages time calculation

The total stoppages time "within" the field is the summation of the total stoppages time for input refill (T_{sir}), total stoppage time for blockage (T_{sb}), and total stoppages time for fuel refill (T_{sfr}) that was calculated as:

$$T_{sf} = T_{sir} + T_{sb} + T_{sfr} \ \ldots\ \ldots (24)$$

where, T_{sf} is the total stoppages time "within" the field.

5. Total field operation time calculation

The total time for field operation was calculated as the summation of the total observed time in the interior field and passes (T_{obs}), total headland round time (T_h), and the total stoppages time in the field (T_{sf}):

$$T_{tfo} = T_{obs} + T_h + T_{sf} \ \ldots\ \ldots (25)$$

where, T_{tfo} is the total time for field operation.

Total time for field operation per hectare was estimated as the ratio of the total time for field operation by the area of the field in hectare.

$$T_{tfoha} = T_{tfo}/A \ \ldots\ \ldots (26)$$

where, T_{tfoha} is the total time for field operation per hectare.

6. Theoretical field time calculation

The theoretical field time was measured based on the machine design specifications. The study followed Lowenberg-DeBoer *et al.* (2021a) to estimate theoretical field time as follows:

$T_T = [\mathrm{A} / (W_{Ts} * v_p * 1000)] \ldots \ldots$ (27)

where, T_T is the theoretical field time, and W_{Ts} is the theoretical swath width.

Theoretical field time per hectare was estimated as the ratio of the theoretical field time divided by the field area in hectare.

$T_{Tha} = T_T / A \ldots \ \ldots$ (28)

where, T_{Tha} is the theoretical field time per hectare.

7. Field efficiency calculation

The study calculated field efficiency, following the estimation procedure of Lowenberg-DeBoer *et al.* (2021a), Bochtis *et al.* (2010), and Shamshiri *et al.* (2013). In the present study, field efficiency is defined as the ratio of theoretical field time based on machine design specifications like the estimates of theoretical field time to its actual field productivity:

$E_f = [T_T / (T_{obs} + \mathrm{T_h} + \mathrm{T_{sf}})] * 100 \ \ldots \ \ldots$ (29)

where, E_f is the field efficiency, T_T is the theoretical field time, $\mathrm{T_{obs}}$ is the total observed time in the interior field and passes, T_h is the total headland round time, and T_{sf} total stoppages time “within” in the field. Simply the above field efficiency algorithm can be represented as: T_{tfoha}/T_{Tha} (see the algorithms in the excel spreadsheet in Supplementary Material i.e., SM1 Rectangular Field Algorithms).

ALGORITHMS TO ESTIMATE FIELD TIMES AND FIELD EFFICIENCY FOR RIGHT-ANGLED TRIANGULAR FIELD

Estimation of field times and field efficiency

The algorithms used for estimating the field times (h/ha) and field efficiency (%) for different sized non-rectangular (i.e., right-angled triangular) fields are also sub divided in seven sub-sections similar to the rectangular field algorithms. Details of the algorithms are as follows:

1. **Main parameters and base calculations**

Field attributes calculation

To test the algorithms, the study used 1 ha, 10 ha, 20 ha, and 25 ha sized right-angled triangular fields equipped with the same equipment sets used in rectangular fields. Details of the field specifications are given in Table A.1 and Supplementary Material (i.e., SM2 Non-Rectangular Field Algorithms). The study assumed that each field has the height equalling twice the base. Following this assumption, the adjacent base of the right-angled triangular field was calculated as the square root of the area:

$Ab_f = Sqrt\ A \ldots\ \ldots$ (1)
where, Ab_f is the adjacent base of the field.

As the study assumed that height equalling twice the base, the opposite height of the triangular field was calculated as:

$Oh_f\ =\ 2 * Ab_f \ldots\ \ldots$ (2)
where, Oh_f is the opposite height of the field.

Following the Pythagorean theorem, or Pythagoras' theorem, the hypotenuse of the right-angled triangular field was calculated as:

$Hyp_f = Sqrt\ ((Oh_f)^2 + (Ab_f)^2) \ldots\ \ldots$ (3)
where, Hyp_f is the hypotenuse of the field.

Right angle of the triangle was calculated as:

$\theta\ =\ \mathrm{Degrees}\ ((\mathrm{PI}()/2)\ =\ \mathrm{Radians}\ (\mathrm{Degrees}) \ldots\ \ldots$ (4)
where, θ is the right angle of the right-angled triangular field. During the calculation of angles, to ensure naturalness in mathematics, trigonometric arcs relationship, and have

more elegant formulation of a number, the degrees (º) were converted to radian (rad) considering the International Systems of Units.

Second largest angle of the right-angled triangular field was estimated using the sine trigonometric function of an angle, where sine is the ratio of the opposite height to the hypotenuse:

$\varphi = \text{Degrees}\ (\text{Asin}\ (Oh_f / Hyp_f)) = \text{Radians}\ (\text{Degrees}) \ldots\ \ldots$ (5)
where, φ is the second largest angle.

Smallest angle of the right-angled triangular field was estimated using the sine trigonometric function of an angle:

$\mu = \text{Degrees}\ (\text{Asin}\ (Ab_f / Hyp_f) = \text{Radians}\ (\text{Degrees}) \ldots\ \ldots$ (6)
where, μ is the smallest angle.

In case of right-angled triangular fields, the study assumed same algorithms similar to rectangular field to calculate effective swath width (W_s) and the total number of passes around the headland (N_{hp}). For details of the equipment specifications and estimation see Table A.1 and Supplementary Material (i.e., SM2 Non-Rectangular Field Algorithms).

2. Headlands area and field time calculation

Time for the headland round was calculated as the sum of the opposite height, adjacent base, and hypotenuse of the right-angled triangular field, minus the width of the previous headland rounds in three sides, minus the square corner distance of the three corners of the right-angled triangular field, which is divided by the implement running speed in the passes, and plus the three corners distances that is divided by the implement turning speed. When the number of passes is less than or equal to the total number of headland passes, the first term is the perimeter of the field. The corner estimates are multiplied by 3 which is before the first slash to give the whole perimeter. In the first headland round the machine travels a path that is half a swath width inside the perimeter; this is why $(0.5 * 2 * \mathrm{W_s})$ is deducted. For each headland round after the first another three swath widths are deducted in each half perimeter (i.e., $(n_{hi} - 1) * 3 * \mathrm{W_S}$); on the opposite height, adjacent base, and hypotenuse of the right-angled triangular field. To avoid double counting two radius lengths are deducted from the first term at pass speed (i.e., 2*r). The study used the following algorithm to calculate headlands round time:

$$T_{hi} = \begin{cases} ((Oh_f + Ab_f + Hyp_f) - (n_{hi} - 1) * 3 * \mathrm{W_S}) - ((2 * \mathrm{r}) + (0.5 * 2 * \mathrm{W_s}))) * 3/(1000 * v_p) \\ +((\mathrm{r} * \theta) + (\mathrm{r} * \varphi) + (\mathrm{r} * \mu))/(1000 * v_t); n_{hi} \le N_{hp} \\ 0; n_{hi} \le N_{hp} \end{cases}$$

… … (7)

After completing the headlands first, the machine entered in the interior field. The time from headland to the first interior pass ($\mathrm{T_{hturn}}$) and the total time in the headland rounds (T_h) was calculated following the same algorithm described in rectangular field algorithm section.

The area of the headland was calculated as follows:

$A_{hf} = A - (0.5 * A_{bif} * Oh_{if})$ … … (8)

where, A_{hf} is the area of the headland, Ab_{if} is the adjacent base of the interior field, and Oh_{if} is the opposite height of the interior field.

3. Interior field and passes time calculation

For right-angled triangular field, interior field refers to the field excluding three-sided width of the headlands. The adjacent base of the interior field indicated the whole adjacent base of the external field minus the headland width on the right-angled corner side minus the horizontal widths across the diagonal headland that was represented by sine function of an angle and minus the horizontal width in the headland corner which was represented by the tangent function of an angle. The sine is the ratio of the opposite height to the hypotenuse and the tangent is the ratio of the opposite height to the adjacent base. The adjacent base of the interior triangular field was estimated as follows:

$Ab_{if} = Ab_f - W_h - (W_h/\mathrm{Sin}(\varphi)) - (W_h/\mathrm{Tan}(\varphi))$… … (9)

where, Ab_f is the adjacent base of the field, W_h is the width of the headland, and φ is the second largest angle.

Projection of the width of the headland on the hypotenuse that is close to the smallest angle of the right-angled triangular field was calculated as the ratio of the width of the headland to the cos trigonometric function of an angle, where cos is the ratio of the adjacent base to the hypotenuse:

$P_{Whhyp} = W_h/\mathrm{Cos}(\varphi)$… … (10)

where, P_{Whhyp} is the projection of the width of the headland on the hypotenuse.

Opposite height of the interior triangular field is the opposite height of the field minus the projected width of the headland on the hypotenuse minus width of the headland, minus the ratio of the width of the headland to the tan trigonometric function of the smallest angle was estimated as:

$$Oh_{if} = Oh_f - P_{Whhyp} - W_h - ((W_h/\mathrm{Tan}(\mu)) \ldots \ldots (11)$$

The number of interior headlands turn that were taken parallel to the adjacent base and the hypotenuse of the external field was estimated as follows:

$$N = \lceil (Ab_{if}/W_s - 1, 0) \rceil \ \ldots \ldots (12)$$

where, N is the total number of interior headlands turn, W_s is the effective swath width. This algorithm ensures that the headland width allows operation of all equipment sets.

The total number of interior passes (N_p) was calculated following the same process described in the rectangular field algorithm section (for further details see the Supplementary Material i.e., SM2 Non-Rectangular Field Algorithms).

To calculate the length of the interior field passes, the study subtracted half of the effective swath width from the adjacent base of the interior triangular field minus the width of the previous headland rounds and multiply this with the tangent function of the second largest angle. The length of the interior field passes was calculated as:

$$l_{pi} = \begin{cases} \mathrm{ABS}((Ab_{if} - W_S/2) - ((n_{hi} - 1) * W_S) * \mathrm{Tan}\ (\varphi), 0);\ n_{pi} \leq N_p \\ 0;\ n_{pi} > N_p \end{cases} \ \ldots \ \ldots \quad (13)$$

where, l_{pi} is the length of the interior field passes (i = 1, 2, … …, 361), n_{pi} is number of passes in the interior field operation (i. e., n_{pi} =1, 2, … …, 361), N_p is the total number of interior field passes, and ABS is used for absolute value function as the study assumed that the equipment ends on the entry side of the field, even if the equipment is operating in the small end passes (i.e., to deal with the negative distance in case of tiny end passes).

