Harper Adams University

Proceedings of the 6th Symposium on Agri-Tech Economics for Sustainable Futures

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Global Institute for Agri-Tech Economics,

Food, Land and Agribusiness Management Department,

Harper Adams University

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Proceedings of the 6th Symposium on Agri-Tech Economics for Sustainable Futures

Global Institute for Agri-Tech Economics (GIATE)
Food, Land & Agribusiness Management Department
Harper Adams University
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Nigel Hill (Assoc. Head FLAM, HAU)	Thank you and FLAM strategy
Professor Deb Roberts (JHI)	Keynote: Tackling the nexus of productivity, trade, sustainability, land use and food security in the UK
Prof Paul Thomassin (McGill University)	Keynote: How to make national research achieve national sustainability targets: the case from Canada

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Centre for Effective Innovation in Agriculture

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Keynote Presentation: Tackling the nexus of productivity, trade, sustainability, land use and food security in the UK

Professor Deb Roberts

The James Hutton Institute, Craigiebuckler, Aberdeen AB15 8QH Scotland UK

Presenter Profile

Deb is the Deputy Chief Executive and Director of Science at the James Hutton Institute. She holds an Honorary Chair in the Business School, University of Aberdeen, is a Director of the Scottish Government's Centre of Expertise in Climate Change ClimateXChange | Scotland's Centre of Expertise on Climate Change , and is a member of the Academic Advisory Panel overseeing agricultural reform in Scotland.

Deb trained as an agricultural economist and her research has focussed on modelling the economy-wide impacts of changes in farm, forestry and agricultural policies. She has also carried research at the micro-level looking at farm household behaviour and the spatial pattern of farm household transactions. Latterly her work has moved into rural development and has focussed on the key drivers for change, and reasons for regional disparities. As Director of Science she is responsible for Research Integrity, ensuring the role of everyone in the research process is recognised, and for promoting Open Science.

Keynote Presentation: How to make national research achieve national sustainability targets: the case from Canada

Professor Paul Thomassin

Natural Resource Sciences, Faculty of Agricultural and Environmental Sciences, McGill University, Ste. Anne de Bellevue, Québec, H9X 3V9 Canada.

Presenter Profile

Paul J. Thomassin is a Professor of Agricultural Economics at McGill University. He received his B.Sc. (Agr) from McGill University and his M.S. and Ph.D. in Agricultural and Resource Economics from the University of Hawaii. His research areas include agricultural and environmental economics, technological change, and the economics of climate change. He leads the socio-economic pillar of a multidisciplinary sustainable agriculture network in Quebec. Current research projects include dairy farmer adoption decisions to meet net-zero goals, plant breeding technology and the adoption of new pulse varieties on the farm and regional levels, and the economic impact of antimicrobial resistance from the food supply chain.

Keynote Presentation: A shared research strategy for UK agricultural universities

Professor Tom MacMillan

Royal Agricultural University, Cirencester, Gloucestershire, GL7 6JS UK

Presenter Profile

As Creak Chair, Professor MacMillan's role is to inform national and international policies on land, the environment and food. Tom is a founding Director of the Centre for Effective Innovation in Agriculture and Deputy Director of The National Innovation Centre for Rural Enterprise (NICRE). He is expert advisor to the Food, Farming & Countryside Commission and was one of the team who supported Henry Dimbleby to develop the National Food Strategy.

Tom joined us from the Soil Association, where he was Director of Innovation. There, he founded the Innovative Farmers network, which supports practical 'field labs' by farmers and led an overhaul of organic standards. From 2003-2011 he was Executive Director of the Food Ethics Council, which received the BBC Food & Farming Derek Cooper Award for its Food & Fairness Inquiry. He has served on various advisory groups and boards, including for the Cabinet Office Food Matters report, ScienceWise, the BBSRC, Sustain and the Brighton & Hove Food Partnership. He has a PhD in geography from the University of Manchester, where he investigated the use and abuse of science in food regulation.

Evaluating the impact of government investment support for crop robots: a multi method approach

Olivia Spykman and Andreas Gabriel

Bavarian State Research Center for Agriculture, Germany

Abstract

Technology plays an important role in the transition towards more sustainable agriculture. The associated costs for farmers may be lowered through government investment support programmes. The German federal state of Bavaria runs such a programme for various technologies, including crop robots that help to reduce chemical plant protection input. Based on official funding application data, an economic model relying on field trial data, and results from an early adopter focus group discussion, the case of the crop robot FD20 (FarmDroid ApS) in sugar beet is evaluated in detail. The funding application data indicates that applicants manage larger farms and work according to organic standards more often than the Bavarian population of farmers. The applicants' counties of residence match areas of sugar beet production, suggesting a use of the robot mainly in sugar beets. The economic evaluation indicates a shift in minimum area of sugar beet production necessary for economical use of the robot caused by the government investment support. The minimum necessary area varies by field size and number and points to the importance of setup times and agricultural structures for robot profitability. The focus group discussion highlights the relevance of the government investment support scheme for farmers' investment into a new type of technology shortly after its market entry. This multi-method approach has provided complementing conclusions from its three components that would not have been possible from each piece of research individually. Overall, the government investment support appears to have been integral to the success of crop robots in Bavaria and may thus serve as an example for other policymakers looking to create similar technology investment support schemes to move forward the digital transition in agriculture.

Keywords

Field robots; early adopters; economic model; focus group; sugar beet production; public funding.

Presenter Profiles

Olivia Spykman works is part of the Digital Farming Group at the Bavarian State Research Center for Agriculture and works on the socio-economic evaluation of crop robots for her PhD. After research crop robot acceptance among farmers and the general society, she currently focuses on questions of labour economics. She has a background in environmental science and agricultural economics.

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Introduction

The European agricultural sector currently faces a lack of manual and skilled labour as well as strict political regulation in response to environmental and societal requirements (cf. European Commission, 2023a), among other challenges. While these issues demand systemic changes rather than technological fixes, shifts in agronomic approaches require longer timescales. Novel (digital) technologies can contribute to the necessary transition both within existing and towards more sustainable systems. Among the digital technologies frequently discussed for this purpose, field robots may contribute to the solution in multiple ways: autonomous operation can reduce the dependency on labour (cf. Lowenberg-DeBoer et al., 2021), and autonomous mechanical weeding can reduce herbicide input and labour cost simultaneously. Furthermore, lower weights than tractors reduce fuel consumption and soil compaction, and electric drives may reduce the dependency of agriculture on fossil fuels. These changes address some of the demands posed in the EU Green Deal to be fulfilled by 2030 (cf. European Commission, 2023a, b). The German federal state of Bavaria has set an even more ambitious goal of halving the use of chemical plant protection by 2028 (StMELF, 2021). Characterized by small-scale agriculture, Bavaria is actively moving forward the transition through an investment support programme (Bayerisches Sonderprogramm Landwirtschaft Digital, "BaySL Digital") for digital technologies that enable the reduction of herbicide use and support organic farming, among others (StMELF, 2023). One such technology eligible for funding through the programme is the seeding and weeding robot FD20 by Danish manufacturer FarmDroid ApS. It is solar-powered and autonomously seeds and weeds sugar beet and other fine seeds, relying on an RTK-enhanced GNSS system as opposed to camera detection. Between October 2019 and December 2022, Bavarian farmers could apply for funding of 40 % for a maximum investment sum of € 100,000 for eligible technologies, including the FD20. After an evaluation break of the technology-specific programme, it was resumed in July 2023. Lowering technology entry costs for farmers while simultaneously moving towards more sustainable agricultural practices is the proclaimed goal of the programme (StMELF, 2023). As such, it addresses financial limitations to technology adoption, which play an important role in farmer decisions for or against new technology.

In the broader context of farm technologization, farmers tend to seek a compromise between costs and realizable benefits of advanced technologies (Kutter et al., 2011). Factors such as farm size, legal framework, operator characteristics, and the relative advantage of farming technologies consistently influence adoption and diffusion (Shang et al, 2021). Against this background, the attitude of farmers in acquiring new technologies is strongly determined by investment cost-related concerns. High investment costs may impede farmers in realizing potential profitability benefits (Eastwood & Renwick, 2020). Other literature indicates that farmers also adopt new farming practices even without an immediate profit (Lehman et al., 1993). However, financial initiatives can support a quicker and broader application of technologies, such as capital grants for technology maintenance, tax breaks, interest rate reductions, and free technical assistance (Tey and Brindal, 2012; Floridi et al., 2013; Shang et al., 2021). One or more of these measures could indirectly change farmers' perceived profitability and improve actual farm productivity or even mitigate technology user risk (Ferrari et al., 2022). A variety of studies shows that the presence of government support services and funding schemes is an important prerequisite for the adoption of digital technologies in agriculture (e.g., Reichardt and Jürgens, 2009; Lambert et al., 2015). However, there are more economic analyses that measure the extent of decoupled farm payments or federally subsidised crop insurance premiums (e. g., Weber et al., 2016). Only few studies document the various country-specific programmes that have a direct impact on the use of digital farming technology. This may also be due to many such programmes having only been implemented in recent years (McFadden et al., 2023). Barnes et al. (2019) postulate that technology-specific subsidies offered by national or regional authorities may be an important driver for adoption of disruptive technologies like crop robots, especially on smaller and low-income farms. In this context, the appropriate type of financial support is also decisive. A very recent study from Switzerland simulated that in the case of site-specific management, coupled payments for reduced nitrogen are more cost-effective than, for example, area-based payments or subsidies for the use of technology (Huber et al., 2023). However, this result is specific to the technology and cannot necessarily be transferred to crop robots, as, for example, savings potentials of herbicides can only be measured in context of the reference (e.g., conventional vs. organic farms).

The Bavarian government's funding scheme for digital farming technologies represents a case study for the role of technology investment support in the transition currently underway in the farming sector. The particular case of the FD20 robot within this regional funding scheme has been analysed from multiple perspectives. The present contribution forms a synthesis of the analysis of official funding data, a model for calculating economic efficiency of the FD20 (Spykman et al., 2023a; Rossmadl et al., 2023) as well as findings from a focus group discussion (Spykman et al., 2023b) to evaluate a regional investment support programme. The overview provides insights for researchers and policymakers in other regions looking to investigate and support the uptake of digital technologies in agriculture.

Methods

A multi-methods approach was used to understand the impact of funding for crop robots through the government investment support programme BaySL digital in Bavaria. First, applications for crop robot investment support approved by the responsible government agency are evaluated to characterise the funded farms. Then, an economic evaluation shows the monetary impact of subsidy payments on the profitability of the FD20 compared to standard weed control in organic sugar beet. Finally, results of a focus group discussion with early adopters provide perspectives from practical agriculture both on experience with the robot as well as on the role of the funding scheme.

(a) Evaluation of funding application progress

The investment support programme was launched in October 2018, with the robot FarmDroid FD20 only being put on the list of eligible technologies in October 2019. The currently ca. 50 technologies on this list fulfilled the requirements of (1) having a digital component and (2) serving the purpose of reducing the input of chemical plant protection products. Other categories of technologies were also supported under the same funding scheme but will not be discussed here. The funding of digital weeding and spraying technologies, which includes crop robots, was continued until December 2022, when it was paused for evaluation. Funding was resumed in July 2023, but this ongoing period will not be considered in the present analysis.

A list of approved applications for robots over the scheme's duration (October 2019 till December 2022) was provided by the Bavarian State Ministry of Food, Agriculture and Forestry under adherence to data protection regulation. Based on the farm identification numbers, farm size and management type (organic/conventional) could be retrieved from the government database. Further information on the status of the funding process was added: after approval for funding, farmers were given 12 months' time to purchase the crop robot. They were then given another three months to submit the invoice as proof of purchase in order to receive an investment support of 40 % of the purchasing price up to an investment sum of net € 100,000. Therefore, at the time of writing, not all approved applications can be evaluated conclusively. This category will be considered "open" applications, as opposed to "completed" (invoice submitted, funding transferred) and "incomplete" (application retracted or no invoice submitted more than 15 months after approved application).

Given the FD20's suitability of sugar beet production, which relies heavily on manual weeding under organic management, the applicants' postal codes were mapped and combined with data on sugar beet production. For this purpose, the first two positions of the five-digit postal code, which indicate the region, were used to create a color-coded map of approved applications for the FD20 per region in QGIS 3.12.3 (QGIS Development Team, 2023). Additionally, county-level ("Landkreis") data on sugar beet production was provided by the two sugar beet growers' associations (Steinberger, 2023, personal communication, 25 July; Beil, 2023, personal communication, 26 July). Since membership in one of the two associations is mandatory and dual membership is not possible for growers, the provided data can be considered comprehensive. The data were also transferred to QGIS 3.12.3 and color-coded.

(b) Modelling the effect of public funding

Given a lack of long-term empirical data, an economic model of different assumption-based scenarios was evaluated in Microsoft Excel. This model compares organic sugar beet production using the FD20 to the standard method of weed control, relying on a tractor and manual labour (see Spykman et al., 2023a; Rossmadl et al., 2023). Only those measures of the sugar beet production process assumed to differ between robot and tractor operations were included in the model. Table 1 summarises the different measures considered in the model comparing the two variants (FD20 vs. standard variant). The model includes labour and machinery costs for both variants. These costs take into account farm-field distance, error frequency and farmer-response time in the FD20 variant, and time needed for the completion of setup tasks, among others. The time data for the FD20 variant are based on experience as well as dedicated time measurements from various field trials in 2021 (Rossmadl et al., 2023). All other parameters are based on standardized data (KTBL, 2021; Achilles et al., 2020). The model's computations include the difference between the FD20 and the standard variant, so that the produced output was the FD20's profit contribution to sugar beet production relative to the standard variant (Spykman et al., 2023a; Rossmadl et al., 2023).

Table 1: Comparison of FD20 and standard variants in the economic evaluation model (adapted from Spykman et al., 2023a)

FD20 variant	Standard variant
1x blind seeding[1]	
1x seeding	1x seeding
1x blind weeding[2]	
3x inter-row weeding	1x manual weeding
3x intra-row weeding	3x tractor-bound mechanical weeding
0.3x manual weeding (canopy closure)	1x manual weeding (canopy closure

Based on experience from field trials (Kopfinger and Vinzent, 2021), it is assumed that the FD20 variant may fully replace the first passes of manual weeding but still requires some manual weeding at canopy closure due to (1) a safety margin around the individual plants not being weeded and (2) the risk of leaf damage by the FD20 during passes at or after canopy closure. Therefore, the FD20 variant contains a pass of manual weeding at a fraction of the time of a regular pass of manual weeding, as it is assumed that farm labourers will be able to proceed at a faster pace compared to the standard variant due to the FD20's frequent passes throughout the season and thus lower weed coverage compared to the standard variant at canopy closure.

For a sensitivity analysis, different scenarios were calculated in the model (Spykman et al., 2023a). The baseline scenario, using data for the research site in Bavaria, assumed an annual capacity of 18 ha (calculated based on FD20 speed and good field days (Achilles et al., 2020)), which was divided over ten fields of 1.8 ha each, based on the average Bavarian field size of 1.74 ha (LfL, 2014). Further scenarios included a variety of field distributions given a constant total area of 18 ha, ranging from a single 18 ha field to 15 1.2 ha fields. Additionally, a range of maximum possible field capacities (8-20 ha), , calculated from the good field days (Achilles et al., 2020) in German sugar beet producing regions (WVZ, 2022) and own data on the robot's speed during seeding and weeding, was investigated. The upper end of the maximum field capacity spectrum is marked by the manufacturer's specification of 20 ha being the seasonal limit (FarmDroid ApS, 2023), which can also be reached in Bavaria according to the calculations. There are two sugar beet growers' associations in Bavaria, which together represent all sugar beet growers in the state. As specified by these growers' associations, between 26 and 29 % of member farms cultivate sugar beet on areas between 8 and 20 ha (Steinberger, 2023, personal communication, 25 July; Beil, 2023, personal communication, 26 July).

Further parameters include the purchasing price of the FD20 at net € 90,000 (Miller, 2022), and wages at 21 €/h for skilled labour and 16 €/h for manual labour (Die Bundesregierung, 2022; Achilles et al., 2020). Fuel costs were assumed to be 1.40 €/l (Offermann et al., 2022), including both the effect of the Russian invasion of Ukraine and the farm diesel subsidy. The resale value of 20 % after ten years is based on standardized data for agricultural equipment (Achilles et al., 2020) since no empirical data on an FD20 second-hand market exists yet. The baseline scenario was calculated without government investment support (Spykman et al., 2023a); for scenarios with government investment support, the purchasing price of the FD20 was reduced by 40 % to net € 54,000.

(c) Focus group discussion with early adopters

In autumn of 2022, the six farms that had received approval of their funding application prior to the start of the 2020 production season and thus had two seasons of experience with the robot were selected from the list of investment support recipients. A further nine farms that had received FD20 investment support after the start of the 2020 season but before the start of the 2021 season were added to the list. Given the applicants' agreement to future research inquiries during the application process, these 15 early adopters were contacted by telephone and invited to participate in an online focus group discussion to discuss their experience with the robot and challenges in their respective areas of operation in different regions of Bavaria (see Spykman et al., 2023b). Focus group discussions, as opposed to individual interviews, allow for a variety of interpersonal interactions to be provoked, despite a limited time frame, to obtain more details and background information (Mayring, 2016). A rough framework of topics outlined by pre-defined questions is typical for this method of data collection (Roller & Lavrakas, 2015). The focus group participants discuss freely within the prepared topics, which covered before-purchase expectations, funding process, user experience, problems and challenges, suggestions for improvement in the present case. The moderator intervenes as soon as the discussion strays from the topic or content is repeated in the discussion.

Seven of the 15 farm managers contacted took part in the online discussion session (two approved applications before 2020 season, five approved applications before 2021 season), with some variability in the group regarding crops grown, location, cultivation method, soil conditions, and age of operator (see Spykman et al., 2023b). Sample heterogeneity is an advantage for focus groups, as homogeneous groups tend to limit the knowledge gained about the population (Grønkjær et al., 2011). The audio track of the 90-minute discussion session was recorded to transcribe discussion for content analysis. In the transcript, individual statements made by the participants were coded and assigned to the original topic areas investigated.

Results

Descriptive statistics of funding applications

Over the course of three years (November 2019-December 2022), 88 applications for funding of field crop robots (65 by organic farmers) were approved by the Bavarian State Ministry for Food, Agriculture, and Forestry. Based on the available data, it is not possible to state the total number of applications to evaluate whether any applications were *not* approved. Of all these applications, only two were for robots other than the FarmDroid FD20, which will not be considered in the further discussion.

Regarding the 86 applications for the FD20 crop robot, it should be noted that one application was submitted by a machinery group with its proper ID; although this machinery group represents two farms, they applied jointly for one robot. Additionally, four tenancies in common also applied for a robot to be shared by two farms, yet in each of these cases, each farm applied individually. That is, these eight applications represent only four robots. Thus, the total number of robots for which applications were approved amounts to 82 and the total number of individual farms having been approved for funding amounts to 87.

At the time of writing, 17 of the 86 approved applications had been retracted or not completed (i.e., invoice submitted within required timeframe) and may thus be considered incomplete. Of the remaining 69 approved applications, six are open as applicants are still within the 15-month timeframe post-approval to submit the invoice for their robot. That is, 80 % of all approved applications so far were or can still be completed. Figure 1 demonstrates the development of cumulative approved applications and submitted invoices in monthly increments over the course of three and a half years, beginning with the first approved applications in February 2020 and leading up to August 2023 (the latest possible date at the time of writing) as submission of invoices remains possible until early 2024 for the last approved applications. It becomes evident that applications were rather slow in the first year but subsequently maintained a steady rate. After the programme was paused (from late December 2022 until resumption in July 2023), submitted invoiced continued increasing for several months.

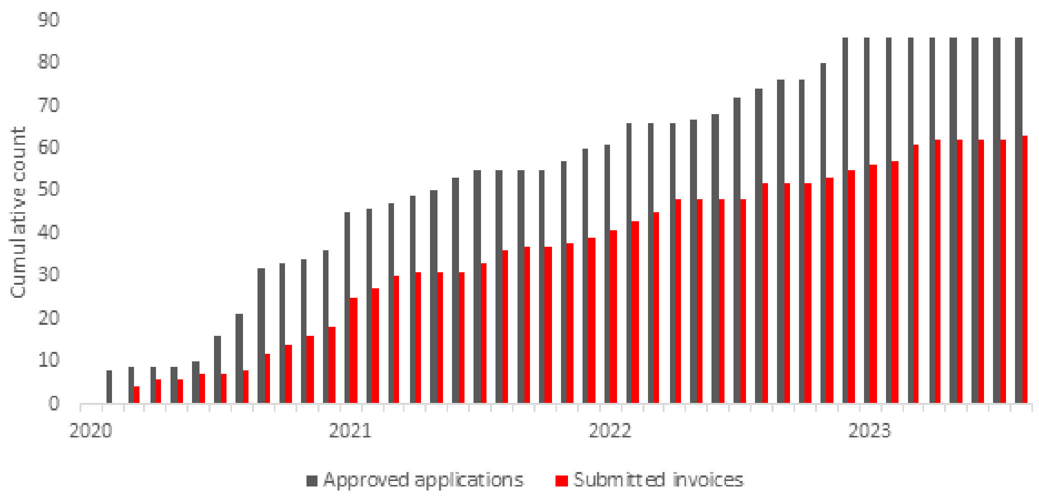

Figure 1: Temporal development of approved applications and submitted invoices for the FD20 (dotted box indicating evaluation pause)

The applicants' farm sizes range from 13 to 458 ha, with a mean of 99.5 ha. The mean farm size is thus markedly larger than the Bavarian average of 36.9 ha (StMELF, 2022). The Bavarian population of sugar beet farmers grows sugar beet on an average of 8.6 ha, although the largest farms reach sugar beet areas of 180-200 ha (Steinberger, 2023, personal communication, 25 July). Additionally, with 87 % of applications coming from organic farmers, the group of applicants quite juxtaposed to the population of Bavarian farmers, of whom only 11 % manage their farm according to organic standards (StMELF, 2022). While the available data did not provide information about the crop(s) in which the robot was planned to be deployed at the time of application, the visualisation of application numbers and sugar beet-producing areas in the federal state of Bavaria in Figure 2 indicates a spatial relationship between FD20 applicators and sugar beet production regions (county/"Landkreis" level). Regions with a higher number of approved applications are concentrated in the major sugar beet growing areas in the north, east and west of the state.

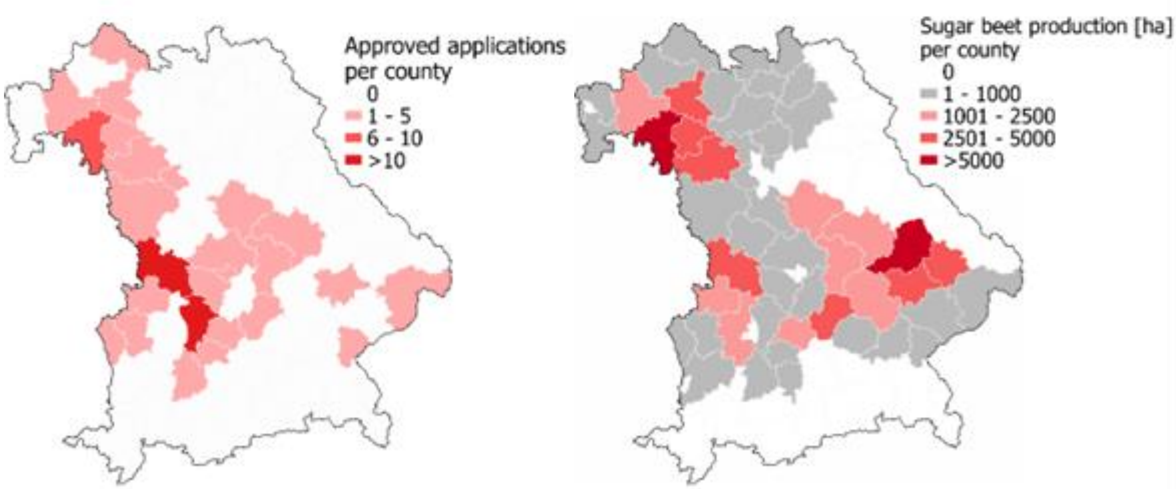

Figure 2: Regional distribution of all 86 approved applications for FD20 (left, own data) and sugar beet producing counties (right, 2022 data from Steinberger, 2023, personal communication, 25 July)

Effect of government investment support on crop robot economics

In the economic model, the baseline scenario (total area operated by robot of 18 ha, distributed evenly over ten fields) resulted in an FD20 profit contribution of 304 €/ha*a at 0 % investment support and 794 €/ha*a at 40 % investment support, respectively. Given the small-scale structure of Bavarian agriculture, different scenarios of field size and distribution were considered. The profit contribution of the FD20 remained positive over all field distribution scenarios for a total area of 18 ha and irrespective of the 40 % investment support. This suggests that investment support is not necessary for economical operations at the upper end of the robot's annual area capacity, even if operations take place on many small fields and thus require substantial set-up time (see Spykman et al., 2023a). However, given the uncertainty about a potential second-hand market, a worst case of 0 % resale value was also considered. It highlights the importance of the investment support scheme for financial risk reduction. Under the assumptions of the baseline scenario (i.e., total area of 18 ha) a 0 % resale value would lower the profit contribution by 60 % for the no-investment-support scenario, but only by 23 % for the investment-support scenario.

The investment support also impacts the minimum total area (see Figure 3) for economical operations. Considering average field sizes of 2 ha (cf. baseline scenario) and 4 ha, the FD20's profit contribution at each total area (range: 8-20 ha) was evaluated, subject to divisibility constraints. If the 40 % investment support is added to the calculation, both field sizes yield positive profit contributions across the considered range. However, without investment support, larger total areas would be necessary for the robot to break even, i.e., 11.5 ha at an average field size of 4 ha and 13.7 ha at an average field size of 2 ha. Thus, even if farmers have larger-than-average fields in Bavaria, they still require a certain minimum area for the robot to be economically advantageous over the standard method. The required minimum area also exceeds the average sugar beet area per farm of 8.6 ha, which, however, ranges widely between growers (Steinberger, 2023, personal communication, 25 July) This disadvantage of small-scale structures may be attenuated by government investment support.

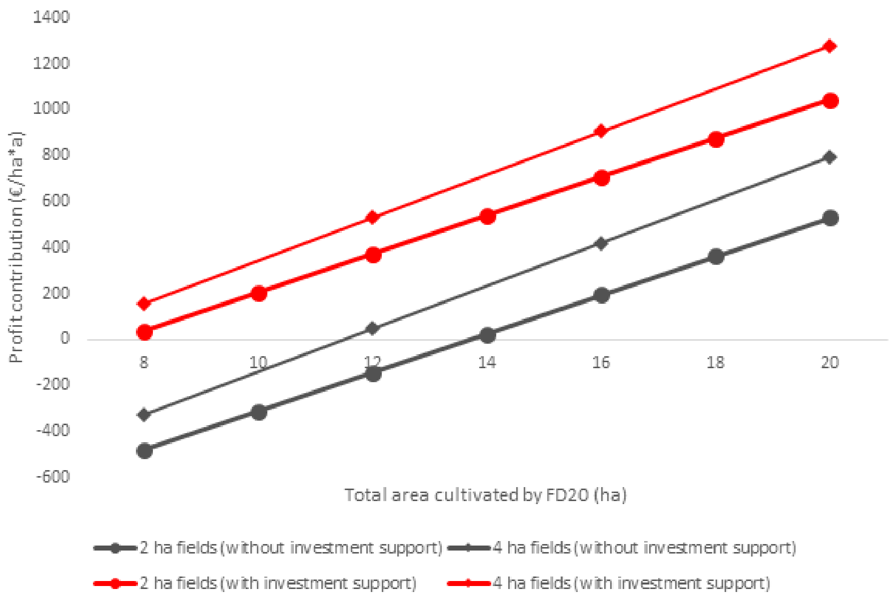

Figure 3: Profit contribution of FD20 under consideration of different field size options with and without investment support

FD20 early adopters' opinion on role of government investment support

Among the early adopters engaged in the focus group discussion, the primary utilisation of the FD20 is in sugar beet production (see Spykman et al., 2023b). In a few instances, it is deployed for sowing rapeseed and subsequently performing hoeing operations between the rows. Notably, one farm manager expressed intentions to employ crop robots in kale cultivation. Regarding the area managed using the FD20, the participants communicated a sizable range from 8 to 25 ha, exceeding the manufacturer's specification of a maximum seasonal usage of 20 ha (FarmDroid ApS, 2022). Most farmers in the focus group found that the robot met their expectations. While the robot successfully reduced manual labour, it did not completely replace it. The FD20's effectiveness in task performance exhibited significant variation depending on the site-specific conditions. Particularly soil structure (i.e., preferably finely textured, minimal presence of stones, and as level as possible) emerged as a pivotal requirement for achieving technical success in utilising the robot.

Main drivers for investing in the robot FD20 were similar across participants. One of the key motivations were Covid-19-driven concerns about not being able to host seasonal workers due to travel restrictions or stricter housing regulation. The market-availability of FD20 in Germany at the start of the pandemic and the possibility to reduce economic risks through the investment support programme presented farmers with the opportunity to increase resilience and decrease cost of organic sugar beet production. They confirm the application process of the funding scheme to be well organized and easy to manoeuvre, so that no suggestions for improvement of the procedure were discussed in the focus group.

Towards the end of the group discussion, farmers were asked whether they would repeat the investment in the FD20, given the knowledge they had gained during the two years since purchase. The farmers' responses to this question were more differentiated. Some were generally happy with the robot's performance but were deterred by the increase in its catalogue price since they had purchased it so that, without investment support, they would not purchase the robot a second time. This sentiment was echoed by another fraction, who highlighted the value of improved resilience in production due to a reduced dependence on seasonal labour. This subgroup agreed also that they would still make the investment under similar conditions, i.e., price and investment support. A third subgroup appreciated the work relief presented by the FD20 but based on their experience would now prefer waiting for further technological developments to improve the relative advantage before investing in a crop robot.

Discussion

The multi-perspective evaluation of government investment support for farmers' participation in the technological transition towards autonomy in agriculture highlighted the importance of farmer characteristics as early adopters and the relevance of targeted support programmes for small-scale regions. The investment support programme in Bavaria has resulted in more than 55 robots being used predominantly in sugar beet production within three years of funding. This represents more than a quarter of all FD20s operating in Germany, according to the manufacturer (Georgsen, 2023, personal communication, 26 July).

While investment support generally lowers the risk for farmers, the ones who invested in the robot directly after its market entrance in Germany in 2020 may still be described as venturesome. The government investment support programme in Bavaria supported this incentive, as opposed to the general CAP subsidy mechanism, which does not grant additional funds to promote innovations for sustainable agriculture (Reinhardt, 2022). In the specific case of the FD20, the high rate of organic farmers among applicants (87 %) suggests that this technology may facilitate organic sugar beet production, which could influence farmers' decision to adopt organic farming practices, thus contributing to a socio-political objective in Bavaria. Further, FD20 early adopters had to find technological solutions on their own to put the robot to its most effective use, adding to the general learning costs that come with the change from tractor to robot. The focus group participants also underscored the importance of direct exchange with the manufacturer (cf. Rial-Lovera, 2018; Rose et al., 2021) and the importance of ongoing technological development of crop robots for their retrospective opinion. Research into the applications of the specific technology in question and possibly subsidies for their early adoption (Sparrow & Howard, 2020) may thus contribute to broader dissemination and lower risk for small-scale farms (Fleming et al., 2018).

Sectoral diffusion at large is linked to incentivising infrastructural conditions and policies. Ferrari et al. (2022) gathered expert opinions and conclude initiatives for public awareness, taxes and subsidies, training and education, cohesion funds, and general policies reducing the risk of use to be important drivers of digital transformation. However, government investment support programmes should be designed with caution. Transparency and care are needed because many farmers feel strongly monitored by the state (due to regulations on subsidies). This leads to fear of data misuse or exposure of grievances among farmers (Linsner et al. 2021). However, the focus group participants did not express any such concerns. The processing of applications for the BaySL Digital funding scheme occurred through the same platform as applications for direct payments, so that necessary operational data was recorded by the funding body anyway.

The economic model assessing the profitability of the use of the FD20 underscores the importance of government investment support in the context of small-scale farming, as is typical in Bavaria. Investment support reduces the total area required to reach break-even by 45 % under the declared assumptions. Given the lack of long-term empirical data on the technology, the resulting profit contributions should be considered only in relative terms, though, being highly dependent on the assumed input values. Nonetheless, the resulting patterns indicate that some farms, depending on their field distribution, may not have been able to use the robot economically without co-funding. This observation indicates that crop robots, too, are subject to economies of scale, which may be attributed to costs of labour for setup tasks (e.g., transport between fields). Thus, despite autonomous vehicles reducing active labour time on the field, they do require increased labour at other stages of the field work process, somewhat analogous to the shift, yet not reduction in labour due to milking robots (cf. Martin et al., 2022). The described difference in economy due to farm size may cause a digital divide, which can be softened by government policy (van Woensel et al., 2016).

Conclusion

The multi-method approach to evaluating technology-specific government investment support by means of the FD20 robot case allowed drawing a combined conclusion from three individual investigations. The economic assessment allows for evaluation of potentials for specific farm types and sizes. The identified range of profitability matches the production areas of almost a third of sugar beet growers in Bavaria, although more detailed analyses will be needed to differentiate between organic and conventional producers. The economic model further suggests government funding to represent a decisive financial incentive, which was confirmed by the focus group. The three perspectives provide an overview of the alignment of funding scheme, farm structures, and target user group in Bavaria, which would not be possible on a stand-alone basis.

Government investment support like the BaySL Digital programme can play an important role in facilitating the adoption of novel technologies such as the FD20 robot. Hardware technology may only become economical when used at a certain intensity, meaning that the investment case may not be clear or given at all for farms below a certain acreage. Investment support programmes may decrease the required acreage by lowering the effective sum of investment, thus enabling otherwise disadvantaged small farms to participate in technological progress.

Technological progress in agriculture is not an end in itself. Rather, current developments aim to make farming more ecologically compatible while guaranteeing economic competitiveness and social support. Government investment support should be coupled to the achievement of milestones in the agricultural transition. In the BaySL Digital programme, this was achieved by restricting funding to technologies that could meet pre-defined objectives (e.g., the reduction of synthetic plant protection inputs). Other options may be devised, but this general aspect should not be omitted by policymakers wishing to implement a funding scheme for agricultural technologies.

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Heterogenous effects of milk price volatility on French dairy farms economic viability: roles technological equipment uses

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Abstract

In a context of increased milk price volatility and dairy farm modernization, our study aims to shed light on whether the costs associated with the financial investments made when acquiring technologies and their maintenance costs exacerbate the damage suffered when the price becomes volatile, or whether the expected productivity gains actually help to cope with this market hazard. To do this, we distinguish three farm categories according to three separate variables that approximate the level of technological tools used. Then, we estimate the variation in the level of viability of each group when price volatility changes.

We apply fixed effect ordered logistic regression on data gathered from the French farm accountancy data network from 2002 to 2020. Sample is divided into three categories according to their levels of intensification and use of technological tools. We estimated separately the viability models of each category to check for heterogeneity.

Our results show positive roles of low intensification and moderate use of technological equipment in mitigating the impact of an increase of milk price volatility on dairy farm viability. These contribute to provide insights on farmers' coping strategies effectiveness and the extent to which modernization is advantageous.

Keywords

economic viability, feologit, milk price volatility, technological tools

Presenter Profile

Marie Rose Randriamarolo-Malavaux is the research project manager of the agricultural risk management Chair, located in Beauvais France. She is specialised in vulnerability, risk and risk management analysis. Her doctoral thesis was focused on dairy farms' milk price volatility management which include the presented article.

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Introduction

Ensuring economic viability constitutes a prerequisite of farm sustainability (O'Donoghue et al., 2016) because not only, a persistent low viability leads to the abandonment of activities (Barnes et al., 2020); but also, good viability encourages the takeover of farms by younger generations (Farrell et al., 2021).

It is acknowledged that risks, such as commodity price volatility, significantly threaten the farm economic viability (Vrolijk et al., 2010), but to our knowledge, studies quantifying the severity of these impacts are rare. Dervillé & Fink-Kessler (2019) highlighted, via a comparative case study, strategies allowing to remain viable in a liberalized French dairy market without assessing the magnitude of the variations in viability according to strategic choices. Brorsen et al. (1984) have investigated through econometric and simulation techniques the impacts of price variability on Texan wheat producers' marketing margins and viability but they didn't examine a differentiating effect in function of the farm's structural characteristics.

As it reduces investment (Schulte et al., 2018; Wibowo et al., 2023), by focusing on French milk sector, our study contributes to fill the knowledge gap by analyzing the impact of milk price volatility on the level of viability, given the farm's technological use degree which require a subsequent investment. Hence, our aim is to shed a light on the consequences of their structural choices to support their decision making and help them to identify the extent of the adjustments needed to face the increasing milk price volatility. Indeed, technological equipment are becoming more and more available and accessible that it is important to be aware of the impact of its adoption in a potentially volatile dairy market context (Butler et al., 2012; Chatellier et al., 2014).

We use agricultural accounting data from the Farm Accountancy Data Network (FADN) to econometrically estimate the effects of milk price volatility by applying an ordered fixed-effect logistic estimator following Baetschmann et al. (2020). This allows us to account for unobserved and unchanged farm or farmer characteristics that influence the level of farm viability, like the management and learning capacity of farmers.

Using ascending hierarchical classification, our sample of farms is divided into three sub-samples according to the level of use of technological tools. The estimates are made separately for the different sub-samples obtained: low, medium and high level of technology use. Then we compare the magnitude of the milk price volatility between the three groups.

Economic viability is a widely used concept, but no consensus exists about its definitions. While scholars agree with Tichit et al. (2004)'s consideration as 'a good health' of a system which require a given reference called 'reproductive threshold' by Saravia-Matus et al. (2021), there is divergence about its determination.

Some studies contend that good health refers to an ability to provide a decent living or a sufficient remuneration to maintain family labour. Thus, viability is based on the comparison of non-salaried workers income to the opportunity cost of working in the farm which may be represented by the average wage in the agricultural sector or the legal minimum wage (Morel et al., 2017; Barnes et al., 2015; Vrolijk et al., 2010; Phimister et al., 2004). Others extend its definition to the ability to cover the operational and replacement costs of all production input, not only the labour. Thus, they refer to economic indicators such as profitability32 and productivity of the activity to judge whether the farm is viable (Assefa et al., 2017; Wolf, 2012)(Martin et al., 2020; Volkov et al., 2021). But these definitions didn't satisfy Barnes et al. (2020) and Hennessy & Moran (2015) who argue that the viability of the farm should consider its wealth which reflects farmers' well-being and conditions the continuation of activities. However, as this wealth relates to fixed inputs, it rather refers to the long-term viability of the farm (Barnes et al., 2015).

Economic viability differs from financial viability which is limited to the ability to meet financial targets like liquidity, debt ratio and rate of return on equity (Aggelopoulos et al., 2007), by the consideration of economic indicators, such as productivity and opportunity costs, in defining the 'good health' (Spicka et al., 2019). As Savickiene et al. (2016) noted the economic viability of the farm relates to "its capacity to survive, live and develop using its resources" (p.105). This emphasizes the need to account for attributes required for farm functioning such as: value added, intermediate consumption, depreciation, and external factors (Wilczyński & Ko\loszycz (2021). We follow this definition of viability which seems the most comprehensive. Thus, being viable means being able to continue one's activity and even ensure growth despite difficulties and uncertainties. That supposes low vulnerability to risks or disturbances. One can distinguish it from resilience which is associated with the ability to resist, adapt and transform in the face of disturbances (Meuwissen et al., 2019) as it implies being efficient during normal periods. Besides, unlike resilience and sustainability, farm economic viability focuses only on enterprises employing agricultural inputs and is based only on the income they provide, excluding off-farm household income (Spicka et al., 2019).