The total length of the interior field passes was estimated as the summation of the length of all interior field passes as follows:

$$L_p = \sum l_{pi} \ \ldots \ \ldots (14)$$

where, L_p is the total length of the interior passes.

The total time in the interior field passes was calculated by dividing the total length of the interior field passes to the running speed of the implement in the passes as follows:

T_p = $\sum L_P$/(1000*V_p) … … (15)

For interior headlands turning time (T_{turn}) and total interior headlands turning time (T_r) calculation, the study used the same algorithms described in the rectangular field algorithms section.

Width of the headland with the second largest angle was calculated as follows, where the adjacent base of the interior triangular field and the headland width on the right-angled corner side was subtracted from the adjacent base of the exterior field:
W_{h2ndlc} = Ab_f - Ab_{if} - W_h … … (16)
where, W_{h2ndlc} is the width of the headland on the second largest corner.

The distance for field entry and exit encompassed the square of the travel distance of the headland width on the right-angled corner side and the headland width on the second largest corner side plus these square corner headlands widths were subtracted from the square of the adjacent base of the external field. To calculate the total time for field entry and exit, these square distances of field entry and exit were divided by the implement turning speed. The algorithm of the total time for field entry and exit passes was as follows:
$T_{fe} = \text{Sqrt}\,((W_h + W_{h2ndlc})^2 + (Ab_f - (W_h + W_{h2ndla}))^2/(1000 * v_t)$ … … (17)

The total observed time in the field and passes (T_{obs}) was calculated using the same procedure described in the rectangular algorithm section.

4. Non-productive times calculation

The non-productive time encompassed replenishing inputs, blockage, and refueling.

Input required for the interior field (IR_{if}) was calculated as multiplication of the seeding rate per ha (Q_s) with the total length of the interior passes (L_p) and effective swath width (W_s) as follows:

$IR_{if} = (Q_s * L_p * W_s)/10000$ … … (18)

The rest of the calculation such as input required for the headlands (IR_h), input required for the headland and interior fields (IR_{hif}), number of refills needed within the field (NRN_f), and time stoppage for input refill (T_{sir}) followed the same estimation procedures mentioned in the rectangular algorithms' sections.

For the calculation of headland and interior field fuel refill time and total stoppages time (T_{sf}) the study used the same procedure described above and in the rectangular algorithms section.

For estimating other sub-sections (5, 6, and 7) which encompass the calculation of total time for field operation (T_{tfo}), theoretical field time (T_T), and estimation of field efficiency (E_f), the study followed the same estimation procedures described earlier in rectangular algorithms sections (for details see excel spreadsheet in the Supplementary Material i.e., SM2 Non-Rectangular Field Algorithms).

Validation of field efficiency estimation

Even though field efficiencies are not constant values that may vary for specific equipment and depends on various factors (Bochtis *et al.*, 2010; Hunt, 2001), to validate the algorithms, the study provides the following field efficiency comparison as shown in Table A.3. The field efficiency estimation is justifiable based on the comparison of Witney (1988) and Hunt (2001). The estimates available in the literature are few decades earlier and unable to address field and equipment heterogeneity, whereas the present study provides the recent experience of field efficiency considering field and equipment heterogeneity. Future attempts should be made to validate with on-field estimation of autonomous machines and conventional machines with human operators. Because the Hands Free Hectare (HFH) was a demonstration project, it was difficult to separate on-field stops and down time while the engineers tinkered from those stoppage that would have occurred in normal field operations. Consequently, the model parameters were based on published machine specifications and farm budget information and guided the experience of the HFH project demonstrated at Harper Adams University, Newport, Shropshire, UK.

Conclusions

Field efficiency maximization is an important consideration in arable field operations. The study developed algorithms for estimating field times (h/ha) and field efficiency (%) of different sized and shaped rectangular and non-rectangular (i.e., right-angled triangular) fields equipped with autonomous machines and conventional machines with human operators. The ultimate objective of the study was to examine the economics of autonomous machines subject to field size and shape with the lens of field efficiency and field times. The study is the first attempt in the development of algorithms for autonomous and conventional machine for arable field operations from planting to harvesting. The calculated field efficiencies were used to estimate the equipment times that were used as an input for estimating the coefficient of labour, tractor, and combine used for Hands Free Hectare - Linear Programming (HFH-LP) model. The coefficient estimation format is available in the supplementary material of Lowenberg-DeBoer *et al.* (2021a), namely field operations and equipment times by crop, month and equipment set of optimum yields. The assessment of the economic implications will guide the farmers, engineers, agribusinesses, and policy makers for further development of the technology, decision making for farm management and machinery selection with the existing farm resource constraints.

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Table A.1: Assumptions of parameters used in the field size algorithms.

Operations	Equipment*	Width of the implement	Interior field speed	Turning speed	Turning radius	Overlap percentage	Input application rate	Bin capacity	Fill time	Fuel consumption rate	Tank capacity	Fill time	Effective swath width	Swath skipped	Width of the headland	Area
	Equipment specifications**										Field specifications***					
	Unit	m	km/h	km/h	m	%	kg/ha	kg	min.	L/ha	L	min.	m	No.	m	m^2
Drilling	HFH	1.5	3.25	1.0833	3.7	10	140	180	10	4	35	10	1.35	2	6.3	*Rectangular Fields*: 10000; 100000; 200000; 500000; 750000; 1000000. *Right-angled Triangular Fields*: 10000; 100000; 200000; 250000.
	Large Conventional	6	5	1.6667	7	10	140	3000	20	8.82	463	20	5.4	0	32.4	
	Small Conventional	3	5	1.6667	4.35	10	140	2000	15	8.82	175	15	2.7	0	21.6	
Spraying	HFH	7	5	1.6667	3.7	10	200	1000	10	4	35	10	6.3	0	6.3	
	Large Conventional	36	10	3.3333	7	10	200	5000	20	8.82	463	20	32.4	0	32.4	
	Small Conventional	24	10	3.3333	4.35	10	200	2000	15	8.82	175	15	21.6	0	21.6	
Harvesting	HFH	2	3.25	1.0833	3.7	10	-	-	-	4	35	10	1.8	2	6.3	
	Large Conventional	7.5	3	1	7	10	-	-	-	8.82	300	20	6.75	0	32.4	
	Small Conventional	4.5	3	1	7	10	-	-	-	8.82	300	20	4.05	0	21.6	

Note: **HFH equipment refers identical 28 kW conventional machine with human operator and autonomous machine, large conventional machine refers 221 kW equipment with human operator, and small conventional machine indicates 112 kW machine with human operator. **HFH equipment characteristics were collected from the HFH demonstration project experience at Harper Adams University, Newport, Shropshire, UK. Large and small equipment (with human operator) specifications were collected from John Deere 6120M; John Deere 7R 270; John Deere T550; Arslan et al. (2014); and Lowenberg-DeBoer et al. (2021a). *** The study assumed that length of the rectangular field is ten times the width of the field as length 316 m and 1000 m and width were 32, 100, 200, 500, 750, 1000 m for calibrating 1ha, 10 ha, 20 ha, 50 ha, 75ha, and 100 ha fields respectively. In addition, for different sized right-angled triangular fields (i.e., 1ha, 10ha, 20ha, and 25ha), where the height equalling twice the base. The 10 ha field was selected for the larger fields and 1 ha field is considered because relatively few fields in the UK are smaller than 1 ha. In addition, 1 ha fields also represent the smallholders' in developing countries such as Asia and Africa, where the average field size is less than 2 hectares (High Level Panel of Experts (HLPE), 2013; Lowder, Skoet and Raney, 2016).*

Table A.2: Parameter definitions.		
Parameters	Description	Unit
A	area of the field	Square meter (m^2)
A_{if}	area of the interior field	m^2
A_{hf}	area of the headland	m^2
A_{bf}	adjacent base of the field	Meter (m)
A_{bif}	adjacent base of the interior field	m
C_b	capacity of the bin	Kilogram (kg)
C_t	capacity of the fuel tank	Litre (L)
E_f	field efficiency	Percentage (%)
H_{ypf}	hypotenuse of the field	m
IR_{if}	input required for the interior field	kg
IR_h	input required for the headland	kg
IR_{hif}	input required for the headland and interior field	kg
L_f	length of the field	m
L_{if}	length of the interior field	m
l_{pi}	length of the interior field passes	m
L_P	total length of the interior passes	m
n	number of swaths skipped during turning	Number (No.)
n_h	number of rounds required for the headland operation	No.
N	total number of interior headlands turn	No.
n_P	number of passes in the interior field operation	No.
N_P	total number of interior passes	No.
N_{hp}	number of passes around the headland	No.
NRN_f	number of refills needed “within” the field	No.
O_{hf}	opposite height of the field	m
O_{hif}	opposite height of the interior field	m
P_{whhyp}	projection of the width of the headland on the hypotenuse	m
Q_s	seeding rate per ha	kg/ha
Q_f	fuel consumption rate per ha	L/ha
r	turning radius of the implement	m
T_{hi}	time required for the headland round	Hour (h)
T_h	total time in the headland round	h
T_P	total time in the interior field passes	h
T_{hturn}	turning time from headland to first interior pass	h
T_{turn}	interior headland turning time	h
T_{fe}	total time for field entry and exit passes	h
T_{obs}	total observed time in the interior field and passes	h
T_r	total interior headlands turning time	h
T_{ssir}	stoppage time for a single input refill	h
T_{sir}	total stoppage time for input refill	h
T_{ssfr}	stoppage time for single fuel refill	h
T_{sfr}	total stoppages time for fuel refill	h
T_{sb}	total stoppage time for blockage	h
T_{sf}	total stoppages time “within” the field	h
T_{tfo}	total time for field operation	h

Table A2: Parameter definitions (Continued).		
T_{tfoha}	total time for field operation per hectare	h
T_T	theoretical field time	h
T_{Tha}	theoretical field time per hectare	h
v_p	implement running speed in the passes	Kilometre per hour (km/h)
v_t	implement turning speed	km/h
W_{Ts}	theoretical swath width	m
W_f	width of the field	m
W_h	Width of the headland	m
W_{if}	width of the interior field	m
W_m	width of the implement	m
W_s	effective swath width	m
W_{h2ndlc}	width of the headland on the second largest corner	m
δ	swath direction	Radians (rad)
θ	right angle of the right-angled triangular field	rad
φ	second largest angle	rad
μ	smallest angle	rad

Table A.3: Field efficiency comparisons subject to field shapes.

Field Operations	Equipment	Present Study (2021) *		Hunt (2001) **	Witney (1988) ***
		Rectangular Field	Triangular Field		
Drilling	HFH equipment	89%	70%	77-90%	75-85%
	Small conventional equipment with human driver	94%	54%		
	Large conventional equipment with human driver	87%	43%		
Spraying	HFH equipment	69%	66%	55-80%	55-65%
	Small conventional equipment with human driver	70%	46%		
	Large conventional equipment with human driver	65%	36%		
Harvesting	HFH equipment	91%	71%	63-90%	65-75%
	Small conventional equipment with human driver	83%	48%		
	Large conventional equipment with human driver	87%	41%		

Note: **Authors estimation, assumed 10 ha rectangular and right-angled triangular field (See Supplementary Materials i.e., SM1 Rectangular Field Algorithms and SM2 Non-Rectangular Field Algorithms); ** See Table 1.1, p. 5, Hunt (2001); *** See Table 3.3, p. 103, Witney (1988).*

Appendix A (ii): Algorithms Spreadsheets (i.e., SM1 Rectangular Field Algorithms and SM2 Non-Rectangular Field Algorithms (i.e., Right-Angled Triangular Field))

For detail of the Algorithms Spreadsheets, please visit as follows:

Al-Amin, A.K.M.A., Lowenberg-DeBoer, J., Franklin, K., Behrendt, K. (2023). Economics of field size and shape for autonomous crop machines. Precision Agric., https://doi.org/10.1007/s11119-023-10016-w

Appendix A (iii): Supplementary Figures (i.e., SFs Sensitivity Tests Figure, which includes Figures of the Sensitivity Tests)

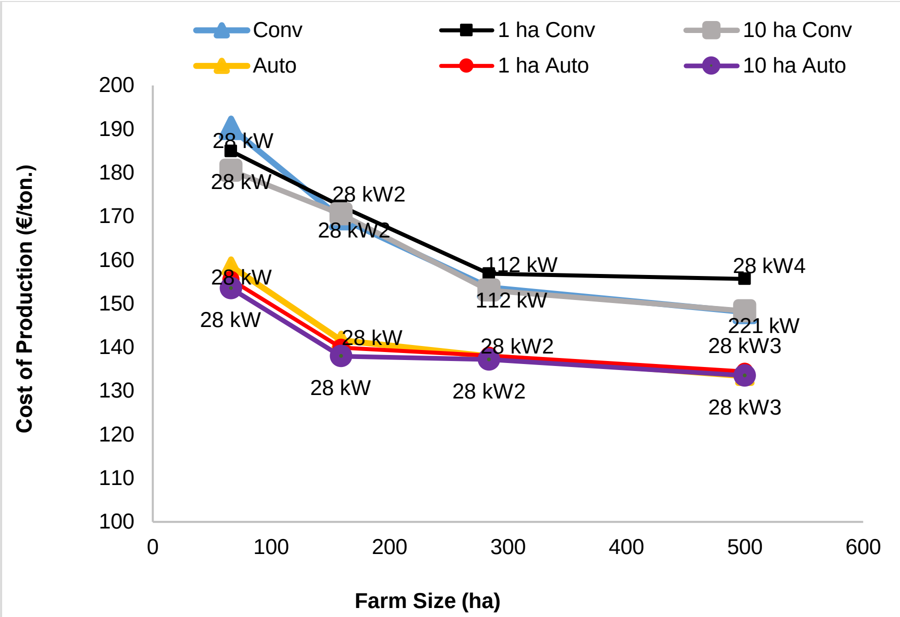

Figure A.1: Sensitivity test (i.e., wage rate double) for wheat unit cost of production in euro per ton for farms with rectangular fields of different sized farms. The labels on the data points for 1 ha and 10 ha fields are the size of the tractor used and the number of equipment sets. The curves without labels are the baseline analysis which was done without field size and shape modelling.

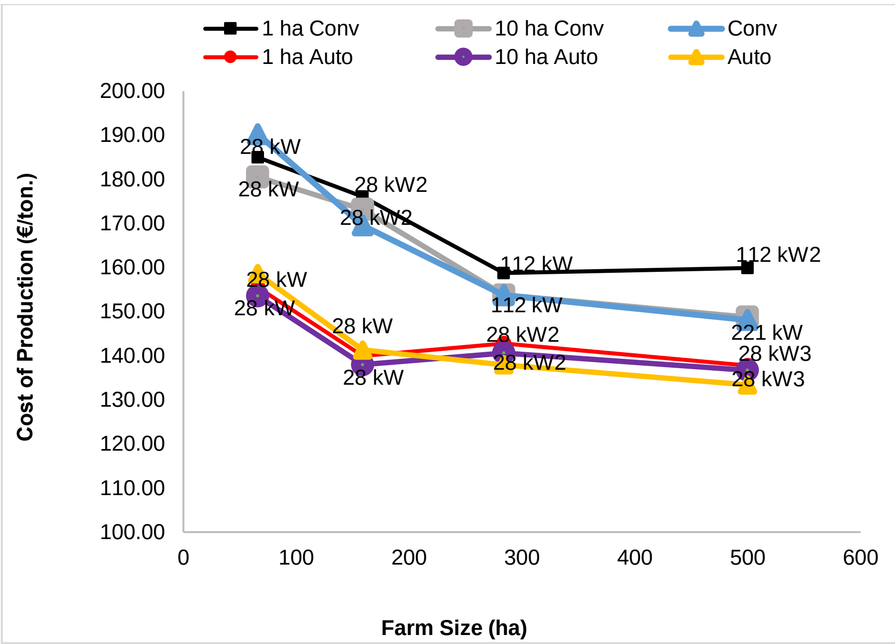

Figure A.2: Sensitivity test (i.e., wage rate triple) for wheat unit cost of production in euro per ton for farms with rectangular fields of different sized farms. The labels on the data points for 1 ha and 10 ha fields are the size of the tractor used and the number of equipment sets. The curves without labels are the baseline analysis which was done without field size and shape modelling.

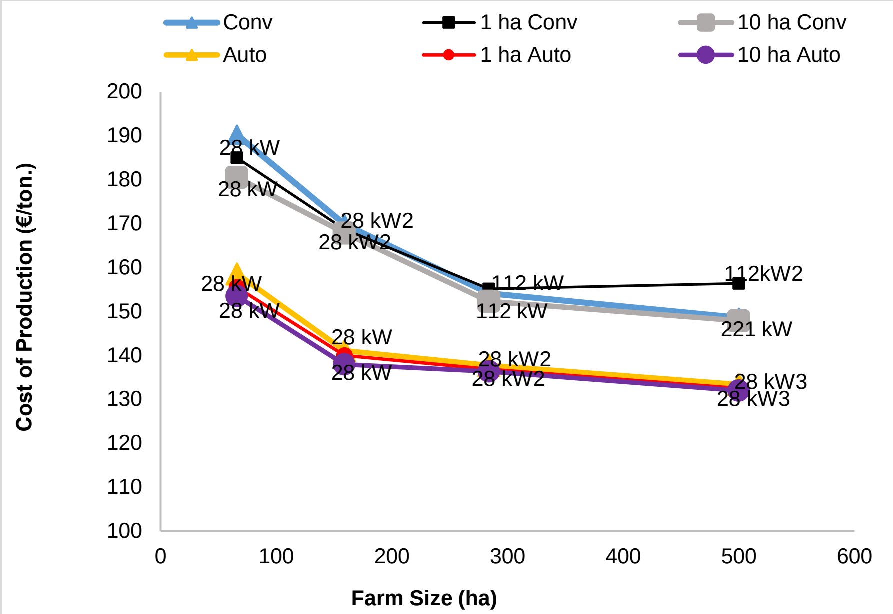

Figure A.3: Sensitivity test (i.e., reduced labour availability of 50 person days per month) for wheat unit cost of production in euro per ton for farms with rectangular fields of different sized farms. The labels on the data points for 1 ha and 10 ha fields are the size of the tractor used and the number of equipment sets. The curves without labels are the baseline analysis which was done without field size and shape modelling.

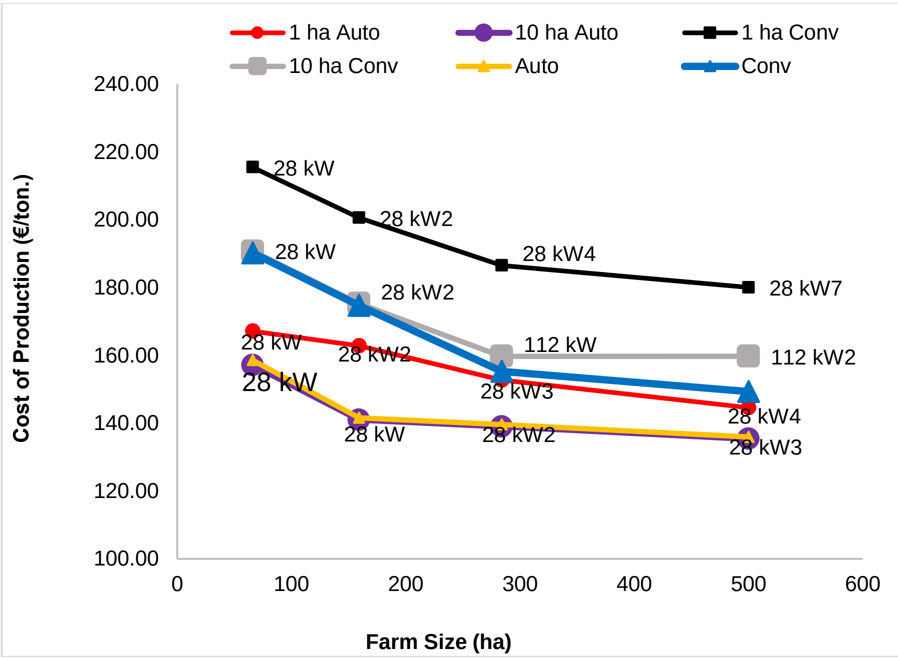

Figure A.4: Sensitivity test (i.e., wage rate double) for wheat unit cost of production in euro per ton for farms with non-rectangular fields of different sized farms. The labels on the data points for 1 ha and 10 ha fields are the size of the tractor used and the number of equipment sets. The curves without labels are the baseline analysis which was done without field size and shape modelling.