The direct relationship between economic viability and agricultural product price volatility has rarely been studied in the literature. Brorsen et al. (1984) found a negative relationship between them in the context of the wheat sector in Texas. They considered farms with a rate of return on capital greater than or equal to 4% to be viable. However, they did not consider the strategies adopted by the farms. Furthermore, we assume that this variation in viability may differ according to the level of use of technological equipment.

To manage agricultural price volatility, including milk, farmers rather use generic means like production intensification than instruments such forward contracts and future markets (Assefa et al., 2017; Wolf, 2012).

Technological change, which includes the extended use of technological equipment like automatic milking systems or manure scrapers, is recognized as factors that improve technical efficiency (Ashkenazy et al., 2018; Blayney & Mittelhammer, 1990). But this advantage is not only attributed to equipment which enables the optimization of direct agricultural inputs such as labour, water, organic matter, biodiversity as defined by Shrestha et al. (2021). It may also include other technologies such as genetics. To our knowledge, Hansen et al. (2019), is one of the few studies that specified the role of one equipment. They showed with a stochastic frontier analysis on 212 Norwegian dairy farms that the use of an automatic milking system implies higher income efficiency. This finding conducts us to the following assumption: the degradation of the economic viability of dairy farms is lower for farms using more technological tools than for farms using less technological tools.

Methods

Data source and study population

To test our hypotheses, we use data from the Farm Accountancy Data Network (FADN), between 2002 and 2020. The chosen period is relevant for our study as it corresponds to the beginning of dairy farms exposition to milk price volatility following the 2003 reform of the Common Agricultural Policy. We also collect data on 2002 for our moving average calculations of volatility. We select French dairy farms whose income depend mainly on dairy production and which appear at least five years consecutively in the database. They are located in the national geographic.

Thus, we obtain an unbalanced panel data composed by 1677 unique farms during the observation period. However, we have a significant inequality in the number of farms observed annually. The year 2015 contains the lowest number of observations due to the crisis which hampered the survey.

The data were processed and analyzed using the 15ème version of the STATA software. We deflated all monetary variables to adjust for inflation before our analysis.

Characterization of the economic viability of the studied dairy farms

In our study, we use the indicators of Wilczyński & Ko\loszycz (2021) since it encompasses attributes that characterizes farm economic viability. It relates to the ability to provide enough outcome including subsidies, valued at market prices, to cover the opportunity cost of inputs. We integer subsidies in farms' outcome because our aim consists in explaining their level of viability given the public payment they receive. Moreover, in France, it is mainly composed by direct payments independent to income variation[1].

Thus, outcome result from the total value of output of crops and crop products, livestock and livestock products, of other output, including that of other gainful activities (OGA) of the farms and subsidies. It is the sum of sales and use of (crop and livestock) products and livestock, the change in stocks of products (crop and livestock), the change in valuation of livestock, the various non-exceptional products, minus purchases of livestock. While, the opportunity costs of inputs are measured by intermediary consumption (IC), depreciation (D), wage (W), rent (R), debt interest paid (I), and taxes (T).

Concerning the opportunity cost of self-employed workers, we have opted for the legal minimum wage (LMW) because it expresses the minimum level of remuneration to guarantee a decent standard of living in France. Thus, this value makes it possible to maintain a worker.

$$\text{Viability} = \frac{\text{Outcome}}{\text{IC} + \text{D} + \text{W} + \text{R} + \text{I} + \text{T} + \text{LMW}}$$

The results can be interpreted as follows:

- Viability ≤ 1: the farm is not viable and called "survival" because the provided outcome is inferior to the potential income receive in other employment. It doesn't allow the activity continuation in good conditions.
- 1< Viability ≤ 1.2: farm is "viable" as the generated outcome is enough to ensure the maintenance of the factors of production and to meet the need of the farmers.
- Viability > 1.2: Farm is "in development" thanks to the extra outcome obtained and which can be allocated to the improvement of farms' potential.

During the observation period, the majority of farms are viable. Only 25% of them are not viable, but this percentage vary annually and follow an increasing trend. In contrast, the share of developing farms decreases sharply.

[1] *For more information about the effects of subsidies, especially income risk management, see Trestini et al.(2018) and Vera & Colmenero (2017).*

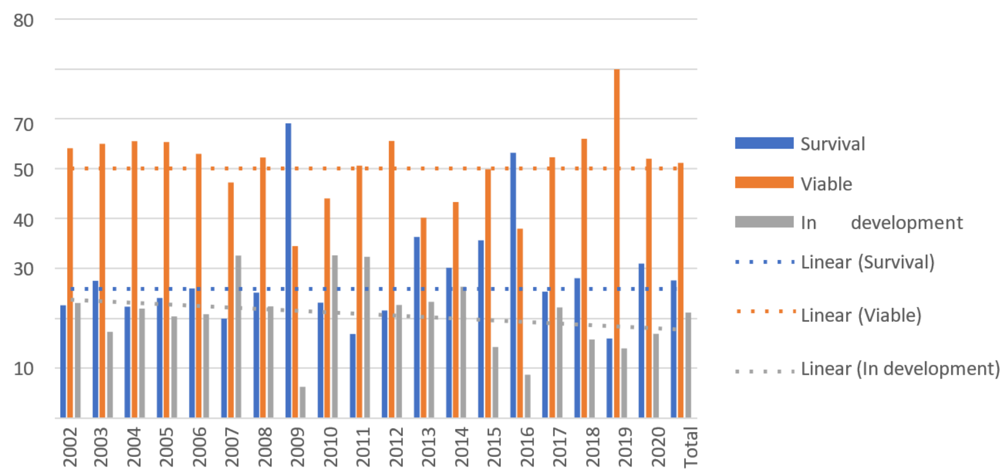

Figure 1: Annual distribution of farms according to their level of viability

Measuring milk price volatility

To calculate the annual volatility of the milk price, we use the method of Santeramo & Lamonaca (2019). Their formula measures how important is the deviation of the current year's price from the trend compared to three-year (y -1, y, y+1) moving average deviation. When it is excessively far from the moving average deviation, the price is considered as volatile in the current year.

We apply this formula to French milk price data from the European price observatory. The use of these aggregated data allows us to avoid the endogeneity problem related to the milk price received by each farm which may depend on a farm's investment ability determined by its viability.

$$\sigma_{3y} = \sqrt{\left(\ln\left(\frac{P_y}{P_{y-1}}\right) - \frac{1}{3}\ln\left(\frac{P_{y+1}}{P_{y-1}}\right)\right)^2} \text{ with } P_y \text{ represents the milk price in year } y$$

Classifications and characteristics of farm sub-samples

To categorize a farm according to the level of use of technological equipment, we carry, for each year, a k-means classification based on several separating variables. We assume that the characteristics of technological equipped farms vary in time following the development in the society.

Since we use accounting data, we cannot obtain precise values of the existing technological equipment in the farm. Therefore, to identify these characteristics, we rely on the cost associated to the corresponding asset which allows us to have an approximation. The following variables are used:

- Equipment rental value per hectare of utilized agricultural area and per livestock unit (LU)
- Equipment rental costs per hectare of utilized agricultural area and per LU
- Maintenance and repair costs of equipment per hectare of utilized agricultural area and per LU
- Specific facilities value per hectare of utilized agricultural area and per LU
- Machinery and equipment value per hectare of utilized agricultural area and per LU

The **Error! Reference source not found.** shows the average characteristics of the three groups o btained: i) barely, ii) moderately, iii) highly equipped farms. The last group spend the highest fees to maintain and repair materials, being up to €126 per LU, while it amounts to €70 for low technology farms. Besides, the value of materials and tools of moderately (€1,120 per LU) equipped farm equals more than double that of the lowly one (€414 per LU).

Table 1: Characteristics of farms according to their level of use of technological tools

	Low Technology	Intermediate technology	High technology	Total (total average)
Rental of equipment by UAA[38] (€/ha)	0,0928482	0,088836	0,0783891	0,0901802
Equipment hired per LU (€/LIVESTOCK UNIT)	8,326493	10,65464	11,3363	9,410322
Rental charges for materials per UAA (€/ha)	0,0051045	0,0042731	0,0054093	0,0048366
Rental charges for materials per livestock unit (€/livestock unit)	0,4248825	0,4790031	0,7262153	0,4700454
Maintenance and repair of materials per UAA (€/ha)	0,0051045	0,0042731	0,0054093	0,0048366
Maintenance and repair of materials per livestock unit (€/livestock unit)	70,21455	97,40813	126,5615	84,70297
Specialised installations by UAA (€/ha)	1,239739	2,128391	1,130065	1,544821
Specialised facilities by LU (€/LU)	100,6461	228,5518	171,8378	152,0637
Materials and tools by UAA (€/ha)	5,420725	10,67278	16,06533	8,198418
Materials and tools by LU (€/LU)	414,783	1120,73	2291,568	826,6346

Choice of control variables

To build the model of the dairy farm economic viability, we based ourselves on economic studies that focus not only on the economic viability of farms, but also on their income stability and resilience. Indeed, as we have shown in the theoretical framework, these concepts are linked. Income stability is an intrinsic condition for farm economic viability.

It turns out that viability depends on farm structural characteristics and practices, the farmer's-economic attributes and random hazards. Therefore, we include in our model the number of dairy cows (Perrin et al., 2020) and the labour intensity (Spiegel et al., 2021) to indicate the structure of the farm. The number of dairy cows gives us information on the size of the dairy farm and allows us to check its role in the economic viability of dairy farms. Indeed, we expect that a large farm potentially benefits from an economy of scale and resources to ensure the stability of their income (Harkness et al., 2021; Wilczyński & Ko\loszycz, 2021), which contributes to the economic viability of the farm (Vrolijk et al., 2010). Labour intensity, measured by the ratio of the number of paid and unpaid workers and the value of assets, informs us about the importance of workers compared to capital, such as farmland. We expect that a farm with low labour intensity is more viable because as Spiegel et al. (2021) highlighted, it enhances resilience by increasing labour productivity.

Concerning the farmer's attributes, we are mainly interested in their age and agricultural training. Age refers to the level of experience (agricultural or otherwise) that the farmer has and which may have enhanced their managerial capacity. As Dhungana et al. (2004) have shown, agricultural producers become more efficient as they get older. Similarly, education is one of the personal characteristics that can influence management quality, as it provides the skills necessary to promote technical and financial efficiency (Nuthall, 2009). We assume that these determinants of managerial capacity contribute to the economic viability of the farm. However, to avoid multicollinearity with technology use, we exclude it from our control variables.

Two other variables are used to identify the agricultural practices. First, the price quartile to which the farm belongs is used to capture the quality of the milk sold by the farm. Indeed, the price paid to producers is composed of the basic price which is increased according to the quality of the milk (the fat and protein content of milk production or other attributes). The specificity of the milk is a source of an added value that constitutes a resilience factor for farms (Ashkenazy et al., 2018), knowing that it is linked to economic viability (Meuwissen et al., 2019). Secondly, type of farming indicates how diversified it is. Harkness et al. (2021) and Sneessens et al. (2019) have shown respectively that agricultural diversification stabilizes farm income and reduces vulnerability. Thus, it could promote the economic viability of the farm.

Finally, we include in our model of dairy farm viability three types of hazards to which dairy farms are exposed. Economic hazards are captured by the volatility of input and milk prices. We consider the price of concentrates, which is an important cost in dairy production. We use aggregate data from the European observatory to measure its instability. We apply the same formula as for milk price volatility to calculate concentrate price volatility.

Climatic and sanitary hazards are measured by the volatility of milk production. The latter is calculated individually as we use data for each farm from the FADN. Thus, the production volatility results from the difference between the production level of the current year and the average production of the period.

Model specification

Our dependent variable y_{it} corresponds to the viability of dairy farm i in year t. It is a qualitative variable composed of three ordered categories noted c such that i) c=1 represents the worst state called "surviving"; ii) c=2, the fairly good state, which is noted "viable" and iii) c=3, the most favored state, "developing". Therefore, it is modelled following Harkness et al., (2021) and Albert & Chib (1993, P.5) on ordered multinomial variables.

We consider a continuous and latent variable y_{it}^* that indicates the value of the underlying viability of farm i in year t and that allowed it to be assigned into one of the three categories c.

Thus, we model the different states c of y_{it} that are generated by the latent variable z_{it} as follows:

$$y_{it} = c \ si \ y_{it}^* \ \in (\tau_{c-1}, \tau_c]$$

Knowing that $\tau_{ic} = \tau_{jc} = \tau_c$ is constant for any individual i and j, such:

$$y_{it} = \begin{cases} 1 & si & \tau_0 < y_{it}^* < \tau_1 \\ 2 & si & \tau_1 \leq y_{it}^* < \tau_2 \\ 3 & si & \tau_2 \leq y_{it}^* < \tau_3 \end{cases}$$

With $\tau_0 = -\infty < \tau_1 < \tau_2 < \tau_3 = +\infty$

y_{it}^* depends on the following function:

$$y_{it}^* = \alpha_i + X_{it}\beta_1 + VPrix_t\beta_2 + VProd_{it}\beta_3 + VInt_t\beta_4 + R_j + u_{it}$$

Where

- α_i: unobservable characteristics of the holding i such as the management capacity of its operator.
- X_{it} : vector of control variables that indicate the observable characteristics of
- holding i in year t.
- $VPrix_t$: measures the aggregate volatility of the milk price in year t.
- $VProd_t$: measures the volatility of the output of farm i in year t.
- $VInt_t$: measures the aggregate volatility of input prices indicated by the price of concentrates in year t.
- β_k : the parameters to be estimated for the variables of interest and the control variables
- u_{it}: time-varying unobservable term

Estimation method

To estimate the parameters of our model, we apply a fixed effect. Indeed, as the random effect assumes a normal distribution and independence from the explanatory variables of the term representing the unobservable and time-invariant characteristics of individuals (Greene, 2012), we prefer to apply the fixed effect which relaxes this strong restriction. Since the fixed effect is only valid with the logistic distribution function (Muris, 2017), the probability of observing modality c is obtained as follows:

$$\Pr(y_{it} = c|X'_{it}, \alpha_i) = P(\tau_{c-1} < \alpha_i + X'_{it}\beta + u_{it} < \tau_c|X'_{it}, \alpha_i)$$
$$= \Lambda(\tau_c - X'_{it}\beta - \alpha_i) - \Lambda(\tau_{c-1} - X'_{it}\beta - \alpha_i)$$

With

$\Lambda(\mathrm{x}) = e^x/(1 + e^x)$ represents the cumulative distribution function of the distribution law logistics.

The probability depends on X'_{it}which is the vector of all explanatory variables and β which is the vector of all parameters.

To estimate the parameter vector β, the maximum likelihood estimator must be used. The likelihood function is expressed as follows:

$$L = \prod_{i=1}^{N}\prod_{t=1}^{T}\prod_{c=1}^{k}(P_{it})^{y_{it}=c}$$

$$L_n(\beta, \tau, \alpha) = \prod_{i=1}^{N}\prod_{t=1}^{T}\prod_{c=1}^{k}[\Lambda(\tau_c - X'_{it}\beta - \alpha_i) - \Lambda(\tau_{c-1} - X'_{it}\beta - \alpha_i)]^{1\{y_{it}=c\}}$$

Then, this function must be expressed in logarithm as follows:

$$Log\ L = \sum_{i=1}^{N}\sum_{t=1}^{T}\sum_{c=1}^{k}(P_{it})^{y_{it}=c}$$

Finally, the following non-linear system of equations must be solved:

$$\frac{\partial Log\ L}{\partial \beta} = 0$$

As our dependent variable is an ordered categorical variable, we estimate the parameter using feologit of Baetschmann (2012), Baetschmann et al. (2015) et Muris (2017). This estimation method presents a lot of advantage as it allows to solve the parameter incidence by using sufficient statistic[1]. The dependent variable is transformed into a binary variable for which the maximum likelihood estimator conditional on this statistic works. Then it recombines them to obtain the parameters of the explanatory variables of our initial dependent variable. Let us note d_{it}^c the new binary dependent variable. It is given by:

$$d_{it}^c = 1(y_{it} \geq c)$$
$$d_{it}^c = 0(y_{it} < c)$$

Let $\bar{d}_i^c$ be the number of times $d_{it}^c = 1$ is observed for holding i during the observation period.

$$\bar{d}_i^c = \sum_{t=1}^{T} d_{it}^c$$

The latter is the sufficient statistic on which the maximum conditional likelihood and approximates α_i.

Thus, the probability of observing our new binary dependent variable d_i^c is equivalent to $(d_{i1}^c, \dots, d_{iT}^c)'$ conditional on the value of $\bar{d}_i^c$. It is obtained by:

$$P_i^c(\beta) \equiv \Pr\left(d_i^c \middle| \textstyle\sum_{t=1}^{T} d_{it}^c = \bar{d}_i^c\right) = \frac{\exp\{d_i^{c'}(X_i\beta - \tau_i^*)\}}{\sum_{j\in B_i}\exp\{j'(X_i\beta - \tau_i^*)}$$

With

$j = (j_1, \dots, j_T)$ tel que j_t={0,1} et $\sum_{t=1}^{T} j_t = \bar{d}_i^c$

B_i represents the set of possible vectors j.

After the log transformation, the conditional likelihood function becomes:

$$LL^c(\beta) = \sum_{i=1}^{N}\log P_i^c(\beta)$$

[1] *A statistic is sufficient when "no other statistic that could be estimated from the sample provides additional information to identify the value of the parameter to be estimated" (Fisher, 1922, p. 310).*

It no longer depends on time-invariant individual unobservable characteristics α_i. After combining the information, the BUC (Blow-up and cluster) estimator is:

$$LL^{BUc}(\beta) = \sum_{c=2}^{k} LL^{c}(\beta)$$

Results

The estimation of models per subsample defined according to the level of use of technological tools was validated by the likelihood ratio test. Indeed, the separation of the samples brings more explanation to our model than integrating the variables of interest in interaction with the other variables. The integration of other control variables such as legal status does not bring us any additional information. Table 2 shows the results of our basic model. It shows that all coefficients are jointly and significantly different from zero according to the Wald test. The coefficients estimated by our main model represent the marginal effects of the explanatory variables on the latent variable of sustainability. However, as we are most interested in the viability categories and in identifying the effect of milk price volatility on category membership, we calculate the marginal effect on average. This parameter tells us the variation in probability to belong on one category following a unit variation in the explanator variable. The direction of the relationship is indicated by the sign of the corresponding coefficient.

Effects of milk price volatility on economic viability differentiated by level of use of technological tools on dairy farms

The results in table 2 below show us that the parameters of milk price volatility estimated using ordered fixed-effect logistic regressions are significantly negative at the 5% confidence level for all three subsamples. Thus, if milk price volatility increases by one unit, ceteris paribus, the probability of surviving increase. However, the magnitudes of the variation differ significantly in function of the level of use of technological equipment. Indeed, the viability of farms with low use of technological tools shows a higher sensitivity (-13.20) to a unit increase of milk price volatility compared to the viability of those with a higher level of use (-11.06). This sensitivity appears to be lowest for farms with a medium level of technology (-4.164). In other words, the use of technological tools reduces the impact of volatility on farm economic viability, but there is a limit of risk reducing equipment.

This result confirms the concerns and roles played by technological tools and the advantages drawn from capital use. The increase in productivity should help to mitigate the consequence of milk price volatility. Agricultural technologies allow farmers to avoid certain tasks that can be automated and potentially free up time for the farmer to focus on farm or milk price volatility management. Besides, it is possible to allocate time for information retrieval, and to react more quickly in an appropriate way. However, as these tools also represent additional costs such as maintenance costs[1], they can increase the farm's operating costs and reduce its financial capacity.