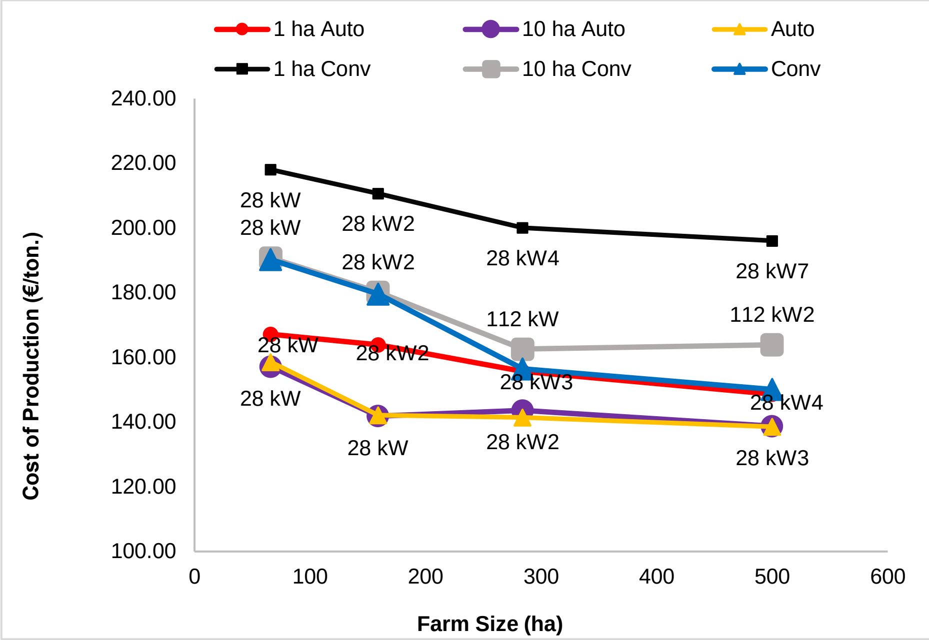

Figure A.5: Sensitivity test (i.e., wage rate triple) for wheat unit cost of production in euro per ton for farms with non-rectangular fields of different sized farms. The labels on the data points for 1 ha and 10 ha fields are the size of the tractor used and the number of equipment sets. The curves without labels are the baseline analysis which was done without field size and shape modelling.

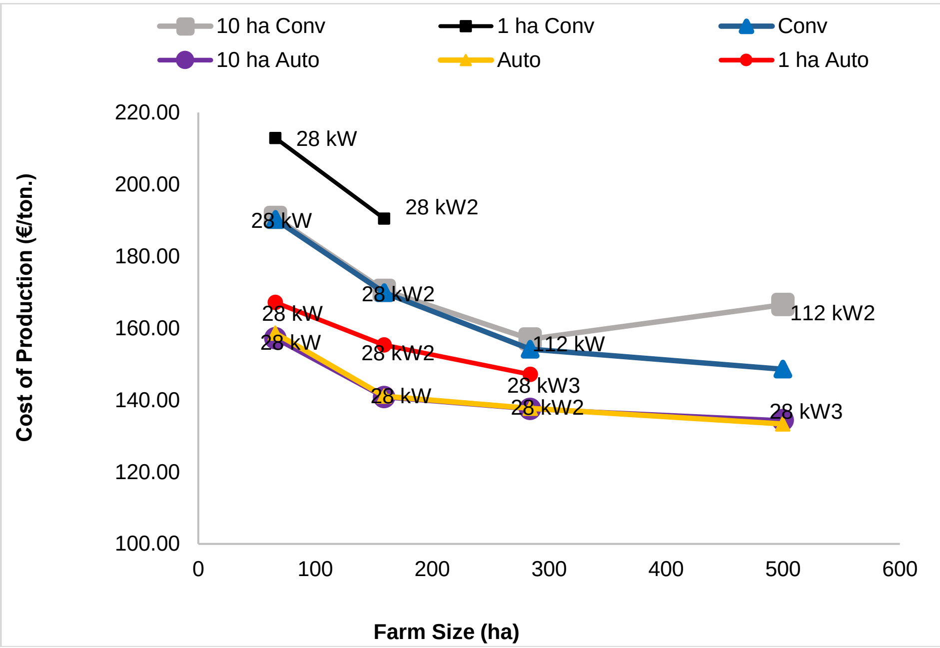

Figure A.6: Sensitivity test (i.e., reduced labour availability of 50 person days per month) for wheat unit cost of production in euro per ton for farms with non-rectangular fields of different sized farms. The labels on the data points for 1 ha and 10 ha fields are the size of the tractor used and the number of equipment sets. The curves without labels are the baseline analysis which was done without field size and shape modelling.

Appendix B

Supplementary materials for: Economics of strip cropping with autonomous machines

The Supplementary Materials incorporate:

(i) Supplementary Tables

(ii) Supplementary Text

(iii) Coefficients Estimation Spreadsheets (i.e., Estimating Coefficients_AJ_VFF.xlsx)

(iv) LP Excel Spreadsheets of the Base Models (i.e., HFH_LP_Strip_Crop_Conv50hp_170922.xlsx; HFH_LP_Strip_Crop_Conv310hp_170922.xlsx; and HFH_LP_Strip_Crop_Robot50hp_170922.xlsx)

Appendix B (i) Supplementary Tables:

Supplementary Table B.1: Machinery choice and corresponding profitability of whole field sole cropping and strip cropping practices under historical average, maximum and minimum soybean/corn (S/C) price ratios.				
Equipment Scenario	Hired labor time (h/ha/yr)	Operator time (h/ha/yr)	Gross margin ($/ha/yr)	Return to operator labor, management and risk-taking ($/ha/yr)
Sensitivity tests: Constant soybean price ($527.27/t), while variable corn prices				
Average S/C price ratio (2.49): (Corn = $211.6377/t)				
Whole field sole cropping: Conventional 228 kW[2]	0.65	0.57	1263.47	-54.89
Strip cropping: Conventional 37.4 kW[5]	2.06	0.66	1433.96	330.14
Strip cropping: Crop Robot 37.4 kW[3]	0.49	0.53	1507.45	491.41
Maximum S/C price ratio (3.19): (Corn = $165.26/t)				
Whole field sole cropping: Conventional 228 kW[2]	0.65	0.57	940.48	-377.88
Strip cropping: Conventional 37.4 kW[5]	2.05	0.66	1087.04	-16.77
Strip cropping: Crop Robot 37.4 kW[3]	0.49	0.53	1154.33	138.29
Minimum S/C price ratio (1.99): (Corn = $264.81/t)				
Whole field sole cropping: Conventional 228 kW[2]	0.65	0.57	1634.55	316.20
Strip cropping: Conventional 37.4 kW[5]	2.06	0.66	1836.83	733.01
Strip cropping: Crop Robot 37.4 kW[3]	0.49	0.53	1912.35	896.31
Sensitivity tests: Constant corn price ($246.05/t), while variable soybean prices				
Average S/C price ratio (2.49): (Soybean = $613.01/t)				
Whole field sole cropping: Conventional 228 kW[2]	0.65	0.57	1682.64	364.28
Strip cropping: Conventional 37.4 kW[5]	2.06	0.66	1874.47	770.66
Strip cropping: Crop Robot 37.4 kW[3]	0.49	0.53	1960.15	944.11
Maximum S/C price ratio (3.19): (Soybean = $785.02/t)				
Whole field sole cropping: Conventional 228 kW[2]	0.65	0.57	2042.13	723.77
Strip cropping: Conventional 37.4 kW[5]	2.05	0.66	2241.16	1137.34
Strip cropping: Crop Robot 37.4 kW[3]	0.49	0.53	2341.43	1325.39
Minimum S/C price ratio (1.99): (Soybean = $489.92/t)				
Whole field sole cropping: Conventional 228 kW[2]	0.65	0.57	1425.65	107.29
Strip cropping: Conventional 37.4 kW[5]	2.06	0.66	1616.38	512.56
Strip cropping: Crop Robot 37.4 kW[3]	0.49	0.53	1686.44	670.40

Supplementary Table B.2: Profitability of strip cropping practice with autonomous machine under different human supervision scenarios.				
Equipment scenario	Hired labor time (h//ha/yr)	Operator time (h//ha/yr)	Gross margin ($/ha/yr)	Return to operator labour, management and risk-taking ($/ha/yr)
Base scenario: 10% supervision	0.49	0.53	1769.50	753.46
Sensitivity test: 50% supervision	1.18	0.59	1754.28	738.24
Sensitivity test: 100% supervision	2.07	0.65	1717.55	701.51

Supplementary Table B.3: Profitability of whole field sole cropping and strip cropping practices under conventional and autonomous machine scenarios at increased field-to-field transition distance.				
Equipment Scenario	Hired labor time (h//ha/yr)	Operator time (h//ha/yr)	Gross margin ($/ha/yr)	Return to operator labor, management and risk-taking ($/ha/yr)
Whole field sole cropping: Conventional 228 kW[2]	0.77	0.60	1490.30	171.94
Strip cropping: Conventional 37.4 kW[6]	2.54	0.73	1649.60	496.99
Strip cropping: Crop Robot 37.4 kW[4]	0.89	0.68	1752.63	684.53

Appendix B (ii) Supplementary Text

SUPPLEMENTARY TEXT: STRIP CROPPING HFH-LP MODEL: ASSUMPTIONS AND PARAMETERS ESTIMATION

This study adopted and re-estimated the HFH-LP maximization model to estimate the gross margin measure of profitability for human operated larger conventional mechanized whole field sole cropping system, human operated smaller conventional mechanized strip cropping and autonomous strip cropping systems. The maximization models were re-estimated subject to the binding constraints of land, operator time, tractor time for field preparation, planting and spraying, combine time for harvesting, good field days, and working capital and cashflow. The models considered in this study were known as 'steady-state' models, adopted from Orinoquia model (Fontanilla-Diaz *et al.*, 2021), imply that solutions would be repeated annually over time. The HFH-LP was developed based on the Purdue Crop/Livestock Linear Program (PC/LP) model (Dobbins *et al.*, 1994). The study also estimated return to operator labor, management and risk taking through subtracting fixed costs from farm gross margin. Following assumptions were considered for maximizing gross margin (GM) and evaluation of return to operator labor, management and risk-taking (ROLMRT):

- **Land scenario:**

The average farm size of Indiana is 180.09 ha (USDA NASS, 2022). However, based on the assumptions of Ward, Roe and Batte (2016) the study modelled 2156.974 ha non-irrigated farm. Because the study examined their hypothesis that profitability of strip cropping could be achieved with autonomous machines as conventional mechanized farms faced labor and fixed costs constraints.

- **Equipment scenarios:**

For ex-ante economic analysis, the study updated the equipment inventory of Ward, Roe and Batte (2016) and added autonomous equipment option. The study used three equipment scenarios:

(i) ***Larger conventional equipment scenario:*** This scenario incorporated approximately 228 kW tractor, 292 kW combine with 6.09 m corn head (8 row) and 10.67 m grain head, and 36.58 m self-propelled sprayer with human operator. A grain cart was included because harvest unloading on-the-go was assumed.

(ii) ***Smaller conventional equipment scenario:*** Small machines encompassed a 37.4 kW tractor, 151 kW combine equivalent to AVERO 240 model with 4.57 m corn head (6 row) and 4.57 m grain head, and 18.29 m trailed sprayer with human operator.

(iii) ***Autonomous equipment scenario:*** The autonomous machine scenario was assumed to have smaller conventional equipment, but retrofitted for autonomy based on the experience of the Hands Free Hectare (HFH) (Hands Free Hectare (HFH), 2021; Lowenberg-DeBoer *et al.*, 2021a). It was assumed that with retrofitting, the equipment can be operated manually on public roads and autonomously for field operations. Consequently, for field-to-field movement, the operator flips the switch to manual and drives to the next field. As with the HFH study, it was assumed that grain hauling on public roads must be done with human drivers. Similarly, in addition to public roads, the strip cropping practice assumed that the grains were unloaded from combine to the grain semi at the end of the field. Consequently, there was no grain cart in this inventory and the grain semi was not retrofitted for autonomy.

The initial investment costs were priced from different equipment manufacturers sites having available list price for the US, like (https://www.deere.com/en/ and https://www.caseih.com/northamerica/en-us/home) and if new equipment list price was not available, prices for recent used equipment was used from websites such as Equipment Trader (https://www.equipmenttrader.com/), St. Joseph Equipment (https://www.stjosephequipment.com/default.htm), Fastline Equipment (https://www.fastline.com/), Machinery Pete (https://www.machinerypete.com/) and Rechtien (https://www.rechtien.com/). For example, the price of approximately 228 kW tractor was estimated based on the average list prices of John Deere 8R 310, Magnum 310 PS AFS C. and Magnum 310 CVT AFS C (for details see: https://www.deere.com/en/tractors/row-crop-tractors/row-crop-8-family/8r-310-tractor/ and https://www.caseih.com/northamerica/en-us/Pages/Build-and-Price-Iframe.aspx?series=MAGNUM%20TRACTORS). Similarly, the price of approximately 184 kW tractor was calculated based on the average price of John Deere 8R 250, and Magnum 250 PS AFS C. and Magnum 250 CVT AFS C. The price of the S770 Combine (292 kW), 8 row 6.09 m corn head and 10.67 m 735D draper head for grain were collected from John Deere as similar implements list price were not available from other manufacturers. To check if the list prices were consistent with those of used equipment, the study reviewed the used equipment price of these implements on used equipment websites. In these used equipment websites, the image of the specific implement and price changes frequently. Consequently, instead of giving the particular implement link, the study provides a general website link. With allowance for depreciation the price of the used machines was consistent with the list price.

The price of 36.58 m sprayer was estimated based on the average of prices of recent used self-propelled sprayers available at TractorHouse (https://www.tractorhouse.com/), where the average price estimation incorporated self-propelled sprayer of John Deere, Miller, HAGIE and New Holland. The price of self-propelled sprayers was not available at John Deere and Case IH as they suggested searching for a dealer instead the of Build Your Own Price option. It was assumed that recent self-propelled sprayers would be equipped with boom control, so that was not priced separately. Prior study mentioned that non-productive times (e.g., refilling fertilizer, herbicide and pesticide) play a significant role in the economics of machinery usage (Al-Amin *et al.*, 2022b; Al-Amin *et al.*, 2021). Therefore, the study used a 9084.99 L portable tank to refill when needed. The tank was assumed to be hauled by the grain semi. The tank was priced based on the price available at Plastic-Mart (https://www.plastic-mart.com/).

The study considered 23 FT VT-FLEX 435 chisel plow list price in the machinery inventory to keep similarity with Ward, Roe and Batte (2016) study. The price was collected from a manufacturer, namely Case IH (https://www.caseih.com/). To check the price, the study reviewed other price options available from different manufacturers, such as Case IH and Machinery Pete. The field cultivator price was collected from TractorHouse and further recheck with John Deere. The 16 row (12.19 m) planter price was estimated based on the average price of 1725 CCS Stack-Fold Planter, ER 2130 PLANTER 16R30 and 1775NT Planter available at John Deere and Case IH.

The grain semi price was considered and rechecked considering typical and present market scenarios. In recent times due to the Covid-19 pandemic and Russia-Ukraine war, the US farm equipment market faced supply side shock and machinery price are highly volatile (details are available here: https://www.agweb.com/news/machinery/used-machinery/machinery-pete-grain-trailers-semis-and-trucks-oh-my and https://www.freightwaves.com/news/the-big-rig-boom-is-finally-slumping). The used grain semi market was particularly volatile. Consequently, the grain semi price was estimated based on the average prices of Durabak used equipment (https://www.durabakcompany.com/blogs/durabak/how-much-does-a-semi-truck-cost). To recheck the grain semi price, the study also reviewed the prices available at TractorHouse, Fastline and Rechtien (https://www.rechtien.com/).

The grain cart (27.29 t) typical list price was estimated from Unverferth (https://www.unverferth.com/) after requesting a price quote. The prices at the time of the study were rising rapidly (details are available at: https://www.wlagrisales.com/default.htm, https://www.randallbros.biz/default.htm, https://www.farms.com/ and https://www.agdealer.com/). To recheck the price, the study reviewed the grain cart price available at TractorHouse and North Star Ag (https://northstar-ag.com/).

The price of the smaller conventional equipment and the autonomous equipment were collected from manufacturer and used equipment websites. The list price of the 37.4 kW tractor was estimated based on the average price of 5050E utility tractor, Massy Ferguson 1749 and Kubota L5740 tractors available as follows: https://www.deere.com/en/tractors/utility-tractors/5-family-utility-tractors/5050e-utility-tractor/; https://www.tractordata.com/farm-tractors/007/4/2/7428-massey-ferguson-1749.html and https://www.tractordata.com/farm-tractors/001/8/3/1838-kubota-l5740.html.

The combine needed for 4.57 m strips are no longer manufactured in the US and are not currently marketed there new. Prices that are available in the US for the used combines of that size are mostly very old and near the end of their useful life span. Therefore, a price estimate is needed to approximate the cost of a new combine of that size in the Corn Belt region of Indiana. The preliminary analysis used a Chinese made Lovol GM80 combine, but none of the co-authors were familiar with the reliability, maintenance cost and salvage value of the Lovol GM80 under the US conditions. Thus, prices were sought for the CLAAS AVERO (151 kW) which is sold and used in the Europe and UK under conditions that are similar to those in the US. It is assumed that if strip cropping were shown to be profitable and it became common in the US, some manufacturer would either resume making combines that size in North America or arrange to import them from a subsidiary or partner in the Europe or Asia.

The study considered AVERO 240 model (151 kW) combine for strip cropping practices (Figure B.1). Even though the HFH did not use AVERO 240 model, from the experience with CLAAS combines the team hypothesized that AVERO 240 would be better fit for corn-soybean strip cropping than the Chinese one. At present, the Hands Free Farm (HFF) is using a CLAAS Crop Tiger 30 retrofitted for autonomy (HFH, 2021).
The price of AVERO 240 model was estimated based on the price quote for a new machine provided by the CLAAS representative in the UK[1]. The price of used AVERO 240 model combines was checked in Agriaffaires (https://www.agriaffaires.co.uk/). With some allowance for depreciation the price of the used AVERO combines was consistent with the list price.

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[1] *The market price of the UK's was multiplied by the last one year (i.e., from Oct. 2021 to Sept. 2022) monthly average exchange rates from GBP to US$ of 1.28 (Board of Governors of the Federal Reserve System (U.S.)., 2022) to address the volatility of exchange rates owing to the supply shocks for COVID-19 pandemic and Russia-Ukraine war.*

Figure. B.1: AVERO 240 model.

Source: *https://www.agriaffaires.co.uk/used/combine-harvester/42832773/claas-avero-240.html*

In the equipment market, 4.57 m corn head and 4.57 m grain head are not typical. For approximation of price estimation, the study used the half price of CLAAS 9.14 m corn and soybean head. Details of 9.14 m heads are available at CLAAS manufacturer's website (https://www.claas.co.uk/).

For strip cropping, 18.29 m trailed sprayer price was estimated based on the average of prices for recent used equipment available at TractorHouse. The study of Ward, Roe and Batte (2016) assumed that the strips were sprayed one at a time with a 4.75 m boom. This is very time consuming. To increase application efficiency, this study assumed that sprayer boom control was used to allow for multiple strips to be sprayed with one sprayer pass through the field. It could not be assumed that boom control was standard equipment on trailed sprayers, so the study estimated the cost of retrofitting boom control. The study assumed the use of automatic boom control sections following the study of Rahman (2018; p.g., 43), for automatic boom control sections in 18.29 m trailed sprayer, the study assumed 4 boom control sections each with 4.57 m boom control section. The study used the price of 6 boom control sections (i.e., in-cab controller (console)), where 4 boom control sections were operated, remaining 2 boom control sections unused. This is because of the unavailability of 4 boom control sections and price (for details of the available boom control section options see: https://ravenind.com/products/applications-booms/scs-control-consoles. Based on the review of Rahman (2018), the study hypothesized that the 4 boom control sections needed 36 Solenoid valves and associated wiring and harness collected from SpraySmarter.com (https://www.spraysmarter.com/) and Farmtronics (https://farmtronics.com/). The price of solenoid valves was estimated as the average of prices available at Dultmeier Sales (https://www.dultmeier.com/). For the strip cropping scenarios the 18.29 m sprayer boom was equipped with section control making it possible to apply chemicals on two strips in one pass.

The price of the small chisel plow 2.44 m was estimated as the average of prices available at MarketBook (https://www.marketbook.ca/), John Deere, and Agriaffaires (https://www.agriaffaires.us/). The price of field cultivators was collected from MarketBook and for rechecking compared with the average of prices available at TractorHouse and Machinery Pete. The list price of the 6-row planter (4.57 m) was collected from Case IH. The price was further rechecked through reviewing and averaging the prices available at Machinio (https://www.machinio.com/). Finally, RTK GPS and Autopilot list price was collected from the HFH experience using 2022 USD conversion due to the unavailability of the US data set for retrofitted machines.

The strip crop scenarios assumed that urea or other granulated N would be used for nitrogen because regulatory approval of autonomous anhydrous ammonia (NH_3) application may be problematic. The list price of fertilizer applicator (Urea and other granulated N) was obtained from 1st products.com (https://1stproducts.com/) by requesting for a quote. The fertilizer applicator assumed is available in Figure B.2 (for details see: https://1stproducts.com/agriculture-wholegoods/dry-fertilizer/). The study assumed that conventional 37.4 kW tractor with human operator and autonomous machine (37.4 kW) for strip cropping scenarios used this fertilizer applicator. For conventional mechanized farming scenarios, the study assumed NH_3 application @13.75 per acre (0.41 ha) using custom hire service (Arnall, 2017).