[1] *The Table 1 (in the section "Classifications and characteristics of farm sub-samples") describing the characteristics of the three groups clearly shows the superiority of the median cost of equipment maintenance the high-tech group compared to the low- and medium-tech groups.*

Table 2: Ordered logistic fixed effect of short-term viability of sub-samples by level of technology use

	(1) Lowly technologized holding	(2) Moderately technologized holding	(3) Highly technologized holding
Milk price volatility	-13,20***	-4,164**	-11,06***
	(2,135)	(1,735)	(2,310)
Volatility of milk production	1,075	-0,336	-1,866
	(0,758)	(0,958)	(1,553)
Price volatility of concentrates	10,03***	2,177	2,650
	(2,475)	(1,567)	(2,600)
MILK PRICE QUARTILE			
Q1	Référence	Référence	Référence
Q2	0,680***	0,623***	0,303
	(0,184)	(0,236)	(0,269)
Q3	0,998***	0,838***	0,338
	(0,190)	(0,270)	(0,308)
Q4	1,162***	1,546***	0,669*
	(0,239)	(0,328)	(0,361)
Type of farming			
Specialized dairy cattle	Référence	Référence	Référence
Mixed beef and dairy cattle	0,186	0,652	0,223
	(0,391)	(0,558)	(0,559)
Poly-breeding	0,703	1,036	0,620
	(0,640)	(0,653)	(0,760)
Mixed crop livestock	0,924	0,412	0,999**
	(0,602)	(0,374)	(0,466)
Intensification level			
Extensive	Référence	Référence	Référence
Semi-intensive	-0,132	0,0351	0,124
	(0,219)	(0,224)	(0,274)
Intensive	-0,353	-0,570	-0,0458
	(0,327)	(0,361)	(0,392)
Labour intensity	0,000431***	0,000269*	0,000318*
	(0,000162)	(0,000154)	(0,000177)
Age of the farm holder	0,0498*	-0,00646	0,0243
	(0,0256)	(0,0183)	(0,0157)
Cow milk herd size	0,0279**	-0,00132	0,0602***
	(0,0124)	(0,0103)	(0,0150)
Observations	1 800	1 280	947

Robust standard deviation in parenthesis; ***, ** et * indicate statistical significance at 1%, 5% et 10%.

To better understand our results, we focus on the variation in the probability of belonging to each viability degree following a unit variation in milk price volatility. These are presented in table 3.

In the case of the two groups, there are significant increases in the probability to be survival or non-viable for all the three groups (low, medium, and high use of technological equipment) when volatility increases, all other things being equal. Farms with a low level of use of technological tools are the most affected, followed by those with a high level of use. Indeed, their probabilities of being non-viable rise respectively by 2.47% and 2.12%. In contrast, the probabilities of becoming non-viable increase by 0.83% for farm using moderately technology.

Concerning the probability of becoming viable, it increases for the low-tech group, although this change is very small, but decreases for the medium and high-tech groups. Despite this positive change in the probability of being viable, the situation seems to be more worrying for the low-tech farms when the milk price fluctuates more. The benefits of technological tools outweigh their limitations, especially in the face of milk price volatility.

Table 3: Average marginal effects of milk price volatility by level of use of technological tools

	Probabilities change
Lowly technologized holding	
1. Surviving	2,470
2. Viable	0,0783
3. In development	-2,548
Moderately technologized holding	
1. Surviving	0,828
2. Viable	-0,102
3. In development	-0,726
Highly technologized holding	
1. Surviving	2,121
2. Viable	-0,233
3. In development	-1,888

The offsetting effects between variables, presented in table 4 tell us about the adjustments needed on labour intensity and on the number of dairy cows to counterbalance the changes in viability level. Low, medium and high technology farms increase respectively the value of assets per worker by €298, €154.8 and €347.8 to compensate for the decrease in viability due to a unit increase in milk price volatility. In other words, they resort to an increase in the number of dairy cows of 4.73 and 1.84 respectively for the low and high technology farms.

Table 4. Offsetting effects of milk price volatility with: i) cow milk number and ii) labour intensity

	Lowly technologized holding	**Moderately technologized holding**	**Highly technologized holding**
Cow milk herd size	4,71**	-	1,84***
Labour intensity (Assets value per worker)	-306,26 ***	-154,8*	-347,8*

***, ** and * indicate statistical significance at 1%, 5% et 10%.

Effects of control variables on the economic viability of dairy farms

Some of the control variables' estimated parameters are also significant at least 90% and even 99% confidence levels. First of all, for low technological farms, the concentrate price volatility coefficients is significantly positive, in opposite to our expectation (negative effect on viability).

We assume that the high dependence of low-tech farms on equipment rental and the low ownership of equipment or facilities makes them flexible to manage concentrate purchases in a countercyclical way to deal with input price volatility. Thus, for example, they can take advantage of a price drop to build up their stock and benefit from this stock when prices rise.

For the other control variables, their correlation with sustainability is rather consistent with our hypotheses. Indeed, the variable indicating the presence of a high payment for the production of high value-added milk (the quartile of the price to which the farm belongs) and the age of the farmer are significantly and positively correlated with the economic viability of the farms. The viability of the group of farms belonging to the upper quartile is higher than that of the group of farms included in the lower quartile. Thus, our result coincides with the prediction of Vrolijk et al (2010) that economic viability depends on the price level in addition to its variability. Furthermore, dairy farms tend to be more viable when their operators are older, especially for low technological use farms. This relationship reflects the importance of experience in determining the viability of dairy farms. We hypothesize that the professional experiences gained by farmers not only in dairy or agricultural production, but also outside the agricultural sector contribute to the multiplication of skills needed to achieve better economic results, without too much technology.

Concerning the results obtained for the type of farming, a significant difference in viability is observed between farms specialized in dairy cattle and diversified farms, mixing crop and livestock, notably for highly equipped farms. In other words, making the available farmland profitable with other productions leading to independent markets or risks or to complementary land uses, favours more flexibility to adapt to the different hazards and would allow to better insure economic viability.

Robustness and limitations of the results

To test the robustness of our results, we made four main modifications.

i) *Changing the measure of milk price volatility:* we calculate the volatility of the milk price paid to individual farms instead of the aggregate milk price. It is obtained by the deviation of the price from its average value during the whole observation period. We cannot calculate the coefficient of variation based on a three-year moving average because the FADN database is a non-cylindrical panel.

ii) *Extension of the sample studied:* we select farm appearing three years consecutively in the database instead of five years.

iii) *Use of other measures of diversification:* following Harkness et al. (2021), we considered two other measures of diversification. We integrate them in the model in a sequential way, to avoid a problem of multicollinearity. a) First, the agricultural diversification which consists in evaluating the diversity of the existing animal and vegetable productions within the farm. This is obtained using the Herfindhal index below. This index is based on the proportion of gross product (p_i) generated by the different types of agricultural activities[41] i. Its value, between 0 and 1, increases (decreases) as the level of specialisation of the farm is high (low). b) Next, we introduce farm diversification which measures the diversity and importance of the farm's non-farm activities such as on-farm processing. The diversification of the holding is calculated by the ratio of the share of products from agricultural production to the total products of the year.

$$Indice\ de\ Herfindahl = \sum_{i=1}^{n} (p_i)^2$$

i) *Non-annual classification of farms according to the level of technological tools use:* We test the effect of an ascending hierarchical classification applied simultaneously on all the observations of the period considered in our study.

The parameters of milk price volatility in our regressions remain significantly negative except for the volatility of the individual milk price. Indeed, the use of an absolute average may lead to an overestimation of volatility and would reduce its correlation with economic viability despite its strong correlation with the relative measure of volatility (coefficient of variation calculated from the three-year moving average of the aggregate milk price).

In addition, the values of the coefficient do not always remain close to the basic model's one. However, the order of magnitude is still almost maintained throughout the sub-samples' regressions. Indeed, the parameters gravitate around the bounds of the confidence interval of those of the basic model, with the exception of the parameters estimated when applying the absolute classification. Consequently, we deduce that our results are relatively robust. However, they are limited in the context of a relative classification of the level of use of technological tools, which we consider to be the most relevant. Indeed, given the structural change that has taken place in the dairy sector, we aim to highlight the sensitivity of farms considered as high-tech according to the criteria of the time.

Table 5. Robustness tests of milk price volatility parameters according to the level of use of technological tools

		(i)	(ii)	(iii) (a)	(iii) (b)	(iv)
	Basic model	Individual milk price volatility	Larger samples (> 3 years) appearance)	Agricultural diversification	Diversification of operation	Overall farm classification
Low-tech holding						
Coefficients	-13.20***	-2.196	-13.77***	-14.72***	-13.31***	-6.649***
Standard deviations	(2.135)	(1.511)	(2.196)	(2.071)	(2.114)	(1.029)
Medium-tech holding						
Coefficients	-4.164**	-1.534	-4.020**	-4.693**	-3.856**	-10.08***
Standard deviations	(1.735)	(1.301)	(1.754)	(1.835)	(1.714)	(1.830)
High-tech holding						
Coefficients	-11.06***	-1.054	-11.92***	-14.68***	-10.33***	-5.313
Standard deviations	(2.310)	(1.832)	(2.318)	(2.593)	(2.303)	(4.250)

*p<0.10, **p<0.05, ***p<0.01

Conclusion

Our work has quantified the impacts of technology use levels on the variation of economic viability of dairy farms when milk price volatility changes. Our results show that the degradation of economic viability is significantly lower for farms with moderate or high use of technological tools compared to those with low levels of use. Thus, the level of technology use is an important heterogeneity factor in determining the evolution of farm viability in a volatile market. Finding the right level of equipment is therefore necessary to reap the benefits it offers without being burdened by the associated costs. Therefore, it is important not to reduce investment in technological tools too much in response to increased volatility in the price of milk to avoid undermining the economic viability of the farm.

The generalization of our results should be carried out with caution because they are sensitive to the methods of calculating the volatility of the milk price and the classification of farms according to their level of technological tools use. Indeed, they indicate the consequences of an increased volatility of the average milk price at national level, without considering territorial specificities. In addition, farms should refer to annual references to situate their level of technological use before referring to our results. Furthermore, our results could be deepened by analyzing the severity of the lack of viability of farms with low technological use following an increase in milk price volatility.

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Digitalisation for Agroecology: Agenda for an inclusive policy roadmap

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Extended Abstract

Agroecological systems have a great sustainability potential, as a path to agricultural development and toward a balanced and economically sound society (D'Annolfo et al., 2017). Regardless of the definition used to define its principles, agroecology is characterised by a holistic approach that comprises environmental, social and economic dimensions (FAO, 2018; Francis et al., 2003; Gliessman, 2018; HLPE, 2019). Agroecology is characterised by having a recognisable social component, promoting participation (and even some form of activism) from all the stakeholders involved in food production (Gliessman, 2014, p. xi).

Digital technologies can improve the agricultural sector in different ways (Finger, 2023; Khanna, 2021). This includes enhancing decision-making processes of farmers, other stakeholders, and institutions; Improving connectivity and networking from data sharing; Improving production from yield increase, improving quality, labour reduction, and minimising environmental impacts. Other benefits include monitoring, traceability, insurance claims, and certifying compliance with standards and regulations.

However, such benefits might not come alone, as, overall, digitalisation increase energy consumption (Lange et al., 2020). A second disadvantage is the adoption rates varying among stakeholders with distinct characteristics. As the agri-food sector is generally conservative, the perceived complexity of digital technologies is one of the barriers preventing a more widespread adoption of digital tools (Giua et al., 2021). Another barrier is the lack of harmonisation of such technologies, with often little interoperability and a poor protection of data sovereignty. Farmers' lack of experience and the organisation required for the correct implementation of digital technologies are examples of the degree to which digitalisation will modify agricultural systems (Schnebelin et al., 2021).

Both barriers to adoption and intrinsic limitations of digital technologies are not necessarily in contrast with the concept of agroecology. Digitalisation makes available a set of tools to improve social fairness and the other ethical principles of agroecology and, at the same time, can be an instrument to increase environmental sustainability (MacPherson et al., 2022).

This perspective is based on the state-of-the -art of the work of the European collaborative consortium action D4AgEcol[1]. It addresses the policy implications of the path toward the transformation of European agricultural production systems to include an agroecological approach, by using digital technologies. The paper presented focuses on the methodological aspects of co-creation, suggesting a framework to operationalise the co-development of policy roadmaps. The focus on transition to agroecology and digitalisation of agri-food production at the same time, with specific focus on policies is exclusive to this project (Giua et al., 2021; Iocola et al., 2023; MacPherson et al., 2022).

Problem statement

Digitalisation touches upon some dimensions that are in common with agroecological principles[2]. However, there are some criticisms about the use of digital technologies to increase sustainable practices. Such criticisms point out how digital technologies are inherently linked to industrial agriculture, hence their usefulness in enforcing agroecological principles is not automatic (Hilbeck, McCarrick, Tisselli, Pohl, & Kleine, 2022). Besides, some scholars emphasise the need for rethinking the way public policies address issues, engaging with local society and stakeholders, designing policies through collaborative methods (Hillgren, Light, & Strange, 2020; Tõnurist & Hanson, 2020). Ultimately, the co-creation of political actions would increase their efficacy and acceptability. Therefore, the general research question for this work will be:

> '*How national and European policies should combine the views of all stakeholders to enable the adoption of digitalisation for the transformation of agricultural systems toward the adoption of agroecological principles?*'

Framework

With the goal of designing policy roadmaps that fuse the voices of stakeholders, experts and policymakers, the overall theoretical framework that best addresses the need for a broad acceptability is the framework of responsible innovation (Stilgoe, Owen, & Macnaghten, 2013). The framework is well suited to design policies for both digitalisation of agriculture and agroecology. Anticipation, Reflexivity, Inclusion, and Responsiveness are the four components of the responsible innovation framework. They all resonate with the principles of agroecology and digitalisation (Shelton et al., 2022; Stilgoe et al., 2013). Namely, reflexivity and responsiveness are critical for linking digitalisation and the dimensions of agroecology related to sustainability and environmental performance, while reflexivity and inclusion are accessory to achieve the social principles of agroecology.

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[1] *Digitalisation for Agroecology' project: https://d4agecol.eu/*

[2] *See for example the OECD policy dimensions, that include trust, society, access, jobs, and innovation among others (https://goingdigital.oecd.org/dimensions, accessed 20th June 2023).*

The level of interaction between stakeholders enabled by the framework of responsible innovation is aligned with the current European programmes on agroecology, and with the expectation from future projects (Iocola et al., 2023). Additionally, the framework is well suited to implement inclusivity and ethics into the national and European policies; two of the essential actions recommended for integrating digitalisation and transition toward agroecological systems (Shelton et al., 2022).

The responsible innovation framework is fit to assess the resilience of the production systems, highlighting the effects of innovation on the system's resilience, adaptability, and, critically, transformability. Those are the three dimensions of the framework described in Meuwissen et al. (2019).

The analysis of the data from the literature and produced involving the stakeholders in the process of planning the transformation of the European agricultural systems is expected to considers the (community) capitals framework (natural, cultural, human, and social capitals), to further connect the different impacts of digitalisation to agroecological principles, and to all the components of the production systems (i.e., all stakeholders and their connections) (Emery and Flora, 2006; Pigg et al., 2013).

Methodology

To operationalise the framework, the formulation of policy roadmap shall include elements of co-creation, through dialogues (workshops), aimed to create the conditions to allow all relevant stakeholders to participate in such dialogue, to enhance the co-creative part of executive solutions.

Overall, the policymaking includes three main activities: 1. Literature review and connection with present and past experiences; 2. Stakeholders' involvement: a series of workshops (feedback from those interested in and affected by the digitalisation process); 3. Expert feedback.

The second point is particularly important, as the digitalisation of agricultural production affects multiple and diverse stakeholders from different European countries, not only farmers and digital tools' providers, but also other actors within the production system and the local community not directly involved in the production.

In relation to the stakeholders' involvement, and as other experiences on co-creation highlight, the main difficulty in promoting a dialogue between stakeholders and civil society is the lack of a common background. Providing all the participants with some basic information is critical to coordinate the workshops in different countries (and to compare the results), and engaged in different production systems (e.g., organic and conventional productions, agroforestry).

For this reason, illustrating an 'ideal scenario', rather than focusing on existing technologies, is a useful tool to increase the level of the discussion, moving the workshop from a discussion about tools to a dialogue where all the participants add to the vision based on their respective experience. A fiction-based approach might be the most effective method for discussing a radical transformation of agricultural systems through digitalisation (Hillgren et al., 2020; Miller and Bennett, 2008), allowing a comprehensive analysis of the co-creative dialogue, easing the task of merging primary and secondary data, and, at the same time, stimulating the engagement of the local stakeholders.

The scenarios shall include all the different uses of digital technologies, that are: Support of stakeholders' decision-making; Support in connection between stakeholders, creation of networks and data sharing (and feedback mechanisms); Direct improvements of production; Monitoring, traceability, increased transparency, and social and environmental performances (certification, both formal and informal, of adherence to agroecological practices).

Based on such scenarios, the discussion will touch upon the consequences of adopting agroecological practices through digitalisation at different scales, from farms to the entire system, and the local communities. The discussion will be moderated, to ensure the analysis of the effects on all dimensions (human, social, and on the environment). Then, the data produced in the workshops in different countries will be analysed and synthetised. Such data will be merged with findings from literature, and a panel of interdisciplinary experts will assess the possible socio-economic impacts, the effect on resilience and the potential for a transition toward agroecology.

Finally, the policy roadmaps will identify the enablers necessary to assist such transition (in term of political, scientific, and social efforts), and how to measure the success rate of such efforts, through qualitative and quantitative indicators. Figure 1 gives a complete overview of the process.

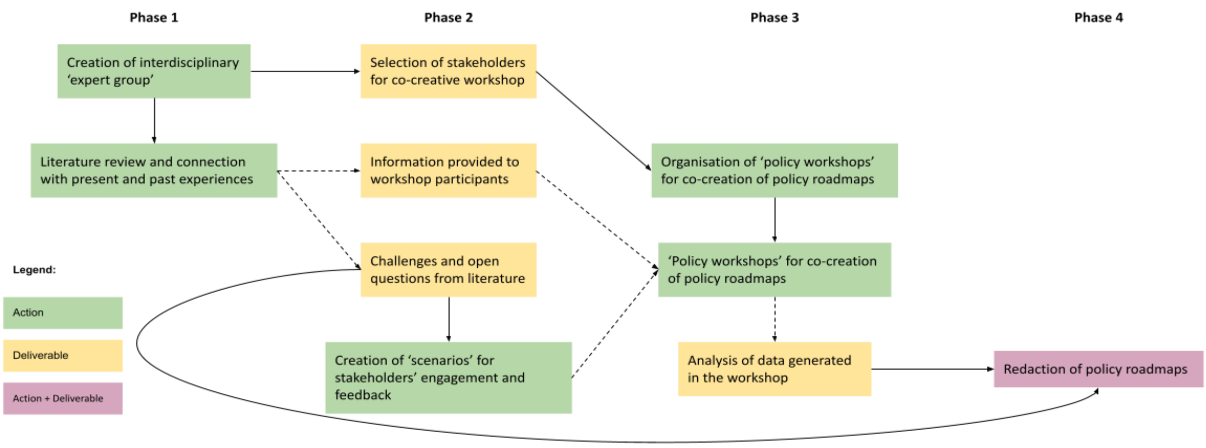

Figure 1: The process of creating national and European policy roadmaps of digitalisation for agroecology

Indicators are necessary for the creation of scenarios in phase 2, to analyse the data generated in the co-creative phase, and to assess the success of the policy roadmaps. Technical and economic indicators about production and economic convenience are critical for determining the economic viability of the proposed solutions. However, increased yield and profitability are object of a widespread discussion in relation to both digitalisation and agroecology, as most studies are inconclusive or send mixed messages (e.g., D'Annolfo et al., 2017; Lio and Liu, 2006; van der Ploeg et al., 2019). Therefore, the indicators that will be discussed during the workshops and represented in the policy roadmap are those related to human and social capitals, to connect some principles of agroecology to the specific outcomes of implementing digital technologies, regardless of the economic potentials.

The path ahead

In conclusion, the goal of this extended abstract is to suggest an approach to the co-creation of knowledge, to incorporate different experiences and cultural backgrounds into multi-country (e.g., across Europe) and national policy roadmaps. The methodology is designed to enhance local differences and between countries. When its development will be completed, to make available to researchers and practitioners a collaborative tool for the formulation of policies. The discussion of future scenarios within the framework of responsible innovation is expected to increase the understanding of the different approaches to business, the relevance of local tradition and social norms for the decision-making processes, and it will be applicable to different production systems (e.g., agricultural production, agroforestry, livestock production, regardless of if conventional or organic).