Figure. B.2: Typical fertilizer hopper for 6 row tool bars.

Source: [*https://1stproducts.com/agriculture-wholegoods/dry-fertilizer/*](https://1stproducts.com/agriculture-wholegoods/dry-fertilizer/)

- **Tillage operation scenarios:**

Whole farm conventional sole cropping and strip cropping tillage operations were assumed to be used a chisel plow and field cultivator following Ward, Roe and Batte (2016) that was unlike the HFH field operations which used direct drill. The post-harvest primary tillage was assumed to be completed month after harvest and for November harvest in November and preplant tillage at the month of planting.

- **Crop rotation and yield scenarios:**

The whole field conventional sole cropping assumed corn-soybean yearly rotations. The strip cropping practices assumed continuous soybean in the headlands and the interior field strips cultivated with yearly rotations of corn and soybean.

Following the Purdue PC-LP Farm Plan (Doster *et al.*, 2006), the optimum planting and harvesting dates are as follows:

- *Corn:* Earliest possible option was corn planted in April and harvested in September. Latest possible options were corn planted in May and June and harvested in October and November, and
- *Soybean:* Earliest possible option was soybean planted in April and harvested in September. Latest possible options were soybean planted in May and June and harvested in October and November.

Further details of the planting and harvesting dates are available at Table B.4. The yield of corn and soybean was taken from 2022 Purdue Crop Cost and Return Guide for rotational corn and soybean of high productivity soil (Langemeier *et al.*, 2022) and the yield adjustment were adopted from the Purdue PC-LP Farm Plan B-21 Crop Input Form (Doster *et al.*, 2006, Pg., 43-44). The HFH-LP model used a monthly time period. Consequently, the PC-LP time periods were combined in monthly time period.

In strip cropping yield scenarios, in addition to the yield adjustment from the Purdue PC-LP Farm Plan, the study considered the yield benefits of corn and penalty of soybean owing to the edge effects following the normal condition of Ward, Roe and Batte (2016). The percentage for 6 row strips was estimated as = (((1st row yield + 2nd row yield + center row yield + center row yield + 2nd row yield + 1st row yield)/Total number of rows)/ center row yield). For instance, based on the field trial of Illinois during 2009 and 2010 mentioned in the study of Ward, Roe and Batte (2016), the corn percentage change over a 6 row strips were = 115% = ((301+237+220+220+237+301)/6)/220) and soybean percentage change over a 6 row strips was = 92% = (((48+61+62+62+61+48)/6)/62). The headlands (i.e., 5% of the field) yield for continuous soybean was considered 80% of total yield due to the penalty of continuous soybean production. Further sensitivity tests could investigate different penalty scenarios for the headlands. The yield adjustment for the whole farm conventional sole cropping and strip cropping are available at the Coefficients Estimation Spreadsheets (i.e., Estimating Coefficients_AJ_VFF.xlsx).

- **Enterprises price and direct costs scenarios:**

The harvest price of the corn and soybean and direct costs for farm operations were collected from 2022 Purdue Crop Cost and Return Guide for rotational corn and soybean production for high productivity soil (Langemeier *et al.*, 2022) on a per ha basis. For corn and soybean price conversion the agricultural conversion calculators were used (https://www.cmegroup.com/tools-information/ag-calculator.html). The direct costs incorporated seed, fertilizer, pesticide, dryer fuel, interest, and insurance from 2022 Purdue Crop Cost and Return Guide for rotational corn and soybean production for high productivity soil except the costs of machinery fuel, machinery repairs and hauling as these items were considered in annual machinery costs estimation. For conventional whole field sole cropping, the study assumed custom hire services for NH3 application and granulated fertilizer. In strip cropping practices, NH3 was not considered due to the technical infeasibility and unavailability of machines for NH3 application in strip cropping practices. Here the study considered granulated urea. Details are available at the Coefficients Estimation Spreadsheets (i.e., Estimating Coefficients_AJ_VFF.xlsx).

- **Transport on public roads scenario:**

Following Lowenberg-DeBoer *et al.* (2021a), the study assumed that autonomous machines were transported by an operator in the public roads considering the safety issue and lack of permission to drive autonomous arable farm machines in the public roads.

- **Hired labor scenario:**

The study considered the $16.95/h wage rate in the US Corn Belt following the USDA 2021 database for economic class of farm regions and states (USDA NASS, 2021, p.g., 20). The human, machine and autonomous equipment time was modelled as eight hours increments following the Orinoquia analysis (Lowenberg-DeBoer *et al.*, 2021a).

- **Field work rates scenarios:**

The field times (h/ha) were estimated following the algorithms of Lowenberg-DeBoer *et al.* (2021a). The field efficiency (%) of the machines for farm operations were adopted from Ward, Roe and Batte (2016). The study assumed zero overlap for farm operations in both sole cropping and strip cropping practices. Combine field efficiency for strip cropping was assumed similar to the conventional larger combines (i.e., considered 10% less from the Ward, Roe and Batte (2016) for small combines) because the study assumed that the grains were unloaded into the grain semi at the end of the field. Details work rates are available at Table B.5. Operations were based on Ward, Roe and Batte (2016) and 2022 Purdue Crop Cost and Return Guide (Langemeier *et al.*, 2022).

In coefficient estimation for each month, the study assumed farm machines always follow the next field during field operations. The study considered field transition times following the assumption of Ward, Roe and Batte (2016) that all fields were 2.01 km apart for transport with road speed between fields were 19.96 km/h except for combine that was 14.97 km/h. Because the field time parameters in the model were given on a per hectare basis, the travel time was proportional over the area of the field operation at each visit: 53.82 ha for the whole field sole crop farming and 26.95 ha for the strip cropping scenarios. Field-to-field time per ha was calculated as: (Distance of field apart for transport/Road speed)/ Field area. Field-to-field time per ha for all equipment except combine was estimated as = (2.012/19.956)/53.823 = 0.0019 h/ha. Field-to-field time per ha for combine was estimated as: (2.012/14.967)/53.823 = 0.0025 h/ha. Considering field-to-field distance for both corn and soybean operation the coefficient was estimated as: (Number of Corn operations*Field-to-field time/ha + Number of Soybean operations*Field-to-field time/ha)/2+(Corn operation Days + Soybean operation days)/2. The study assumed half of the field produced corn and the rest is Soybean. For strip cropping field-to-field time/ha for all equipment except combine was estimated as = (2.012/19.956)/26.952 = 0.0037 h/ha. Field-to-field time/ha for combine was estimated as: (2*2.012/14.967)/26.952 = 0.0050 h/ha. Considering field-to-field distance for both corn and soybean operation the coefficient was estimated as: (Number of Corn operations*Field-to-field time/ha + Number of Soybean operations*Field-to-field time/ha)/+(Corn operation Days*0.475 + Soybean operation days*0.525). Details of the field times required for each month by crop and equipment sets and farming systems are available at the Coefficients Estimation Spreadsheets (i.e., Estimating Coefficients_AJ_VFF.xlsx).

- **Good field days scenario:**

The study collected the good field days data from the AgManager.info. (2022) at 80th (more) percentile available at: https://agmanager.info/farm-management/machinery/days-suitable-fieldwork-all-states. Apart from a good field day scenario, the study assumed that autonomous tractor operated for 22 h and conventional tractors with human operators for 10 h. With the advent of technological development, the conventional tractor could operate 22 h. Further sensitivity tests could address this issue.

- **Input resupply and finance scenarios:**

Following Lowenberg-DeBoer *et al.* (2021a), the study assumed refilling and refueling during field operations are part of normal workload for conventional systems and were part of human supervision for autonomous system.

- **GAMS coding:**

Details of the GAMS coding are available at Lowenberg-DeBoer *et al.* (2021a).

- **Return to operator labor, management and risk-taking scenarios:**

The return to operator labour, management and risk taking (ROLMRT) was estimated as gross marging minus overhead costs following Witney (1988) and Lowenberg-DeBoer *et al.* (2021a). In this estimation processes the following assumptions are considered:

a) *Depreciation:* The study used straight line depreciation assuming 7 years for combine and planter and 10 years for other equipment sets (Langemeier *et al.*, 2022).
b) *Opportunity cost of capital:* The opportunity cost of capital is assumed 5% of the original investment (Langemeier *et al.*, 2022).

c) *Insurance:* Considered as a percentage of original investment that was 1% for tractor and combine, 0.25% for other implements (Agro Business Consultants, 2018) and in case of grain semi the study assumed 3%. For the grain semi, the insurance, repair and maintenance, and fuel and lubricant percentage was adjusted for the fact that a used truck was priced. The ratio of a new semi-truck list price to a used truck price is about 1.5 (i.e., 150,000/100,000). The price of an average new semi is from the Durabak Company (https://www.durabakcompany.com/blogs/durabak/how-much-does-a-semi-truck-cost). Thus, insurance, repair and maintenance, and fuel and lubricant estimates were based on the price of a new grain semi (1.5 x 2% =3%).

d) Repair and Maintenance: Considered 2% of the original investment (Agro Business Consultants, 2018) and for grain semi 3%.

e) Fuel and Lubricant: Considered 2% of original investment for tractor and combine (Agro Business Consultants, 2018) and 3% for the grain semi.

Due to the unavailability of overhead costs items in 2022 Purdue Crop Budget, to make representative estimation, the following fixed costs assumptions were considered to calculate return to operator labor, management and risk taking:

a) *Land Rent:* High quality farmland was considered $741.30/ha following the Purdue Farmland Survey (Kuethe, 2021).

b) *Property and Building Repairs:* Assumed $16.05/ha following the average costs of building repair and rent for systematic corn and soybean rotations on high productivity farmland from Illinois Crop Budget 2022 (Schnitkey and Swanson, 2022).

c) *Professional Fees and Subscriptions:* Assumed $28.41/ha following the average costs of insurance and interest (non-land) for systematic corn and soybean rotations on high productivity farmland from Illinois Crop Budget 2022 (Schnitkey and Swanson, 2022).

d) *Water, Electricity, etc.:* Assumed $14.82/ha based on the average costs of utilities for systematic corn and soybean rotations on high productivity farmland from Illinois Crop Budget 2022 (Schnitkey and Swanson, 2022).

e) *Building Depreciation:* Assumed $29.64/ha following average costs of building depreciation for systematic corn and soybean rotations on high productivity farmland from Illinois Crop Budget 2022 (Schnitkey and Swanson, 2022).

f) *Miscellaneous Fixed Costs:* Assumed $29.64/ha based on the average costs of miscellaneous costs for systematic corn and soybean rotations on high productivity farmland from the Illinois Crop Budget 2022 (Schnitkey and Swanson, 2022).

Table B.4: HFH-LP enterprises production activities and yield.

Enterprise production	Corn yield (t/ha)*	Soybean yield (t/ha)*	Description
Corn_April-Sept/Soy_April-Sept	12.95	4.02	Corn planted in April & harvested in Sept./Soybean planted in April & harvested in Sept.
Corn_April-Sept/Soy_April-Oct	12.95	4.24	Corn planted in April & harvested in Sept./Soybean planted in April & harvested in Oct.
Corn_April-Sept/Soy_April-Nov	12.95	3.99	Corn planted in April & harvested in Sept./Soybean planted in April & harvested in Nov.
Corn_April-Sept/Soy_May-Sept	12.95	4.02	Corn planted in April & harvested in Sept./Soybean planted in May & harvested in Sept.a
Corn_April-Sept/Soy_May-Oct	12.95	4.27	Corn planted in April & harvested in Sept./Soybean planted in May & harvested in Oct.
Corn_April-Sept/Soy_May-Nov	12.95	4.03	Corn planted in April & harvested in Sept./Soybean planted in May & harvested in Nov.
Corn_April-Sept/Soy_June-Oct	12.95	3.82	Corn planted in April & harvested in Sept./Soybean planted in June & harvested in Oct.
Corn_April-Sept/Soy_June-Nov	12.95	3.68	Corn planted in April & harvested in Sept./Soybean planted in June & harvested in Nov.
Corn_May-Oct/Soy_May-Oct	12.88	4.27	Corn planted in May & harvested in Oct./Soybean planted in May & harvested in Oct.
Corn_May-Oct/Soy_April-Sept	12.88	4.02	Corn planted in May & harvested in Oct./Soybean planted in April & harvested in Sept.
Corn_May-Oct/Soy_April-Oct	12.88	4.24	Corn planted in May & harvested in Oct./Soybean planted in April & harvested in Oct.
Corn_May-Oct/Soy_April-Nov	12.88	3.99	Corn planted in May & harvested in Oct./Soybean planted in April & harvested in Nov.
Corn_May-Oct/Soy_May-Sept	12.88	4.02	Corn planted in May & harvested in Oct./Soybean planted in May & harvested in Septt.
Corn_May-Oct/Soy_May-Nov	12.88	4.27	Corn planted in May & harvested in Oct./Soybean planted in May & harvested in Nov.
Corn_May-Oct/Soy_June-Oct	12.88	3.82	Corn planted in May & harvested in Oct./Soybean planted in June & harvested in Oct.
Corn_May-Oct/Soy_June-Nov	12.88	3.68	Corn planted in May & harvested in Oct./Soybean planted in June & harvested in Nov.
Corn_June-Nov/Soy_June-Nov	8.06	3.68	Corn planted in June & harvested in Nov/Soybean planted in June & harvested in Nov.

Table B.4: HFH-LP enterprises production activities and yield (Continued).

Corn_June-Nov/Soy_April-Sept	8.06	4.02	Corn planted in June & harvested in Nov/Soybean planted in April & harvested in Sept.
Corn_June-Nov/Soy_April-Oct	8.06	4.24	Corn planted in June & harvested in Nov/Soybean planted in April & harvested in Oct.
Corn_June-Nov/Soy_April-Nov	8.06	3.99	Corn planted in June & harvested in Nov/Soybean planted in April & harvested in Nov.
Corn_June-Nov/Soy_May-Sept	8.06	4.02	Corn planted in June & harvested in Nov/Soybean planted in May & harvested in Sept.
Corn_June-Nov/Soy_May-Oct	8.06	4.27	Corn planted in June & harvested in Nov/Soybean planted in May & harvested in Oct.
Corn_June-Nov/Soy_May-Nov	8.06	4.03	Corn planted in June & harvested in Nov/Soybean planted in May & harvested in Nov.
Corn_June-Nov/Soy_June-Oct	8.06	3.82	Corn planted in June & harvested in Nov/Soybean planted in June & harvested in Oct.
Corn_April-Oct/Soy_April-Oct	13.96	4.24	Corn planted in April & harvested in Oct/Soybean planted in April & harvested in Oct.
Corn_April-Oct/Soy_April-Sept	13.96	4.02	Corn planted in April & harvested in Oct/Soybean planted in April & harvested in Sept.
Corn_April-Oct/Soy_April-Nov	13.96	3.99	Corn planted in April & harvested in Oct/Soybean planted in April & harvested in Nov.
Corn_April-Oct/Soy_May-Sept	13.96	4.02	Corn planted in April & harvested in Oct/Soybean planted in May & harvested in Sept.
Corn_April-Oct/Soy_May-Oct	13.96	4.27	Corn planted in April & harvested in Oct/Soybean planted in May & harvested in Oct.
Corn_April-Oct/Soy_May-Nov	13.96	4.03	Corn planted in April & harvested in Oct/Soybean planted in May & harvested in Nov.
Corn_April-Oct/Soy_June-Oct	13.96	3.82	Corn planted in April & harvested in Oct/Soybean planted in June & harvested in Oct.
Corn_April-Oct/Soy_June-Nov	13.96	3.68	Corn planted in April & harvested in Oct/Soybean planted in June & harvested in Nov.
Corn_April-Nov/Soy_April-Nov	12.88	3.99	Corn planted in April & harvested in Nov/Soybean planted in April & harvested in Nov.
Corn_April-Nov/Soy_April-Sept	12.88	4.02	Corn planted in April & harvested in Nov/Soybean planted in April & harvested in Sept.
Corn_April-Nov/Soy_April-Oct	12.88	4.24	Corn planted in April & harvested in Nov/Soybean planted in April & harvested in Oct.

Table B.4: HFH-LP enterprises production activities and yield (Continued).

Corn_April-Nov/Soy_May-Sept	12.88	4.02	Corn planted in April & harvested in Nov/Soybean planted in May & harvested in Sept.
Corn_April-Nov/Soy_May-Oct	12.88	4.27	Corn planted in April & harvested in Nov/Soybean planted in May & harvested in Oct.
Corn_April-Nov/Soy_May-Nov	12.88	4.03	Corn planted in April & harvested in Nov/Soybean planted in May & harvested in Nov.
Corn_April-Nov/Soy_June-Oct	12.88	3.82	Corn planted in April & harvested in Nov/Soybean planted in June & harvested in Oct.
Corn_April-Nov/Soy_June-Nov	12.88	3.68	Corn planted in April & harvested in Nov/Soybean planted in June & harvested in Nov.
Corn_May-Nov/Soy_May-Nov	11.94	4.03	Corn planted in May & harvested in Nov/Soybean planted in May & harvested in Nov.
Corn_May-Nov/Soy_April-Sept	11.94	4.02	Corn planted in May & harvested in Nov/Soybean planted in April & harvested in Sept.
Corn_May-Nov/Soy_April-Oct	11.94	4.24	Corn planted in May & harvested in Nov/Soybean planted in April & harvested in Oct.
Corn_May-Nov/Soy_April-Nov	11.94	3.99	Corn planted in May & harvested in Nov/Soybean planted in April & harvested in Nov.
Corn_May-Nov/Soy_May-Sept	11.94	4.02	Corn planted in May & harvested in Nov/Soybean planted in May & harvested in Sept.
Corn_May-Nov/Soy_May-Oct	11.94	4.27	Corn planted in May & harvested in Nov/Soybean planted in May & harvested in Oct.
Corn_May-Nov/Soy_June-Oct	11.94	3.82	Corn planted in May & harvested in Nov/Soybean planted in June & harvested in Oct.
Corn_May-Nov/Soy_June-Nov	11.94	3.68	Corn planted in May & harvested in Nov/Soybean planted in June & harvested in Nov.

Note: *The yield here adopted from 2022 Purdue Crop Cost and Return Guide representing high productivity soil rotational corn and soybean yield (Langemeier et al., 2022) and the yield adjustment were adopted from Purdue PC-LP Farm Plan B-21 Crop Input Form, Pg., 43-44* (Doster *et al.*, 2006). *Because the HFH-LP used a monthly time period, the PC-LP time periods were combined as follows in the optimization model of the study as: April: April 22-May 2; May: May 3-May 30; June: May 31-June 13; Sept.: Sept. 20-26; Oct.: Oct.: Sept. 27-Oct. 31, Nov.: Nov. 1-Dec. 5.*

Table B.5: Estimate hectares per hour and hours per hectare for key items in each equipment set.						
Machine	Width of the Implement (m)	Overlap	Field speed (km/h)*	Field Efficiency*	Ha/h**	H/ha
Conventional, Larger (228 kW):						
Primary tillage (chisel plow)	6.706	0%	9.012	85%	5.14	0.19
Preplant tillage (field cultivator)	14.326	0%	9.012	80%	10.33	0.10
Planter	12.192	0%	9.012	75%	8.24	0.12
Sprayer	36.576	0%	9.012	65%	21.43	0.05
Combine	6.096	0%	14.9669	65%	5.93	0.17
Conventional, Smaller (37.4 kW)						
Primary tillage (chisel plow)	2.438	0%	9.012	90%	1.98	0.51
Preplant tillage (field cultivator)	3.658	0%	9.012	85%	2.80	0.36
Fertilizer Applicator	4.572	0%	9.012	85%	3.50	0.29
Planter	4.572	0%	9.012	90%	3.71	0.27
Sprayer	18.288	0%	9.012	80%	13.18	0.08
Combine	4.572	0%	14.9669	65%	4.45	0.22
Autonomous - HFH Type (37.4 kW)						
Primary tillage (chisel plow)	2.438	0%	9.012	90%	1.98	0.51
Preplant tillage (field cultivator)	3.658	0%	9.012	85%	2.80	0.36
Fertilizer Applicator	4.572	0%	9.012	85%	3.50	0.29
Planter	4.572	0%	9.012	90%	3.71	0.27
Sprayer	18.288	0%	9.012	80%	13.18	0.08
Combine	4.572	0%	14.9669	65%	4.45	0.22

Note: **Following 9.012 Km/h for tillage implements, planter and sprayer and 14.97 Km/h for combine assumptions of Ward, Roe and Batte (2016). **Field efficiency following Ward, Roe and Batte (2016) with 0% overlap percentage. For strip cropping cases, the combine efficiency was assumed 10% less similar to conventional whole farm combine efficiency as the combine was hypothesized to unload grain to the grain semi at the end of the field.*

Appendix B (iii) Coefficients Estimation Spreadsheets (i.e., Estimating Coefficients_AJ_VFF.xlsx)

Appendix B (iv) LP Excel Spreadsheets of the Base Models (i.e.,
HFH_LP_Strip_Crop_Conv50hp_170922.xlsx;
HFH_LP_Strip_Crop_Conv310hp_170922.xlsx; and
HFH_LP_Strip_Crop_Robot50hp_170922.xlsx)

Both Appendix B (iii) and (iv) are be available on request to the author at: abdullah.alamin@live.harper.ac.uk or abdullah.alamin@bau.edu.bd.