Keywords

Agroecology, co-creation, digitalisation, policy roadmap, agri-food production.

Presenter Profile

Andrea Landi is a postdoctoral researcher at the University of Copenhagen. His research focuses on investigating the decision-making process of food business, and food production. Business cultures and the nexus between people and their creations is his main interest, and the topic of his research during the past years. Andrea has an interdisciplinary background: before the PhD in international economics and business management, he obtained a MSc in development studies, and another in environmental sciences. His work experience includes research in academia and consultancy in the private sector for several years.

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Keynote: Lessons Learned in 30 years of Precision Agriculture Research

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Presenter Profile

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Economic Evaluation of Variable Rate Application using On-Farm Precision Experimentation Data

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Extended Abstract

Variable rate application (VRA) is a most fundamental precision agriculture technology that applies varying rates of inputs in different sites of a field. However, its profitability in commercial farming has remained unclear, and has been a key constraint to growers' adoption. Indeed, evaluating VRA's profitability is an extremely challenging task. In theory, it requires the full knowledge of true crop response function at each field site, based on which the optimal (profit-maximizing) site-specific input rates can be derived. But in practice, estimating accurate site-specific response functions is very difficult due to the complexity of crop response and the lack of data. Thus, the economic value of VRA is still largely unknown despite several decades of precision agriculture research and practices.

In the agronomy literature, numerous small-plot experiments have been conducted to estimate crop responses. Each experiment was established in a small, uniform piece of land with carefully controlled and collected trial data. While crop responses can be accurately estimated for those specific experimental sites, however, the small-plot data can represent neither the management conditions nor the spatial variability of actual large-scale commercial farming fields. Recognizing those limitations, recent years have seen a growing number of site-specific crop response estimation studies using on-farm experiments that were conducted in growers' production fields. The number of observations and spatial variability in field characteristics collected from on-farm experiments are often much larger than those of small-plot trials, though the data quality might also be considerably lower. Many studies have reported the VRA economic evaluations based on on-farm experimental data. However, so far most of those evaluations were case studies using only one or several experimental fields, as well as their unique estimation methods. As can be expected, given the large variations across individual fields, those results can hardly be generalized and provide reliable guidance for growers' VRA investment decisions.

This study attempts to evaluate the economic return of VRA by using 42 field-years' data of on-farm precision experimentation (OFPE) and consistent evaluation techniques. All experiments were for corn yield response to nitrogen fertilizer conducted in Corn Belt states, spanning from 2016 to 2021. The nitrogen trial rates were determined by varying from growers' currently applied rates (status quo) in each field. Nitrogen rates were applied by growers' own variable rate equipment following the trial design maps provided by researchers, and the yield data were collected by combine yield monitor during the harvesting process. Inexpensive field characteristic information (e.g., elevation, soil type, EC) were also collected for each field. The data were cleaned, processed, and organized in spatial units of

about 6 meters wide and 20 meters long. An average experimental field contained about 2,000 units.

In spite of numerous existing studies on site-specific yield response estimation in the literature, there is still no consensus on what models are the most appropriate. In this study we tried two different modeling strategies. The first strategy directly interacted field characteristics with nitrogen rates to explicitly capture the variations in nitrogen response (i.e., marginal effects of nitrogen). Instead of imposing linear interaction terms like many existing studies, we used a machine learning model, Multi-Arm Causal Forest (MACF), to allow more complex interaction patterns. The MACF model predicted each observation's yield changes caused by nitrogen rate changing from base rate (the lowest trial rate) to any other trial rates, which can be regarded as relative site-specific yield responses. The second strategy, however, did not directly use field characteristics, but first divided the field into several management zones, and then estimated a uniform response function in each zone. The zone delineation was based on the spatial distribution of coefficient from an exploratory Geographically Weighted Regression estimation. Two econometric models were used to estimate the uniform response: Spatial Error Model (SER) with a quadratic functional form, and Generalized Additive Model (GAM) that allows a more flexible non-parametric response pattern.

Based on the estimated site/zone-specific yield response functions and current corn ($6.5/bushel) and nitrogen fertilizer ($1/lb) prices, the optimal variable rate nitrogen applications (VRA) were derived. Economic return of VRA was measured by the profit of VRA over growers' currently applied rate. Final estimation results showed the VRA return varied substantially across individual fields, ranging from zero to about $150 per acre. By SER estimation, only one (1) field's VRA return was lower than $5/acre, 43% of the fields had moderate return ($5 to $20/acre), and 55% of the fields had high return (>$20/acre). The average VRA return across the 42 fields was $29/acre, an economically significant amount that is worth considering by growers. GAM results (average of $33/acre) were similar to SER. By MACF estimation, however, the average VRA return was at a lower amount of $19/acre, and 29% of the fields had low VRA return (<$5/acre). Those findings demonstrated the VRA return estimation depends heavily on the estimation model selection. Unfortunately, it is difficult to tell which model's result is closer to the true value. The zone-specific models (SER and GAM) might over-fit and exaggerate the variations of response, or the interaction model (MACF) might overlook key field variables and underestimate the response variations. Without knowing the true situations, our estimations by different models provided a range of VRA values ($19 to $33/acre) to the best of our knowledge for growers' VRA investment decisions.

Additionally, we also calculated the optimal uniform nitrogen rate application (URA) for the whole field. That helps to decompose the total VRA return into two parts: (i) profit increase from correcting grower's rate to URA, and (ii) profit increase from URA to VRA. Our results showed that part (i) took a large portion (($16 to $18 per acre) of the total VRA return. Since URA does not require expensive variable rate equipment, this portion of economic return can be more easily acquired by growers. It also means the "pure" VRA returns (i.e., part ii) were actually much smaller ($2.6/acre by MACF, $12/acre by SER, and $15/acre by GAM).

Note that all the estimations in this study are ex post evaluations, which represent the potentials of VRA return. In reality, growers can rarely achieve the optimal VRA and the potential returns. To estimate more realistic VRA economic returns, we need to develop ex anti VRA decision algorithms by more sophisticated models, and test their profitability using more out-of-sample experimental fields.

Keywords

Variable Rate Application (VRA), Economic Evaluation, On-Farm Precision Experiments, Optimal Nitrogen Rate

Presenter Profile

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Measuring the Estimation Bias of Yield Response to N Using Combined On-Farm Experiment Data

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Abstract

Accurately evaluating yield response to nitrogen can increase crop management profitability and sustainability. Many studies estimate yield response by fitting a regression model to data collected from different fields. But analysing such combined data requires that heterogeneity across fields be accounted for in the regression analysis along with the variation in input rates. This study uses data from 27 large-scale on farm experiments to test the potential danger of getting biased estimates of yield response functions. Models with and without field fixed effects are run. The yield response functions from the two models showed different slopes, which provides a visual representation of the bias resulting from the pooled estimation. Use of the Mundlak approach indicated that ignoring the endogeneity of regressors with respect to field effects leads to an unreliable estimation of yield response to N.

Keywords

Field fixed effects, yield response, on-farm precision experimentation, endogeneity.

Presenter Profiles

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Introduction

Use of nitrogen (N) fertilizer in crop production is important both economically and environmentally. Over-fertilization can lead to N leaching, causing pollution, whereas under-fertilization may produce yield below the economic optimum (Schlegel, Dhuyvetter, and Havlin 1996; Magdoff 1991). Accurately evaluating the yield response to N can improve the accuracy of estimating economically optimal N rates, thereby increasing farmers profitability and improving the sustainability of agricultural activities (W. Raun et al. 2017; Ransom et al. 2020).

The supplemental N requirement of corn and supply from soil can vary substantially among fields (Bundy and Andraski 1995). Numerous studies have estimated yield responses to N for individual fields (Scharf and Lory 2002; Schmidt et al. 2002). However, since statistical analysis needs adequate variations in input levels and yield observations to provide understanding of yield response functions, in previous studies, researchers have been combining observed application data from multiple locations to estimate yield response to inputs (e.g., Spillman 1923; Tumusiime et al. 2011; Lory and Scharf 2003; Sela, Woodbury, and Van Es 2018; Wang, Shi, and Wen 2023). At the early stages of finding optimal corn N rates based on yield response data, yield response functions were estimated based on combined data from numerous experiments of N trials (Osterhaus, Bundy, and Andraski 2008; Scharf 2001; Oberle and Keeney 1990; Pias et al. 2022; Roberts et al. 2013; Lory and Scharf 2003). Among those N trials, the majority of them received different N rate treatments across different fields; some of them were based on the crop management history (Andraski and Bundy 2002), some of them were chosen by producers (Scharf et al. 2011), some of them have no information about how the trial rates were chosen (Vanotti and Bundy 1994a, 1994b; Lory and Scharf 2003; Barker and Sawyer 2010; Roberts et al. 2013). An N recommendation approach, Maximum Return to N (MRTN) (Morris et al. 2018; Sawyer et al. 2006; Nafziger 2018), is a good and significant example of using combined multiple N trials data to recover yield response. Since its goal is to have regional recommendations of nitrogen application rates, it incorporated data from diverse locations with varying N rates and a wide range of field characteristics into the model. Consequently, the MRTN research is conducted using data from hundreds of N trials in the database from each state or a specified region within the state, without specifying consistent N rates or increments across fields.

Even though some studies may have sufficient variations of N treatments within each trial, including more observations from multiple trials can provide additional information to the regression process. This, in turn, enhances the precision of the estimates and leads to the development of better decision-making tools (Bullock et al. 2019). Also, as the management of agricultural activities increasingly relies on big data and machine learning methods, the need to incorporate more observations into the analysis process is intensifying. More studies are now using a significantly larger volume of data than before, which often necessitates the combination of observations from multiple fields. (Van Klompenburg, Kassahun, and Catal 2020; Qin et al. 2018; Ransom et al. 2019; Su et al. 2022).

However, despite the benefits of combining data from separate field experiments, there are challenges in combining data from different trials. During the process of combining data, the heterogeneity of fields' characteristics will be brought into the regression analysis along with the variation in input rates. If these field characteristics are not controlled for in the regression, their effects on yield may be attributed to other variables. This can lead to a biased estimation of the marginal effect of N on yield. Oglesby et al. (2022) compared the Economically Optimal Nitrogen Rate (EONR) and the Agronomically Optimal Nitrogen Rate (AONR) obtained from models analysing each field individually with those obtained by combining data by year or both field and year. They found that pooled data tends to mislead the estimation of impact of the input on yield. To address this issue, previous studies have proposed methods that incorporate location-specific models to potentially improve input rate recommendations (W. Raun et al. 2017; W. R. Raun et al. 2019).

The main objective of this study is to examine the potential bias in estimating the causal effects of N on yield due to omitted variable bias when using combined data from multiple fields. I will use unique datasets from the Data Intensive Farm Management project (DIFM) (Bullock et al. 2019) that allow us to test this hypothesis. The DIFM uses precision agricultural technology to conduct on-farm experiments (OFPE) in large-scale farm trials in different states. Because the initial goal of DIFM is to generate profit-enhancing information for each specific participating farmer, targeted input rate are decided upon separately by each field. Given that the amounts of N treatment are determined by farmers for individual fields and may correlate with their fields' characteristics, combining the DIFM data should present the endogeneity problem previously mentioned. On the other hand, multiple (usually 5 to 7) treatment rates are applied by variable rate technology in each field based on Latin square trial design maps, making sure the input rates and other elements are independent. These project protocols introduce two dimensions of N variation when combining data from multiple fields: within-field N variation and across-fields N variation. Of these, only the within-field N variation is independent to other elements within each field, ensuring the yield response curve reflects the real impact of N on yield. This provides a great opportunity to test the potential danger of getting biased yield response to N using combined fields data.

Models with and without adding field fixed effects were estimated using on-farm experimental data combined across fields. The results show that the estimated marginal impact of N on yield were different from the two models and the two yield response curve showed different slopes, resulting in different EONR estimations. This is consistent with my hypothesis, which is that the correlation between the unobserved farm characteristics and the choice of N treatments will cause omitted variable bias in the analysis. Mundlak's method (Mundlak 1978) was applied to check for endogeneity. Results show that ignoring the endogeneity of regressors with respect to field characteristics leads to an unreliable estimation of yield response to N. It is very important to be aware of this problem, as this issue has not been widely recognized in previous literature and the use of big data, machine learning, or on-farm experiments for managing agricultural activities has increased dramatically, which increasingly necessitates the combination of observations from multiple fields.

Methods

Experimental Data

The Data Intensive Farm Management (DIFM) project (Bullock et al. 2019) works with participating farmers conducting on-farm precision experiments (OFPE) on fields. Latin square field trial design is established by researchers at the beginning of each growing season for each trial. The N treatment rates were determined around farmers' status quo rates, which were chosen based on farmers' experience and expectations for the field. The dimension of the plots was designed to fit the swath width of the machinery available. Other farming practices stayed the same throughout the field. Figure 1 shows an example of a trial design. This field was partitioned into 253 plots and each plot is assigned to one of the N treatment rates around 117 lb/ac N.

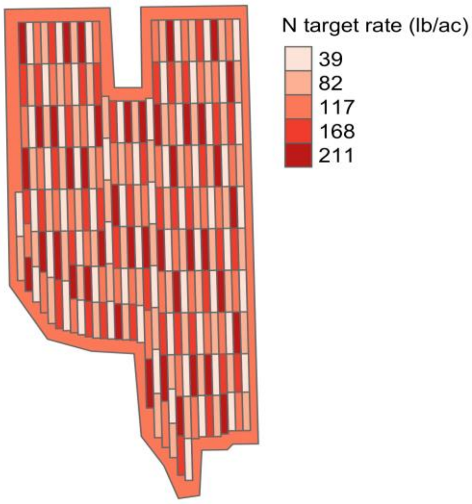

Figure.1: An example Latin square trial design map

Twenty-seven corn N trials in 2021 (15 trials) and 2022 (12 trials) growing season from the DIFM project were used for this study. These trials were conducted across Illinois, Ohio, Arkansas, and Oklahoma in the U.S., as well as in Quebec, Canada. N treatments were implemented in the field using variable rate applicators according to the trial design. Figure 2 shows the applied N treatments for each trial. The red points represent the average N rate in each field, it varies across different fields because farmers chose different status quo rates.

In October, yield monitors were at harvest to collect yield level data. See Figure 3 shows an example of applied variable N trial and observed yield data.

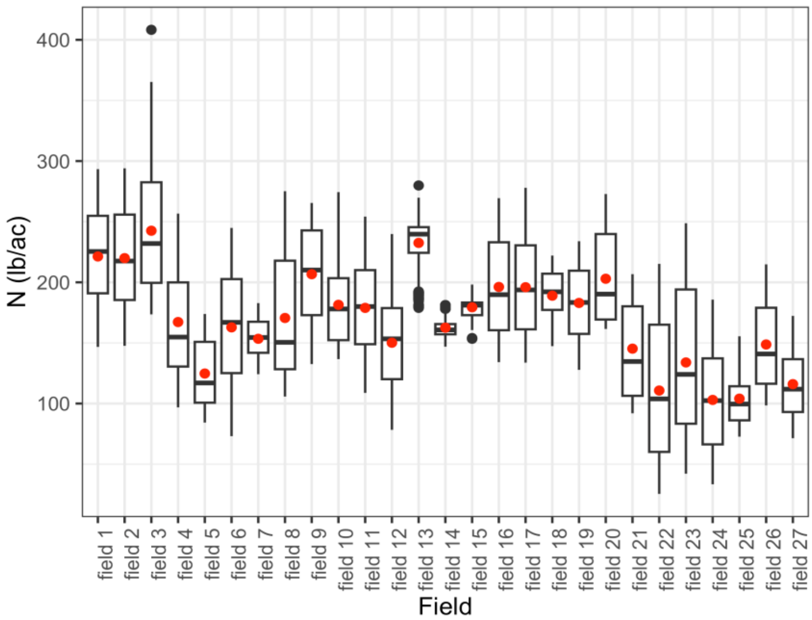

Figure 2: N treatment rates in each field

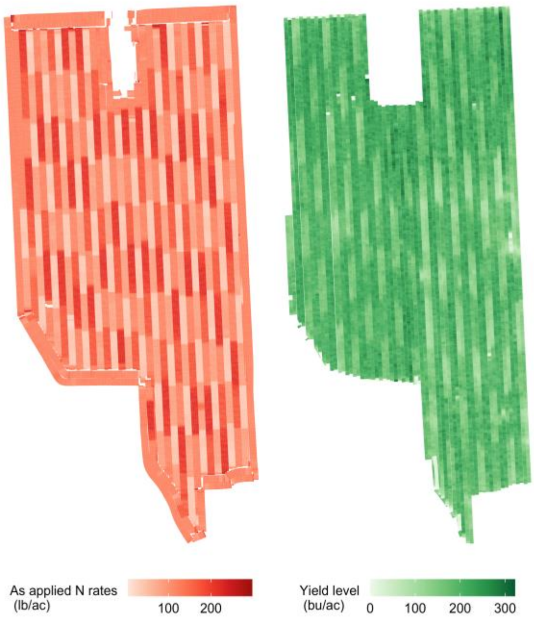

Figure 3: As-applied N rates and observed yield

Data quality was maintained through data cleaning and processing, as discussed briefly by Bullock et al. (2019). Through data processing, extreme as-applied rates and yield were removed from raw data retrieved directly from applicators and yield monitors. Data from side-of-field, headlands, too-small plots, geometrically irregular areas was excluded from the experiment, since the farming practice in these cases are less consistent than the interior of the field due to different machine driving speed, potential application overlaps, etc. An approximately 10m-long "transitional buffer zones" were applied at the end of each plot to mitigate the yield monitors' reading delays between different yield zones.

The georeferenced raw yield data were used to generate yield polygons, which were used as the "observation units" in analysis. The creation of these polygons depended on factors such as the plot's original length, swath width, headings, and the distance between points. Within each field, the area of each polygon remained constant. The N rate assigned to each polygon was calculated as the average value of the as-applied N rates falling within that specific polygon. If the N treatment values at points within a yield polygon exceed three times of their standard deviation, the polygon is removed from the analysis, ensuring that the yield observations originate from a single N treatment rate.

Since DIFM runs OFPE in large-scale farms, the abundance of observations within each farm (Figure 4) provides sufficient treatment variation to estimate its yield response function. Considering that the OFPE are conducted at multiple locations and farmers select the central treatment rates, the combined DIFM data can reflect the variations of N demands both across different fields and within each individual field. This combination of two different dimensions of data enables the estimation of both the pooled yield response, incorporating variations in N levels across all fields, as well as field-specific yield response, accounting only for within-field N variations.

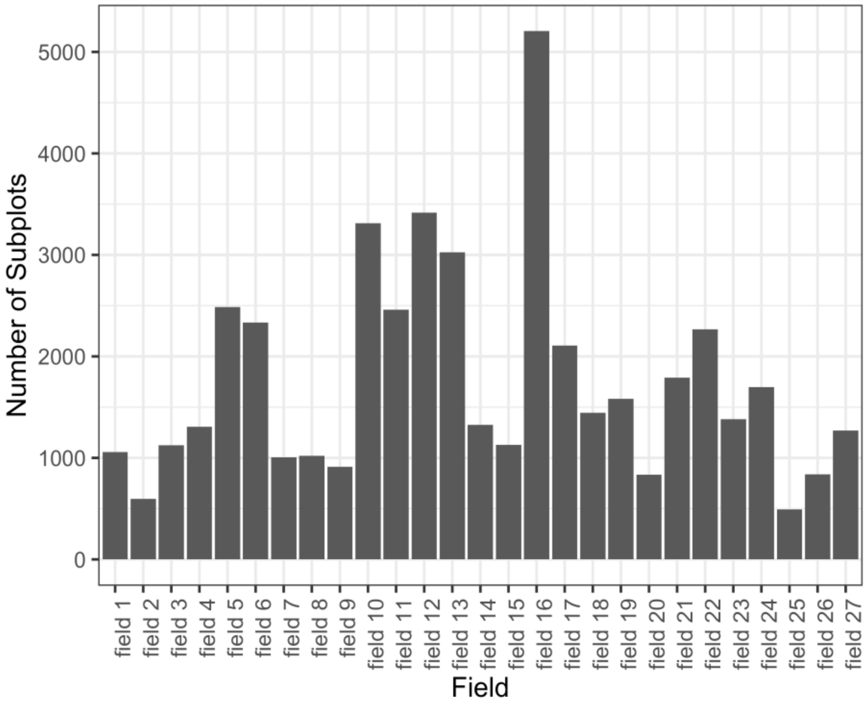

Figure 4: Number of observations in each trial

Non-experimental data

The soil and weather data were obtained using R software (R Core Team 2022). Elevation data for each field was obtained using the elevatr package (Hollister et al. 2022). Digital elevation maps were used to calculate the values of terrain slope and curvature. Slope data was obtained using the raster package (Jacob van Etten 2012). Curvature data was obtained using the spatialEco package (Evans and Murphy 2023). All of the soil data was calculated from subplot-level measurements, consistent with the observation unit.

Daily weather data is obtained from Daymet (Thornton et al. 2022). Monthly precipitation and the number of extreme degree days (EDD) (Schlenker and Roberts 2009) are included in the regression analysis. Precipitation and temperature are assumed to stay the same in the fields in northern Illinois, central Illinois, southern Illinois, Ohio, Arkansas, and Oklahoma. The number of EDD were calculated as follows:

$$EDD = \sum_{i=1}^{n} max\left(0,\ T_{max,i}\ - T_c\right),$$

where $T_{max,i}$ is the maximum temperature on the *i*th day from April to September, T_c, 29$^{\circ}C$ for corn (Schlenker and Roberts 2009), is the critical temperature threshold that will lower yield.

Data merging

Soil data was computed for each observational unit in analysis. The average values for elevation, slope, and curvature from each subplot were merged with applied N and yield levels, using their geographic references through R programming. Weather information was integrated into the dataset based on the fields' locations.

Econometric Model and Analysis

Potential endogeneity problem when using data from multiple fields

As discussed, many studies estimated yield response by fitting a regression model to data collected from different fields without accounting for the unobserved heterogeneity among those different fields. Figure 5 illustrates a potential problem of this approach. As found in previous literature, field-specific characteristics vary from field to field, leading to different yield potentials. For example, consider a two-field case, where field 1 reaches a higher yield potential compared to field 2 due to field or soil characteristics that are not observed by researchers. It is known that some farmers follow yield-based management algorithm, where farmers tend to apply more N for the fields with higher yield potentials (Rodriguez, Bullock, and Boerngen 2019). In this example, farmers tend to apply more N in field 1 (the orange points has higher average than the blue points). The points represent the as-applied N rates and yield level observed by researchers in each field, capturing their own yield response. However, when combining the observed data from both fields, the cross-sectional fit is the black line, consequently biasing the estimation of the relationship between N response and yield.

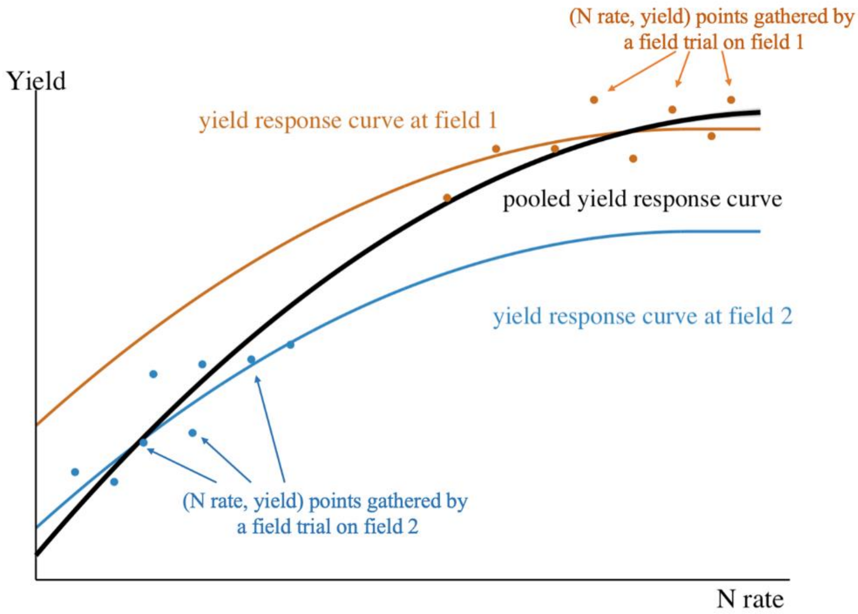

Figure 5: Conceptual demonstration of the potential endogeneity problem when using data from multiple fields.

The fact that farmers select N rates based on their understanding of the fields, accounting for unobserved field characteristics, is not the sole cause of leading to the endogeneity problem from using a pooled model with data from multiple fields. Weather, varies from location to location, can significantly change yield response to N. However, there are numerous approaches to representing weather variables, which can be calculated using minimum, maximum, or average values on a daily, weekly, monthly, or entire growing season basis. Diverse criteria can also be used to construct weather variables. For instance, one could use the absolute temperature or precipitation values or count the number of days surpassing specific thresholds. More importantly, it is nearly impossible to model the interactive and non-linear weather effects on corn yield response (Schlenker and Roberts 2006; Bassu et al. 2014).

Therefore, it is not realistic to perfectly account for weather variables in regression analysis, meaning that the unaccounted impacts will be left in the error term. This idea also applies to soil variables. The Soil Survey Geographic Database (SSURGO), soil tests from experimental fields, etc. are common sources of soil information. However, the accuracy of soil data can limit the extent to which can be controlled for the impact of soil characteristics on yield in regression analysis. This can, again, result omitted variable bias in the yield response estimation.

For the sake of demonstration, assume yield response follows linear functional form

$$y_{fi} = \mathbf{X}_{fi}\boldsymbol{\beta} + v_{fi} \qquad (1)$$

$$v_{fi} \equiv c_f + u_{fi} \qquad (2)$$

where y_{fi} is the yield level in field f and subplot i, X_{fi} is a vector of all the independent variables including N treatment rates and other controlled covariates.

The error term v_{fi} contains all of the factors that affect yield but are not measurable or controllable (not in $\mathbf{X}_{fi}$). Equation (2) decomposed it into two parts. u_{fi} is the idiosyncratic error across all subplots. c_f represents the unobserved field characteristics, which are assumed to be constant within each field but vary across locations. Examples of c_f are unobserved the farmer's human capital or management ability, and non-measurable soil characteristics. However, these unobserved field characteristics can impact the yield level and subsequently influence the N rates chosen by farmers. For instance, farmers tend to apply more N on the fields that have historically shown higher yields. Consequently, the correlation between uncontrollable field characteristics and N treatment rates causes an endogeneity problem. This is, $E\left(\mathbf{N}_f^{gc'}\mathbf{c_f}\right) \neq 0$, then pooled OLS estimator will be biased, $E\left[\widehat{\boldsymbol{\beta}}|X\right] \neq \boldsymbol{\beta}$.

Field fixed effects

Thanks to the protocols of the DIFM trial design, the across-field heterogeneity was caused by the trial design rates being centered on farmers' status quo rates and the Latin square trial design was implemented to ensure clean variation in N levels within each field. Therefore, the combined fields data provides a great opportunity testing the potential danger of getting biased estimated yield response functions ignoring field heterogeneity. To eliminate the heterogeneity across fields in the regression analysis, the fixed effects model (Mundlak 1978) can be applied. By including field fixed effects, only the variation within a field is used as identifying information to estimate β^N, which can solve the endogeneity problem due to unobserved field-specific characteristics.

Models with and without field fixed effects are run respectively using the 27 corn-N trials. Quadratic model was used to estimate the impact of N on yield. The quadratic functional form of crop yield functions remains attractive as it is simple to implement, easy to understand, and it can capture the non-linearity of yield response to inputs. The shape-constrained generalized additive (SCAM) model (Pya and Wood 2015) is also applied to estimate the yield response to N. Instead of defining a specific functional form, SCAM lets the data determine the nature of the relationship between inputs and output, which allows for a more flexible specification of yield response function. The results from SCAM and quadratic models are very similar (Figure S1 in Appendix). Based on the simplicity of the quadratic model, we used it for this study.

The statistical model can be written as Equation (3),

$$y_{fi} = \mathbf{N}_{fi}\boldsymbol{\beta}^N + \mathbf{X}_{fi}\boldsymbol{\beta}^X + v_{fi} \qquad (3)$$

where $\mathbf{N}$ contains the N treatment rates in each subplot and their quadratic term, $\mathbf{X}$ includes all other subplots-level soil and weather covariates, including elevation, slope, curvature, monthly precipitation from April to September and EDD. All yield, N, and soil features are in site-specific level with f representing field and i representing subplot.

The error term v_{fi} has the same structure as Equation (2). Since N treatment rates were applied based on Latin square trial design, it is orthogonal to any other factors that affect yield. However, as mentioned earlier, the presence of unobserved field characteristics is highly likely to influence farmers' chosen rates, resulting in a correlation with the input treatment rates. These implies,

$$E(N_{fi}\ v_{fi}) = 0,\ \forall f \in \{1,2,\dots,F\}$$
$$E(\mathbf{N^{gc\prime}}_f\mathbf{c}_f) \neq 0$$

where $\mathbf{N}^{gc}$ is a $(F \times 1)$ matrix contains all the grower chosen N rates, which are the centers of the variable Nitrogen rates in each field. Again, $\mathbf{c}$ is a matrix contains unobserved field-level characteristics.

Combining Equation (3) and Equation (2) yields:

$$y_{fi} = \mathbf{N}_{fi}\boldsymbol{\beta}^N + \mathbf{X}_{fi}\boldsymbol{\beta}^X + \mathrm{c}_f + u_{fi} \qquad (4)$$

Note, since c_f are the field-level characteristics, the impact of it on yield stays the same in each farm f and doesn't vary among subplots i within the field. The fact of $\bar{c}_{fi} \equiv c_f$ for each field f provides the condition that including field fixed effects can eliminate cross-field variation and only use within-field variation to estimate the yield response curve.

Taking average of the independent and dependent variables in Equation (4) over each farm f can get,

$$\bar{y}_f = \bar{\boldsymbol{N}}_f\boldsymbol{\beta}^N + \bar{\boldsymbol{X}}_f\boldsymbol{\beta}^X + c_f + \bar{u}_f \qquad (5)$$

Subtract equation Equation (5) from Equation (4) yields Equation (6).

$$y_{fi} - \bar{y}_f = (\boldsymbol{N}_{fi} - \bar{\boldsymbol{N}}_f)\boldsymbol{\beta}^N + (\boldsymbol{X}_{fi} - \bar{\boldsymbol{X}}_f)\boldsymbol{\beta}^N + u_{fi} - \bar{u}_f \qquad (6)$$

Define $\ddot{y}_{fi} = y_{fi} - \bar{y}_f$, $\ddot{\boldsymbol{N}}_{fi} = \boldsymbol{N}_{fi} - \bar{\boldsymbol{N}}_f$, $\ddot{\boldsymbol{X}}_{fi} = \boldsymbol{X}_{fi} - \bar{\boldsymbol{X}}_f$, and $\ddot{u}_{fi} = u_{fi} - \bar{u}_f$, Equation (6) can be written as:

$$\ddot{y}_{fi} = \ddot{\boldsymbol{N}}_{fi}\boldsymbol{\beta}^N + \ddot{\boldsymbol{X}}_{fi}\boldsymbol{\beta}^N + \ddot{u}_{fi} \qquad (7)$$

In this case, $E[\widehat{\boldsymbol{\beta}^N}|\ddot{\boldsymbol{N}};\ \ddot{\boldsymbol{X}}] = \boldsymbol{\beta}^N$ due to the orthogonality of N treatments ($\mathbf{N}_{fi}$) and other covariates ($\mathbf{X}_{fi}$) from Latin square trial design. This will lead to an unbiased estimation of causal impact of Nitrogen on yield, generating an unbiased yield response function.

Specification test

Mundlak's method (Mundlak 1978) is used to test the statistical significance of the unobserved field heterogeneity, which lead to the endogeneity of the model. A Wald test based on the coefficients on the means of the field varying variables from a random effect model (Equation 8) was performed to identify if the observed variables are statistically significantly correlated with the unobserved field characteristics.

$$y_{fi} = \alpha + \mathbf{N}_{fi}\boldsymbol{\beta}^N + \mathbf{X}_{fi}\boldsymbol{\beta}^X + \bar{\mathbf{N}}_f\boldsymbol{\beta}^{\bar{N}} + \bar{\mathbf{X}}_f\boldsymbol{\beta}^{\bar{X}} + v_{fi} \qquad (8)$$

where $\mathbf{N}_{fi}$ and $\mathbf{X}_{fi}$ contains the same variables as Equation (3). $\bar{\mathbf{N}}_f$ and $\bar{\mathbf{X}}_f$ have all the mean values of each variable by field.

The Null hypothesis has all the coefficients on the means ($\boldsymbol{\beta}^{\bar{N}}$ and $\boldsymbol{\beta}^{\bar{X}}$) are zero indicates that there's no endogeneity in the pooled regression.

Results

Table 1 shows the regression results of the models, both with and without including field fixed effects, respectively. After adding field fixed effects into the model, the coefficient of the N variable changed from 0.494 to 0.407 and became less significant. Moreover, the quadratic N term turned no longer significant. Since N is orthogonal to any other factor that might influence the yield level within field, the coefficients from the model with fixed effects truly represent the marginal effect of N on yield. This provides evidence that using pooled model can bias the yield response to N. The impact of slope on yield changed from positive to negative after including field fixed effects, this is more consistent with agronomic expectations as steeper slopes can lead to poor water drainage, increased runoff, shallow soil depth, and challenges related to planting and N application. The elevation and curvature also became lass significant after including field fixed effects into the model, indicating that these factors showed effects on yield beyond their individual influences in the pooled model.

Table 1: Regression results from pooled model and field fixed effects model

	Pooled Model	Field Fixed Effects Model
N	0.494***	0.407+
	(0.015)	(0.231)
N^2	-0.001***	-0.001
	(0.000)	(0.001)
elevation	0.058***	-0.079*
	(0.002)	(0.035)
slope	0.283***	-0.134*
	(0.030)	(0.051)
curvature	0.000***	0.000*
	(0.000)	(0.000)
Apr precipitation	-0.233***	
	(0.019)	
May precipitation	-0.335***	
	(0.009)	
Jun precipitation	0.123***	
	(0.006)	
Jul precipitation	0.220***	
	(0.011)	
Aug precipitation	-0.164***	
	(0.021)	
Sep precipitation	-0.945***	
	(0.012)	
EDD	-0.041***	
	(0.002)	
Num.Obs.	47405	47405
Std.Errors	IID	by: field
FE: field		X

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

From the results, all the monthly precipitation and EDD variables are statistically significant (weather was assumed to be consistent within each field and were thus controlled by field fixed effects). This aligns with the agronomic expectation that weather influences yield levels. However, as previously mentioned, it is nearly impossible to perfectly reflect the impacts of weather and soil on yield in regressions. Therefore, it is very likely that there is omitted variable bias in the pooled yield response regression analysis.

Figure 6 shows the results of estimated yield response curves from the pooled model and the fixed effect model. The figure shows that the two models resulted in two yield response functions with different slopes, providing a visual representation of the bias resulting from the pooled estimation. Because the field fixed effect eliminated the heterogeneity across fields and only used the N variation within each field for the regression. As N is orthogonal to other factors based on the trial design, the within-field N variation can be considered clean. Therefore, the yield curve depicted by the red line represents the true yield response to N. Any deviation between the two curves can be attributed to the bias arising from the estimation conducted using the pooled model.

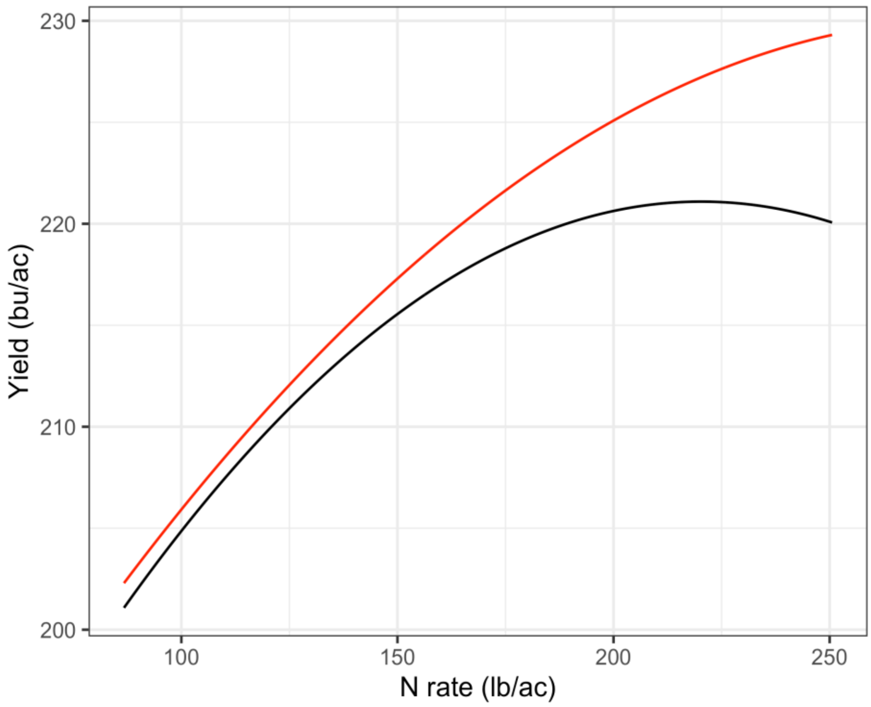

Figure 6: Predicted yield response functions with and without field fixed effects (black is pooled)

Following the Mundlak approach, the Wald test yielded a χ^2 statistic of 116.9, which rejected the Null hypothesis indicating that ignoring the endogeneity of regressors with respect to field effects leads to an unreliable estimation of the yield response to N. This is important, As EONR is found as the solution to the problem of applying N at the profit maximizing rate, which happens when the yield response curve has the same slope as the crop-N price ratio, the estimation of the yield response to N directly affect the estimation of EONR. More accurate N fertilizer guidelines can help with raising farm profits and reducing environmental damage. In this study, for example, the EONR estimated for each individual field is 214 lb/ac, while the EONR estimated from the pooled regression is 176 lb/ac. The difference between the two

EONR comes from the biased estimated yield response function using pooled data without recognizing field heterogeneity.

Sufficiently many N input rates and observations are essential to the accurate estimation of yield response. Many researchers have obtained data from multiple sites or studies, as combining yield and N data from various site-years is an easy-to-implement and cost-effective process. However, the results from this study showed the potential bias arising from ignoring unobserved field heterogeneity when analyzing datasets obtained from multiple site-years. It is important to acknowledge this, as managing agricultural activities using big data and machine learning methods have become hot topics, those studies now require much larger volumes of data, necessitating the combination of observations from multiple fields.

Conclusion

Accurately evaluating yield response to N can increase crop management profitability and sustainability. Many studies estimate yield response by fitting a regression model to data collected from different fields, as statistical analysis requires varied input application levels. Even with sufficient variation in N treatments within each trial, having more observations contributes to a more continuous distribution of N and field characteristics, which is desirable for developing N recommendation approaches. One way to attain additional observations, of course, is to combine data from multiple fields. But analyzing such combined data requires that heterogeneity across fields be accounted for in the regression analysis along with the variation in input rates. In other words, noisy variation among different fields may challenge yield response estimation for each field.

This study used data from 27 large-scale on-farm precision experiments with trial design rates centered on farmers' status quo rates to test the potential danger of generating biased estimates of yield response functions. A Latin square trial design was used to make N orthogonal to other factors, so within-field N variation can be considered clean. The field fixed effects in the model eliminated cross-field variation and only used the input variation within each field as identifying information to estimated yield response, ensuring an unbiased measurement of the response to N. Models with and without field fixed effects were run. The yield response functions from the two models showed different slopes, which provided a visual representation of the bias resulting from the pooled estimation. The results of this study indicated that ignoring the endogeneity of regressors with respect to field effects leads to an unreliable estimation of yield response to N. It is important to recognize this potential problem when use combined data from multiple locations, particularly as studies now demand vast amounts of data with the rise of big data, machine learning, and OFPE in agriculture management.