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Appendix C

GAMS code used

The GAMS code for this study was adopted from Lowenberg-DeBoer et al. (2021a).

Appendix A – UK-Wheat-OSR-Barley_EditedRobot3-20190117.gms – The GAMS source code for the preliminary version of the HFH-LP

```
* The origins of this model are from Preckel et al. (2019), and were modified by
* Lowenberg-DeBoer et al. (2019). This program may be distributed or further modified
* provided that this comment remains and is updated according to the future
  modifications
* and provided that any modified program continues to be freely distributed.
* Citations:
* P. Preckel, C. Fontanilla, J. Lowenberg-DeBoer, J. Sanders, “Orinoquia agricultural
  linear
* programming model – documentation.” (Colombia Purdue Partnership, Purdue
  University,
* https://www.purdue.edu/colombia/partnerships/orinoquia/docs/OrinoquiaLPDoc.pdf,
*  2019).
* Lowenberg-DeBoer, James, Karl Behrendt, Richard Godwin and Kit Franklin, “The
  Impact of
* Swarm Robotics on Arable Farm Size and Structure in the UK.” – paper presented at
  the
* Agricultural Economics Society (AES) Conference, April 2019, Warwick, UK.
* Note that if you change the name of the data spreadsheet, then the name
* of the first Excel file in the line below to the name of your new file.
$call copy UK-Wheat-OSR-Barley_Conv38hp_20190125.xlsx Orinoquia_Tables.xlsx
* If you would like to see the equations, increase limrow in the line below.
* If you would like to see the activities, increase limcol in  the line below.
Option limrow=0,limcol=0 ;
* Note all of the data are read from the spreadsheet; so not data appears in this
program.
Sets
 t(*)         Time periods
 e(*)          Enterprises
 c(*)          Commodities
 l(*)         Land type ;
```

```
Scalars
 flab          Family labor available (no. of workers)
 plab           Permanent labor available already employed (no. of workers)
 trac          Autonomous Tractors available (man days)
 comb             Autonomous Combines available (man days)
 thlab          Maximum hired temporary labor in each period (man days)
 phlab           Maximum additional permanent labor hired (man years)
 twlab          Temporary wage (GBP per 8 hour man day)
 pwlab           Permanent worker wage (GBP per man year)
 initcash        Initial cash available (GBP)
 intrst         Monthly interest rate
 mxborrow        Borrowing constraint in GBP ;
* The following does imports of data from Gams_Tables.xlsx.
$onecho > tasks.txt
set=t rng=Scalars_and_Parameters_(R)!f4 dim=1 rdim=1
set=e rng=Labor_use_(R)!b2 dim=1 rdim=1 maxdupeerrors=50
set=c rng=Commodity_produced_(R)!c2 dim=1 rdim=1 maxdupeerrors=50
set=l rng=Commodity_produced_(R)!a2 dim=1 rdim=1 maxdupeerrors=50
par=flab rng=Scalars_and_Parameters_(R)!c3 rdim=0 cdim=0
par=plab rng=Scalars_and_Parameters_(R)!c4 rdim=0 cdim=0
par=trac rng=Scalars_and_Parameters_(R)!c5 rdim=0 cdim=0
par=comb rng=Scalars_and_Parameters_(R)!c6 rdim=0 cdim=0
par=thlab rng=Scalars_and_Parameters_(R)!c7 rdim=0 cdim=0
par=phlab rng=Scalars_and_Parameters_(R)!c8 rdim=0 cdim=0
par=initcash rng=Scalars_and_Parameters_(R)!c9 rdim=0 cdim=0
par=intrst rng=Scalars_and_Parameters_(R)!c10 rdim=0 cdim=0
par=mxborrow rng=Scalars_and_Parameters_(R)!c11 rdim=0 cdim=0
par=twlab rng=Scalars_and_Parameters_(R)!c12 rdim=0 cdim=0
par=pwlab rng=Scalars_and_Parameters_(R)!c13 rdim=0 cdim=0
$offecho
$call GDXXRW Orinoquia_Tables.xlsx  trace=3 @tasks.txt
$GDXIN Orinoquia_Tables.gdx
$LOADDC t,e,c,l,flab,plab,trac,comb,thlab,phlab,initcash,intrst,mxborrow,twlab,pwlab
$GDXIN
Set
 fnt(t)          Final time period ;
fnt(t) = Yes$(ord(t) eq card(t)) ;
* Display those sets and scalar values in case we need to verify the data got
```

```
* read in all right.
Display t,fnt,e,c,l,flab,plab,trac,comb,thlab,phlab,initcash,intrst,mxborrow,twlab,pwlab;
* Declare the parameters whose values will also be read from the spreadsheet.
Parameters
 lnd(l)         Land of type l available (ha)
 gfd(t)         Good field days available in period t (days per period)
 wu(l,e,t)       Labor use of enterprises by period
 tu(l,e,t)      Autonomous tractor use of enterprises by period
 comu(l,e,t)     Autonomous combine use of enterprises by period
 cu(l,e,t)       Cash use for enterprises by period
 lu(l,e,t)      Land use of enterprises by period (ha per period)
 entcom(l,e,c,t) Quantity commodity c produced per unit of enterprise e on land l
* fu(l,e,c,t)     Commodity use of enterprises by period (intermediate inputs)
 sprc(c)        Selling prices for commodities (GBP per unit)
 lobd(l,e)       Lower bounds on commodities by enterprise (ha)
 upbd(l,e)       Upper bounds on commodities by enterprise (ha) ;
* Import parameter values.
$onecho > tasks.txt
par=lnd rng=Scalars_and_Parameters_(R)!b16 dim=1 rdim=1
par=gfd rng=Scalars_and_Parameters_(R)!f4 dim=1 rdim=1
par=sprc rng=Scalars_and_Parameters_(R)!j4 dim=1 rdim=1
par=wu rng=Labor_use_(R)!a1 rdim=2 cdim=1
par=tu rng=Trac_use_(R)!a1 rdim=2 cdim=1
par=comu rng=Comb_use_(R)!a1 rdim=2 cdim=1
par=cu rng=Cash_use_(R)!a1 rdim=2 cdim=1
par=entcom rng=Commodity_produced_(R)!a1 rdim=3 cdim=1
par=lu rng=Land_use_(R)!a1 rdim=2 cdim=1
* par=fu rng=Commodity_use_(R)!a1 rdim=3 cdim=1
par=lobd rng=Scalars_and_Parameters_(R)!n4 dim=2 rdim=2
par=upbd rng=Scalars_and_Parameters_(R)!s4 dim=2 rdim=2
$offecho
$call GDXXRW Orinoquia_Tables.xlsx o=Orinoquia_Tables_par.gdx trace=3 @tasks.txt
$GDXIN Orinoquia_Tables_par.gdx
$LOADDC lnd,gfd,sprc,wu,tu,comu,cu,entcom,lu,lobd,upbd
$GDXIN
* Display those parameter values in case we need to verify the data got
* read in all right.
Display lnd,gfd,sprc,wu,tu,comu,cu,entcom,lu,lobd,upbd ;
```

```
* Set the enterprise-land type mapping based on whether the enterprise
* produces any commodity in any time period on the specific land type.
* If it doesn't produce anything, it gets supressed.
Set
 el(e,l)        Enterprise-land type included if enterprise has output on land l ;
el(e,l) = Yes$(sum((c,t),entcom(l,e,c,t)) gt 0) ;
el(e,l)$(lnd(l) eq 0) = No ;
Display el ;
Positive Variables
 produce(l,e)    Produce enterprise e on land type l (ha)
 sell(c,t)       Sell commodity c in period t (commodity units)
 phire           Permanent labor hired (man years)
 thire(t)        Temporary labor hired in period t (man days)
 save(t)         Cash stored from period t to t+1 (GBP)
 borrow(t)       Cash borrowed in period t and repaid in period t+1 (GBP) ;
Variables
 netret          Net return to the farm (GBP) ;
Equations
 land(l,t)       Limit on land use for land of type l in period t (ha)
 labor(t)        Define amount of labor to hire in period t (man days)
 autotrac(t)     Define autonomous tractor use in period t (man days)
 autocomb(t)     Define autonomous combine use in period t (man days)
 comuse(c,t)     Sources and uses for commodity c in period t (commodity units)
 cash(t)         Sources and uses of cash in period t (GBP)
 nrobj           Net return objective ;
land(l,t) ..
sum(e$el(e,l),lu(l,e,t)*produce(l,e)) =l= lnd(l) ;
labor(t)  ..
 sum(el(e,l),wu(l,e,t)*produce(l,e)) =l=
 (flab+phire)*gfd(t) + thire(t) ;
autotrac(t)  ..
 sum(el(e,l),tu(l,e,t)*produce(l,e)) =l=
 (trac)*gfd(t)  ;
autocomb(t)  ..
 sum(el(e,l),comu(l,e,t)*produce(l,e)) =l=
 (comb)*gfd(t) ;
comuse(c,t) ..
 sell(c,t)
```

```
 =l=
 sum(el(e,l),entcom(l,e,c,t)*produce(l,e)) ;
cash(t) ..
 sum(el(e,l),cu(l,e,t)*produce(l,e))
 + phire*pwlab/card(t)
 + thire(t)*twlab + save(t)
 + borrow(t-1)*(1+intrst)
 + initcash$fnt(t) =l=
 initcash$(ord(t) eq 1) + sum(c,sprc(c)*sell(c,t))
 + save(t-1) + borrow(t)$(not fnt(t)) ;
nrobj ..
netret =e= sum(fnt,save(fnt)) ;
* Set bounds on individual variables.
produce.lo(l,e) = lobd(l,e) ;
produce.up(l,e) = upbd(l,e) ;
thire.up(t) = thlab ;
phire.lo    = plab ;
phire.up    = plab + phlab ;
borrow.up(t)= mxborrow ;
Model finca / land,labor,autotrac,autocomb,comuse,cash,nrobj / ;
option lp=cplex ;
finca.optfile=1 ;
Solve finca using lp maximizing netret;
```

Thank You

End