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What is the Value of On-Farm Precision Experiment Data as a Public Good?

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Extended Abstract

On-farm precision experiments (OFPE) is a popular and widespread method to help farmers have better information about their field's spatial characteristics map and associated yield response function. Thus, with an OFPE trial, farmers can improve their expected profits by estimating yield response function more accurately. Despite these advantages, some costs hinder farmers from running OFPE privately. This research proposes a way to use OFPE data as a public good, which can generate valuable information in a field where OFPE has not been implemented. We conceptually define the value of OFPE data as a public good and test if the information acquired from multiple other fields' OFPE data promotes as much expected profits as running OFPE in the field we want to manage. The results show that the multiple OFPE data is not yet a valuable public good since the quality, quantity, and spatial diversity of data are limited.

OFPE is a large-scale farm trial that uses precision agricultural technology to conduct randomized input experiments over a whole field. When an OFPE runs in an entire field, it still maintains a small-plot first-principal concept (Bullock et al., 2019). That is, OFPE applies randomized variable rates input on the designated grid cells by following a trial design. Global Positioning System (GPS) linked vehicles enable farmers to apply the designed variable rates very accurately.

Therefore, OFPE requires little work on the farmers' part to operate the trials, while conventional small-plot trials demand intensive labour to apply inputs. OFPE also helps lower the cost of generating profit-enhancing information since it collects data in real-time when the vehicle applies inputs and harvests crops. With this advantage, OFPE provides a better idea about yield response and helps farmers raise the profitability of input management decisions.

Despite the merits of OFPE, some costs still hinder farmers from conducting OFPE on their fields. First, farmers are usually afraid of losing profits from applying a wide input rate range for this trial. For instance, if OFPE applies ten different fertilizer rates over a whole field, then, in most of the field, yield response usually increases fast at a low quantile of the applied fertilizer range and does not increase beyond an economically optimum input rate (EOIR). Thus, when the targeted input rates are quite different from the EOIR, it creates a profit loss. Farmers should also pay to learn how to communicate with consultants to interpret an analysis result of the OFPE data, or they need to hire services to aid in those processes. Another cost to mitigate uncertainty in ex-ante estimated yield input response is that we need to observe how variable weather events could impact yield response by conducting multiple repeated OFPE for a given field. These repeated field experiments aggravate farmers' burden of time spent on these processes. In addition, field characteristics and soil nutrition status change while we run multiple-year OFPE, so it is difficult to keep controlling experiment settings with consecutive biennial trials under the crop rotation system.

To retain the advantages but reduce farmers' burden of conducting OFPE, researchers can consider the potential benefits of using multiple other field OFPE data. Suppose that a researcher can acquire a lot of same-year OFPE data from multiple fields around diverse spatial weather regions. The collected OFPE data might be able to estimate how spatially different weather impacts yield response function. Thus, it might be possible to capture the spatial weather impact on yield response by collecting multiple fields OFPE data, instead of conducting multiple-year OFPE to estimate temporal weather impact on yield response. Moreover, the collected OFPE data has much more observations than single site-year OFPE data, and it is expected to predict yield response to input and field characteristics interactions well. If this idea works, by using multiple other fields OFPE data, farmers can generate valuable information about the field they want to manage. Thus, OFPE data can be regarded as a public good with public policy implications since the trial information in one place is useful for another place without paying additional costs. Therefore, information about whether OFPE is a public good has social value.

The objective of this paper is to investigate whether OFPE data is a valuable public good. If the information obtained by multiple other fields OFPE data can achieve as much expected profit as conducting OFPE, then we can claim that the multiple OFPE data is a valuable public good.

To test this objective, I use 39 OFPE field data collected from 24 different fields around the Midwest corn belt from 2016 to 2021 under the biennial crop rotation. First, I estimate the yield response function of each of the 39 OFPE data by using Generalized Additive Model (GAM) regression and it is assumed to be true. To focus on how well the method estimates yield response, the only manageable input is restricted to a nitrogen fertilizer(N). From this estimated yield response, we calculate the Economically Optimum Nitrogen RATE (EONR). After that, we cross-validate the profit of true EONR by using the OFPE data from other fields.

In this study, we found that a prediction of EONR is inaccurate in most fields, and 39 OFPE data have a low value as a public good. The results imply that it requires more space and temporal diversity of OFPE data to make the multiple fields OFPE data have a social value.

Keywords

(OFPE) On Farm Precision Experiment, Value of Information, Yield Response

Presenter Profile

Jaeseok Hwang is a fourth-year Ph.D. student in Agricultural and Consumer Economics at UIUC. He has been participating Data-Intensive Farm Management (DIFM) project for six years since 2018 as a master's and Ph.D. student under the guidance of Dr. David Bullock.

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Profitability of regenerative agriculture with autonomous machines: An ex-ante assessment of British farming

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Abstract

In regenerative agriculture soil health is considered the key to achieving biodiversity, ecosystem restoration and climate change management. Farmers, agroecological innovators and research have suggested mixed cropping as a way to promote soil health. The simplest form of mixed cropping is strip cropping. In conventional mechanized farming use of mixed cropping practices (i.e., strip cropping, pixel cropping) is limited by labour availability, rising wage rates, and management complexity. This study hypothesized that regenerative strip cropping with swarm robots could be profitable, thereby helping Great Britain simultaneously meet food security, carbon-net-zero targets and other sustainability challenges of biodiversity, animal welfare and rural levelling up. Using the unique autonomous whole farm commercial farming demonstration experience of the Hands Free Hectare (HFH) project at Harper Adams University in the UK, this study evaluated the ex-ante economics of wheat - barley - grass ley - spring bean autonomous regenerative strip cropping practice. Results from the 'steady state' Hands Free Hectare-Linear Programming (HFH-LP) mathematical model applied to a 500 ha British farm shows that autonomous regenerative strip cropping achieved comparable profitability to conventional whole field monoculture cropping and conventional regenerative strip cropping systems. Further sensitivity scenarios exploring strip edge effects, input saving and reduced labour availability found that autonomous regenerative strip cropping practice was more profitable than conventional systems. Autonomous strip cropping with forage and livestock could viably promote the five soil health principles of regenerative agriculture in Britain. The farm economics reveal that autonomous swarm machines have the potential to enable the adoption regenerative agricultural practices and reconcile the production goals of productivity and profitability, and environmental goals of sustainable agriculture.

Keywords

Crop robots, agricultural diversification, strip cropping, mixed cropping, sustainable agriculture, economics

Presenter Profile

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A Model-Averaging Approach for Accurate Estimation of Economic Optimum Nitrogen Rate in Site-Specific Nitrogen Fertilization

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Abstract

Efficient nitrogen management is a paramount concern in modern agriculture to achieve optimal crop productivity, conserve resources, and mitigate environmental impacts. Central to this endeavour is the estimation of the economic optimum nitrogen rate (EONR), which represents the nitrogen application rate that maximizes crop yields while balancing input costs and potential environmental risks. Over the years, several approaches have been proposed to estimate the EONR, ranging from simple to sophisticated mathematical models. While these methods provide valuable insights for a more accurate estimation of the EONR, most publications fail to report the statistical uncertainty inherent to the parameter estimation and the model choice. Moreover, questions remain regarding how to accurately estimate EONR taking into account the inherent spatial variability in crop yields, which can significantly influence the optimal nitrogen rates required for various yield zones within a field. Therefore, we tested a model-averaging approach that utilizes information criteria to compute weights for different response functions to obtain the EONR estimates. The weights are assigned based on model performance, ensuring an accurate representation of the EONR for different yield zones. Overall, the results demonstrate that the averaging approach is a promising method for estimating the economic optimum nitrogen rate, particularly in the context of diverse yield zones within a field.

Keywords

Precision farming; yield spatial variability; sustainable nutrient management; modelling bias.

Presenter Profile

Custódio Efraim Matavel is a researcher at the Leibniz Institute for Agricultural Engineering and Bioeconomy (ATB). He holds a PhD in Agricultural Sciences and a Master's in Agricultural Economics. With a strong background in research and multiple publications, Custódio Matavel's current work revolves around the economic analysis and assessment of digital tools in the agricultural sector.

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A microeconomic perspective on the value of OFPE data in management zone delineation

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Abstract

Precision agriculture researchers began investigating "management zone" (MZ) delineation as variable-rate technology emerged in commercial markets in the 1990s. A large part of that research has focused pm questions about what clustering or delineation methods should be used on past yield data and spatial field and soil characteristics data to delineate MZs. The literature's MZ delineation methods have grown in complexity over the years, but several widespread flaws in this literature persist. Using microeconomic theory to define MZs, we show that creating MZs for a generic input is suboptimal as the input type, management decisions, and zones are fundamentally connected. Specifically, a profitable MZ delineation requires a selected managed input and sufficient knowledge about site-specific yield response functions, and in particular marginal yield response to input application rates, which can only be estimated with data from on-farm precision experiments (OFPEs). Thus, OFPE is vital for the proper establishment of MZs.

Keywords

management zones, on-farm precision experimentation.

Presenter Profile

David S. Bullock is a Professor in the Department of Agricultural and Consumer Economics at the University of Illinois. He studies the economics of agricultural technology and information and has published research on precision agriculture technology since 1998. He is the Principal Investigator of the eight-year USDA-sponsored Data-Intensive Farm Management project, which uses precision agriculture technology to conduct large-scale, on farm agronomic experiments which generate data to aid farmers' management of nitrogen fertilizer and other inputs. He teaches graduate courses in microeconomic theory. He received his Ph.D. from the Department of Economics at the University of Chicago in 1989.

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Introduction

Precision agriculture researchers began investigating "management zone" (MZ) delineation as variable-rate technology emerged in commercial markets in the 1990s. A large part of that research has focused on questions about what clustering or delineation methods should be used on past yield data and spatial field and soil characteristics data to delineate MZs. The literature's MZ delineation methods have grown in complexity over the years, but several widespread flaws in this literature persist. Using microeconomic theory to define MZs, we show that creating MZs for a generic input is suboptimal as the input type, management decisions, and zones are fundamentally connected. Specifically, a profitable MZ delineation requires a selected managed input and sufficient knowledge about site-specific yield response functions, and in particular marginal yield response to input application rates, which can only be estimated with data from on-farm precision experiments (OFPEs). Thus, OFPE is vital for the proper establishment of MZs. We maintain that the methods used to delineate MZs over the past generation are a product of the data-*extensive* methods of input management guidelines that were developed in an era of expensive data generation. But increased employment of OFPE methods are creating a world of inexpensive field trial data generation. The obvious implication is that management zones can now be determined empirically, using copious data analysed in the context of meaningful, rigorous microeconomic theory.

Brief Literature Review

There are several limitations and gaps in the existing management zone literature. First, it is exceedingly common for studies to declare *determination of management zones without specifying how the zones should be managed*. They make no attempt to estimate economically optimal input rates for each zone or evaluate the profitability of the rates compared to the optimal uniform input rate for a field. Rather, they tend to claim validity of their management zone determinations on the variations of soil and field characteristics or yield within and across zones (Cillis et al. 2018; Colaco and Bramley 2018; Kayad et al. 2021; Velasco 2020).

Yield-based MZ research has typically taken three steps in MZ determination: identifying variables associated with yield, choosing the number of zones, and then using cluster analysis to define those zones. Several methods are available for each step of this process. Principal component analysis is commonly used to choose the relevant variables (Gustaferro et al. 2010; King 2005; Peralta et al. 2014; Tagarkis et al. 2013; Yan et al. 2007). Other studies have used normalized classification entropy to determine the optimal number of management zones through balancing the variation within a zone and the variation across zones, but alternative methods have been proposed by Zhang et al. (2010) and Vendrusculo and Kaleita (2011). Similarly, fuzzy c-means and k-means clustering are common methods to delineate management zones with the chosen numbers of zones and characteristics variables, but Velandia et al. (2008) proposed a new method to account for spatial correlation. By using Moran's I scatter plots, these zones account for the spatial structure of the field or soil characteristics.

A Microeconomics-based Definition of Management Zones

Consider a field partitioned into some number of sites, where a site is defined as a piece of the field on which vector of *characteristic* variables $\mathbf{c} = (c_1, \ldots, c_M)$ takes on some value. For example, on some site *A*, the levels of those characteristics variables may be represented by the vector value $\mathbf{c}^A = (c_1^A, \ldots, c_L^A)$, where, c_1^A = 23% may be soil clay content, c_2^A = 3.7 may be terrain slope in degrees, etc. Similarly, let $\mathbf{c}^B = (c_1^B, \ldots, c_L^B)$, where maybe clay content on site B is c_1^B = 12%, terrain slope on site B is c_2^B = 1.7, etc. Characteristics values for sites C and D, $\mathbf{c}^C = (c_1^C, \ldots, c_L^C)$ and $\mathbf{c}^D = (c_1^D, \ldots, c_L^D)$, are defined similarly. Now define a per-acre yield response function dependent on the input choice variable N and the characteristics variable $\mathbf{c}$: $y = f(N, \mathbf{c})$.

It seems natural that a management zone should be defined as a part of crop production field in which the input or inputs being considered are best managed with the same management strategy. Here the word "should" is normative, and implicitly requires that the strategist have an objective. In managing a field, many farmer objectives are plausible: the farmer may wish to maximize profits, maximize expected profits if the decision involves uncertainty, or maximize some function of the higher moments of the profit distribution. For the purposes of the current discussion, we maintain simplicity by modelling farm management conducted under conditions of certainty and perfect information, and we assume a risk-neutral neutral farmer whose objective is to maximize profits. Continuing to keep things simple, assume that the producer wants to site-specifically manage the input N, to maximize per-acre net revenues on the field. Let s^j represent the area of site j, in acres. Indexing sites by $j = 1, 2, 3, \ldots, J$, let N_J be a variable representing the producer's choice of the input on a site j, the farmer's net revenues maximization problem is to solve the following:

$$\max_{N_1, \ldots, N_J} \{\textstyle\sum_{j=1}^{J} s_j [pf(N_j, \mathbf{c}^j) - wN_j]\}. \tag{1}$$

Equivalently, we can say that the producer wants to maximize net revenues by maximizing net revenues on each site, thus solving J different problems:

$$\max_{N_j} [pf(N_j, \mathbf{c}^j) - wN_j], \; j = 1, \ldots J. \tag{2}$$

For some generic $j \in \{1, \ldots, J\}$, let N_j^* be the solution to the problem above. N_j^* must depend on the maximization problem's parameters, which are p, w, and $\mathbf{c}^j$, so we can write $N_j^*(p, w, \mathbf{c}^j)$ This function is implicitly defined by the necessary condition for profit maximization, solved using ordinary calculus:

$$p \frac{\partial f(N_j^*(p,w,\mathbf{c}^j), \mathbf{c}^j)}{\partial N} - w = 0, \tag{3}$$

or equivalently,

$$\frac{\partial f(N_j^*(p,w,\mathbf{c}^j), \mathbf{c}^j)}{\partial N} = \frac{w}{p}. \tag{4}$$

Using the Theoretical Framework to Critique the Literature

Equation (4) above makes clear that a management zone is a part of the field in which the marginal product schedule is invariant. Figure 1 illustrates this point. The top panel of Figure 1 shows the yield response functions specific to some field section A and specific to some field section B. The two areas have different values, $\mathbf{c}^A$ and $\mathbf{c}^B$, of the vector of field characteristics variables, which results in each site having its own yield response function, shown as $f(N, \mathbf{c}^A)$ and $f(N, \mathbf{c}^B)$. In is assumed that the two yield response curves are vertically parallel. Two (input price, output price) situations are shown in the illustration. In the first situation, the output price is p = 10 and w =5, making w/p = 0.5. In the second situation, the output price is p = 10 and the input price is w = 3, making w/p = 0.3. The profit-maximization condition shown in equation (4) is illustrated in the top panel of Figure 1. Because the yield response curves are vertically parallel, their slopes equal 0.5 at the same input application rate, which is shown as $N^*(10{,}5,\mathbf{c}^A)$ = $N^*(10{,}5,\mathbf{c}^B)$. In the same way, their slopes equal 0.3 at the same input application rate $N^*(10{,}3,\mathbf{c}^A)$ = $N^*(10{,}3,\mathbf{c}^B)$. The bottom panel of Figure 1 presents an alternative diagram that makes the same point was is made in the top panel. Because the two yield response curves are parallel, then their partial derivatives with respect to N are the same. This partial derivative is often called the marginal product of N, and putting the price ratio w/p on the panel's vertical axis shows that no matter the value of the price ratio w/p, the economically optimal input application rate is the same for site A as for site B. That is, these two sections are in the same management zone, even though site A is "more productive" than site B.

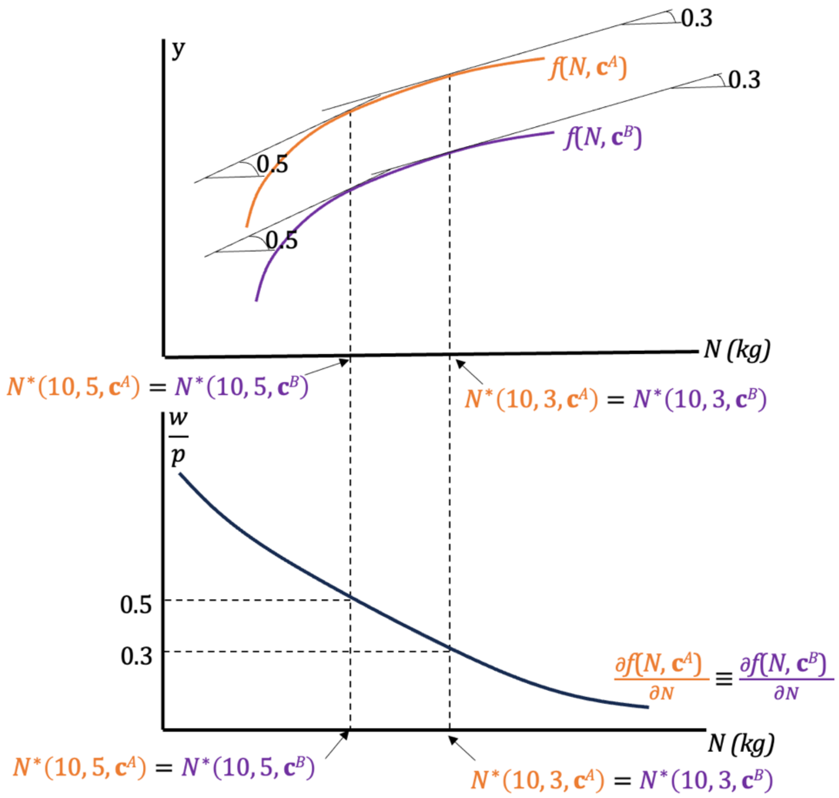

Figure 1. Management zones are determined by the input price, the output price, and the marginal yield response to the input application rate.

Figure 2 is another depiction of why finding sites that have different levels of yield productivity need not be helpful for delineating management zones. Rather, you gathered data on past yields. Assuming that MZs are determined using past yield data from a field that was managed uniformly in the past, the data would show a yield of 250 at sites A and B, and a yield of 125 at sites C and D. If site A with site B were grouped because they have similar yields, and similarly site C with site D were grouped because they have similar yields., then the management zones have badly created. Sites can have similar yields without having similar economically optimal input application rates. The two management zones that should come out of Figure 1 are one that combines site A with site C, since their optimal N rate is 100, and one that combines site *B* with site *D*, since their optimal N rate is 200. Grouping sites with similar yields into management zones does not maximize profits.

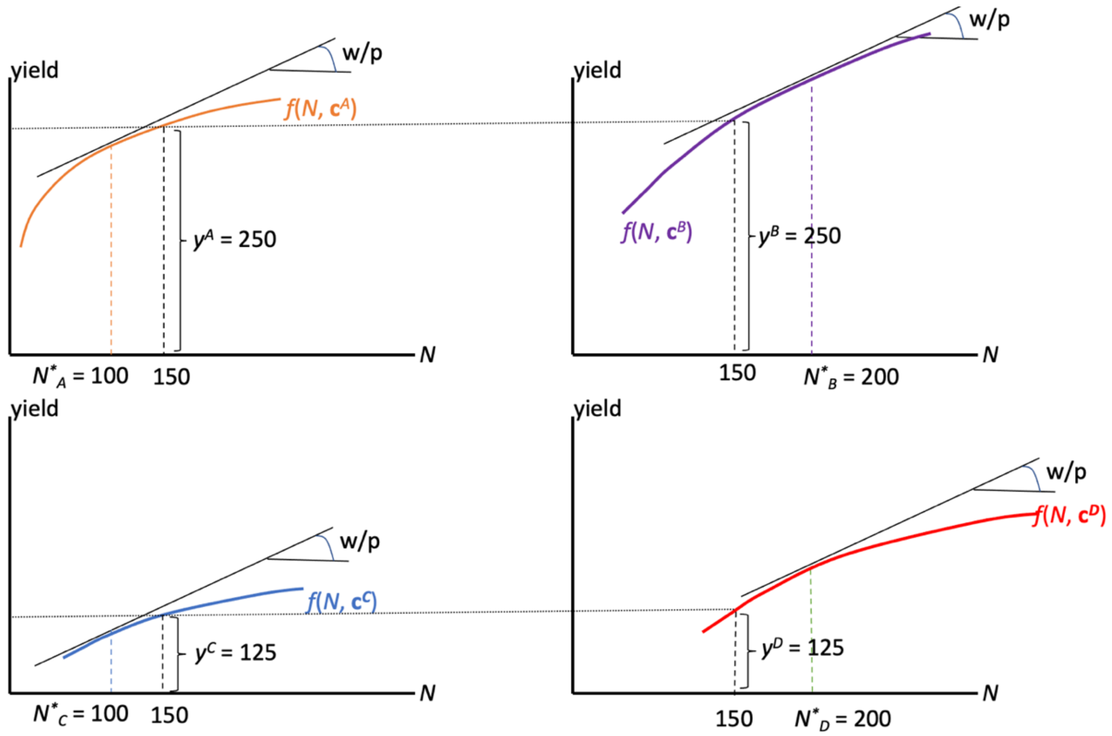

Figure 2. Similar yield values do no imply similar optimal management strategies

Conclusion

The discussion above shows that management zones should be delineated by marginal yield response functions. Knowing a site's yield response function is sufficient for knowing it marginal yield response function. Agricultural scientists have been running field trials for hundreds of years to generate the (input rate, yield) data needed to estimate yield response functions, and in many ways estimation of yield response functions was the principal motivation behind R.E. Fisher's development of modern statistical methods. The problem with the types of "small plot" field trials that Fisher and many others ran to generate data useful for crop input management is that running them has traditionally been labour-intensive and therefore *expensive*. This led Stanford (1966, 1973) and others to attempt to come up with data-*extensive* methods of recommending input application strategies (Rodriguez, et al., 2019). Trying to use yield maps or field characteristics maps to determine input management zones is a continuation of this pattern of data-extensive strategies. Basic microeconomic theory makes it clear that field trial data are needed to obtain empirically-identified management zones. Relatively recently, on-farm precision experimentation (OFPE) has been greatly lowering the costs of running very large agronomic field trials (Bullock, et al. 2019; LaCoste, et al. 2022). OFPE has to potential of generating just the kinds of data needed for empirically-determined input management zones.

Acknowledgements

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Keynote: Implications of technological progress and renewable energy transitions for environmental policies from sustainable development perspectives

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Presenter Profile

Dr. Fakhri J. Hasanov is a senior fellow and leads the KAPSARC Global Energy Macroeconometric Model projects with over 20 years of experience in econometric modeling and forecasting. Since 2015, he has been involved in multistakeholder projects, leading and executing macroeconomic analysis of various policy choices and initiatives (e.g., energy prices, energy demand, and fiscal reforms) for the Kıngdom's economy. He has extensive experience working with policymakers. Prior to KAPSARC, he was a post-doc fellow at George Washington University.

His research mainly covers macro-econometric modeling of energy and environment for policy analyses. His research is recognized internationally (e.g., he is listed among the top 2% of scientists globally by Elsevier in 2022). Dr. Hasanov authored over 50 studies published in reputable journals such as Energy Policy, Energy Economics, and Empirical Economics. He is an editorial board member of peer-reviewed journals, such as Frontiers in Environmental Science. He holds a Ph.D. in econometrics.

Environmental impacts of rubber-based agroforestry systems

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Abstract

Background: Rubber, a significant cash crop, is grown by smallholders in over 30 countries, with Asia contributing to 75% of the global output. Some nations have amplified export-oriented monoculture rubber production, while others advocate interplanting with diverse crops such as fruit trees. Despite this, rubber-based farming diversification has seen limited implementation. Natural rubber (Hevea brasiliensis) intertwines intricately with the climate change narrative, impacting poverty, food security, and biodiversity. The vast 14 million hectare expanse of rubber plantations supports the livelihoods of 40 million smallholders. By 2024, an additional 3 million hectares are projected for rubber monoculture, amplifying the urgency to promote climate-smart practices like rubber-based agroforestry. Understanding the environmental impacts of rubber-based agroforestry could significantly shape climate policy, and enable its inclusion in global climate financing initiatives. This leads us to our primary research question: How does rubber-based agroforestry compare environmentally to monoculture rubber farming systems?

Methods: This review follows Collaboration for Environmental Evidence guidelines and ROSES reporting standards. Multiple databases (e.g. Scopus, Web of Science and EBSCO) will be searched. Literature in English providing primary environmental impact evidence of both monoculture and diversified rubber farming will be screened via EPPI Reviewer following a rigorous inclusion and exclusion criteria. Following the initial screening, eligible studies will undergo a full-text review, data extraction, and quality assessment. The extracted data will be synthesised for comparison of environmental impacts.

Results (anticipated): The systematic review of existing literature will identify the environmental trade-offs between these two farming systems. Such insights will enable policymakers to tailor interventions, advise farmers and agricultural extension officers, and advocate for sustainable farming practices. By identifying knowledge gaps, this study will also guide future research directions, ensuring the simultaneous preservation of smallholder livelihoods and our planet's health.

Keywords

Rubber-based Agroforestry, Monoculture, Environmental Impacts, Systematic Review, Climate-Smart Practices.

Presenter Profile

Dr Iona Yuelu Huang is a senior lecturer at Food, Land and Agribusiness Management Department, Harper Adams University. Her primary research interest is in agri-food business decision making and behaviour change. This includes food loss and waste management, sustainable land use and food supply and agri-tech innovation adoption. She has been a member of several research teams, including Paludiculture Innovation Project, AgroCycle (a Horizon 2020 funded project on valorisation of agri-food waste) and t "Sustainable Agribusiness Model for Poverty Reduction among Thai Small-scale Rubber Farmers".

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Site-specific calculation of corn bioethanol carbon footprint with Life Cycle Assessment

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Abstract

The agricultural stage is a hotspot in the carbon footprint (CF) of the production of corn bioethanol and, within this stage, the production and use of nitrogen fertilisers is the sub-process that has the greatest incidence. The current research project aims to incorporate the environmental impacts in the analysis of optimum nitrogen fertiliser rates, in addition to the agricultural and economic outputs that have been widely used in previous studies. We seek to obtain functions that describe the CF at different nitrogen rates, topographic positions and climatic conditions, incorporating them as objective functions in multiobjective optimization procedures. In order to achieve this aim, the first step is to quantify the corn bioethanol CF with Life Cycle Assessment (LCA) methodology, for fertilisation and yield data at a site-specific scale. On-farm research trials were conducted in 18 corn fields where agricultural producers applied up to 6 levels of strip nitrogen fertilisation, through an elevation gradient, in 5 crop seasons distributed over 12 years, in the centre-south region of Córdoba province, Argentina. The corn transportation and its industrial process were considered as fixed subsystems for this research. The LCA methodology follows the ISO 14067:2018 standard and the Intergovernmental Panel on Climate Change (IPCC) guidelines (2019). The R software was used to process the large datasets. A bioethanol corn CF map at a site-specific scale was achieved. As opposed to a single CF value per field, assessing the CF at a site-specific scale allows us to explore the within-field variability caused by different input rates, its interaction with environmental factors and crop yields. Spatial and temporal statistical analysis is needed to understand the relation between nitrogen fertilisation and corn bioethanol CF. Furthermore, we expect to consider the function that best represents this relation in the definition of optimum site-specific nitrogen rate.

Keywords

Carbon footprint; life cycle assessment; corn bioethanol; precision agriculture; site-specific management.

Presenter Profile

Karen Ponieman holds a Bachelor's degree in Environmental Sciences from the University of Buenos Aires. Since April 2020, she is a PhD student in Agricultural Sciences at the University of Buenos Aires and a Doctoral fellow from the National Scientific and Technical Research

Council (CONICET) and the National Agricultural Technology Institute (INTA). Her PhD project focuses on the multiobjective optimisation of nitrogen fertilisation rate on corn in Argentina to simultaneously meet minimum carbon footprint and maximum agricultural and economic outputs at site-specific scale. Her research is part of the Environmental Footprints Platform and of the Bioenergy project at INTA.

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Introduction

The term carbon footprint (CF) has been widely used as an indicator to quantify the human pressure on the environment (Hoekstra & Wiedmann, 2014). The CF measures the greenhouse gases (GHG) emissions per unit of outcome produced (Kim & Dale, 2008; Kraatz et al., 2013; Boone et al., 2016; Xu & Lan, 2016; Arrieta et al., 2018; Mekonnen et al., 2018). Due to the fact that the manufacture of a product requires the use of multiple raw materials, energy and transportation, the identification of the GHG emissions throughout the entire process is necessary for an integral and systematic analysis. The Life Cycle Assessment (LCA) methodology is one of the most known methodologies to calculate and compare CFs and other environmental impact indicators across different regions and a long time. The International Organization for Standardization (ISO) has two sets of standards (14040 & 14060) that provide tools for the assessment. The LCA of a product takes into account the environmental impact throughout all the stages of the production process, such as the production and transportation of raw materials from the field to the industry, the manufacture, its use and the residues generated after its use (Hauschild et al., 2018; Roy & Dutta, 2019).

Biofuels emerge as an alternative to reduce carbon dioxide emissions resulting from the extraction and use of fossil fuels and to contribute to the Sustainable Development Goals of the United Nations Agenda (United Nations, 2015). The agricultural stage is a hotspot in the production of corn bioethanol (Pieragostini et al., 2014; Moreira et al., 2020; Bongiovanni & Tuninetti, 2021; Hilbert et al., 2021) and, within this stage, the production and use of nitrogen fertilisers is the sub-process that has the greatest incidence in the total corn CF (Ma et al., 2012; Wang et al., 2015; Yan et al., 2015; Qi et al., 2018; Piñero et al., 2019; Bongiovanni & Tuninetti, 2021; Hilbert et al., 2021; Lee et al., 2021). However, the use of appropriate nitrogen fertiliser rates is a key factor for obtaining high yields in corn (Adeyemi et al., 2020; Agyin-Birikorang et al., 2020; Seleiman et al., 2021). That is why it is very important to optimise the use of fertilisers, and the CF is an adequate indicator as it considers not only the GHG emissions but also the amount of output generated with those inputs.

Sustainable intensification of agriculture pursues high product demand by optimising agricultural management and reducing its impact on the environment, by means of increases in the yield per area with less or same use of inputs (Rosales Álvarez et al., 2004; Andrade, 2020; Cassman & Grassini, 2020). In this context, Precision Agriculture (PA) is a technology that generates the nexus between the need for a more intensified agricultural production and that of increasing concerns regarding environmental sustainability (Muschietti-Piana & Zubillaga, 2014; Finger et al., 2019). Variable fertilisation rate is a PA technology that allows the application of the optimum rate in each specific site, according to the crop requirements and soil variability in each production field. Consequently, it can reduce nitrogen loss to the environment and increase the nitrogen use efficiency and crop and economic yields (Bongiovanni & Lowenberg-Deboer, 2004; Gregoret et al., 2006; Albarenque et al., 2016; Muschietti-Piana et al., 2018).

Although the environmental impacts caused by different PA technologies with site-specific management in comparison with a uniform management have been studied in corn (Brown, 2013; Balafoutis et al., 2017), those studies did not consider the environmental indicators in the decision-making process; they just assessed the impact after the management strategy had been already implemented. Instead, the current research project aims to incorporate the environmental impacts in the analysis, in addition to the agricultural and economic outputs that have been widely used in previous studies. We seek to obtain functions that describe the CF at different nitrogen rates, topographic positions and climatic conditions, incorporating them as objective functions in multiobjective optimization procedures. In order to achieve this aim, the first step is to quantify the corn bioethanol CF with LCA methodology, for fertilisation and yield data at a site-specific scale. Here we will focus on this specific objective.

Methods

Study site

The study site is located in the centre-south region of Córdoba Province, Argentina (Figure 1). Córdoba province is a major corn producer in Argentina, with a total production that represents more than a third of the total corn production in the country. Moreover, the main corn starch bioethanol production plants are located in this area, which produce most of the bioethanol in Argentina (MINEM, 2021).

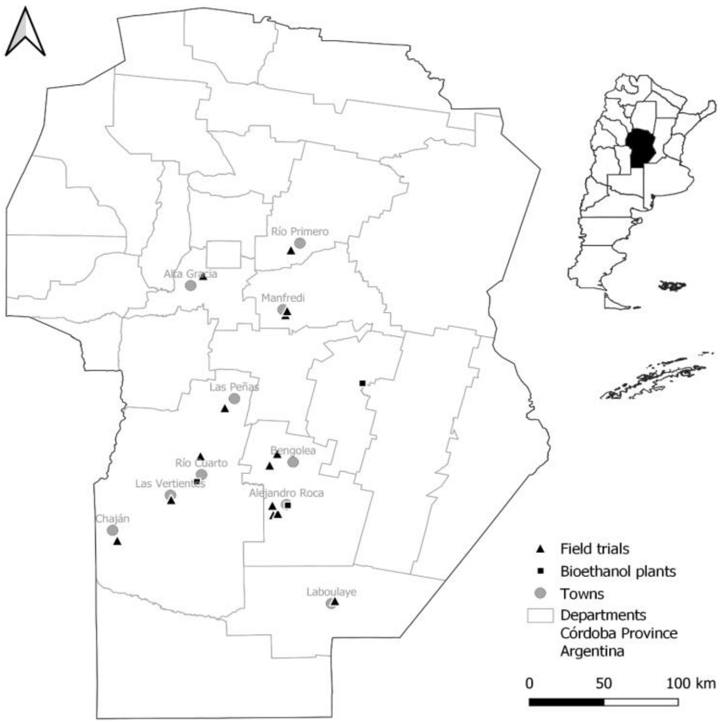

Figure 1: Location of the 18 study sites and the main bioethanol plants in Córdoba Province, Argentina.

Experiment design

The georeferenced database has 18 maize real field cases where agricultural producers applied up to 6 levels of strip nitrogen fertilisation, through an elevation gradient, in 5 crop seasons distributed over 12 years, in the centre-south region of Córdoba province. Each crop season covers the period between July 1 and June 30 of the following year, and the study period is from the year 1998 through 2010. The elevation gradient was assessed with digital elevation maps. From it, a topographic index (CTI) was calculated (Tarboton, 1997). It has been demonstrated that CTI index is a good indicator of water accumulations and organic carbon in soil (Schmidt & Persson, 2003; Liu et al., 2006; Terra et al., 2006; Huang et al., 2008). Three topographic zones were classified in each one of the 18 fields. The minimum value, the two terciles and the maximum value of CTI were considered as threshold values for the zone classification. Higher values of CTI index correspond to lower zones within the field, whereas lower values of CTI index correspond to higher zones. The daily precipitation was recorded with a manual rain gauge in each field and the accumulated precipitation (PP_{ACUM}) was calculated during each corn season. In addition, the historical average value of accumulated precipitation ($PP_{HISTORIC\ ACUM}$) was collected for that same period, considering the series of years that each field had a record. Then, a Precipitation Index (IPP; $IPP=PP_{ACUM}/PP_{HISTORIC\ ACUM}$) was calculated to identify wet or dry years with respect to the historical values of each field. Half of the trials presented values higher and lower than 1, wet or dry seasons respectively; being a value of 1 a combination of location per campaign with normal rainfall for the crop season.

The agricultural management in each field followed standard practices widely adopted in the region (i.e. planting date, plant density, crop protection, weed control, rotations, etc.). Thus, corn management was assumed to be constant during the study period, and this information was obtained from technical reports of the magazine Márgenes Agropecuarios (2010). Yield data were obtained with AgLeader yield monitor and georeferenced by GPS with RTK (Real Time Kinematic) precision technology.

On-farm research trials were carried out according to Bouder & Nielsen (2000). The area of the fields is 10 hectares on average (ranging from 4 to 16 ha). In each field, 4 to 6 fertilisation rates were applied in strips including an unfertilized control. The width of the strips was the same width of the combine harvester (9 metres) and the length was the field. Rectangular grids were created as polygons on top of the observations, in order to normalise the dataset. The maximum rates reached in each trial ranged between 115 and 288 kg N ha^{-1}, and the plant stands were never subjected to a nitrogen limitation. The nitrogen fertilisation source was urea (46-0-0) applied in the moment when the crop presented between V4 and V6 (Abendroth et al., 2011).

Data of the transportation of raw material from the field to the industry and of the industrial process were provided by a biorefinery located in Villa María, Córdoba, Argentina. Annual data correspond to the crop season 2020/2021, and these are considered to be representative of the transportation of raw material and of the industrial process of corn bioethanol in Argentina. Ninety-two percent of the trucks travelled less than 250 km per trip transporting the raw material from the fields directly or indirectly to the industry. The corn transportation and its industrial process were considered as fixed subsystems for this research, because the industry has a processing capacity independent of the crop yield.

Carbon footprint calculation

LCA methodology was used to calculate the CF in each square polygon of the regular grid. The LCA methodology follows the ISO 14067:2018 standard and the Intergovernmental Panel on Climate Change (IPCC) guidelines (2019). The R software was used to process the large datasets. The LCA recognizes four main stages, which are: the definition of the objective and scope of the system to study; life cycle inventory analysis, which collects the relevant inputs and outputs of the system; the evaluation of the environmental impacts generated by the use of inputs and outputs; and the interpretation of the impacts in each phase of the inventory.

The functional unit was 1 MJ of corn bioethanol at the industry's gate, according to the Renewable Energy Directive 2018/2001 (European Union, 2018). In the bioethanol production process, not only biofuel was generated, but also other by-products. The emissions that correspond to each by-product were assigned according to the energy criteria. The resulting bioethanol CF was expressed as $gCO_2eq\ MJ^{-1}$.

The GHG emissions were estimated by multiplying the consumption quantities of each input to the corresponding Emission Factor (EF) obtained from databases. The EF for the use of fertilisers, crop residues and the use of fuels in agricultural machinery and transportation of raw materials were obtained from IPCC Guidelines (2019) Tier 1; the EF for the production of fuels was obtained from Hilbert & Caratori (2021); the EF for the production of fertilisers and agrochemicals, and the production of inputs for the industrial stage, were obtained from Biograce V4; the EF for the seed production was obtained from EcoInvent 3.7. It was assumed that there was no soil carbon sequestration, because all fields have more than 20 years of continuous agriculture, hence the system was considered to be stabilised (ISO, 2018; IPCC, 2019).

The impact category evaluated was global warming. The impact assessment method used was the Global Warming Potential method (GWP) with a horizon of 100 years; based on the IPCC Fifth Assessment Report (IPCC, 2013). The GWP considered were for the three main GHGs: Carbon Dioxide CO_2, Methane CH_4 and Nitrous Oxide N_2O (IPCC, 2013).

Results

A bioethanol corn CF map at a site-specific scale was achieved. Figure 2 illustrates the results, taking field number 14, randomly, as an example. Both yield and CF values for each nitrogen rate present differences in wet and dry seasons (Figure 3). Moreover, there may be differences in yield and CF values among topographic zones (Figure 4). Nevertheless, statistical analyses are needed.

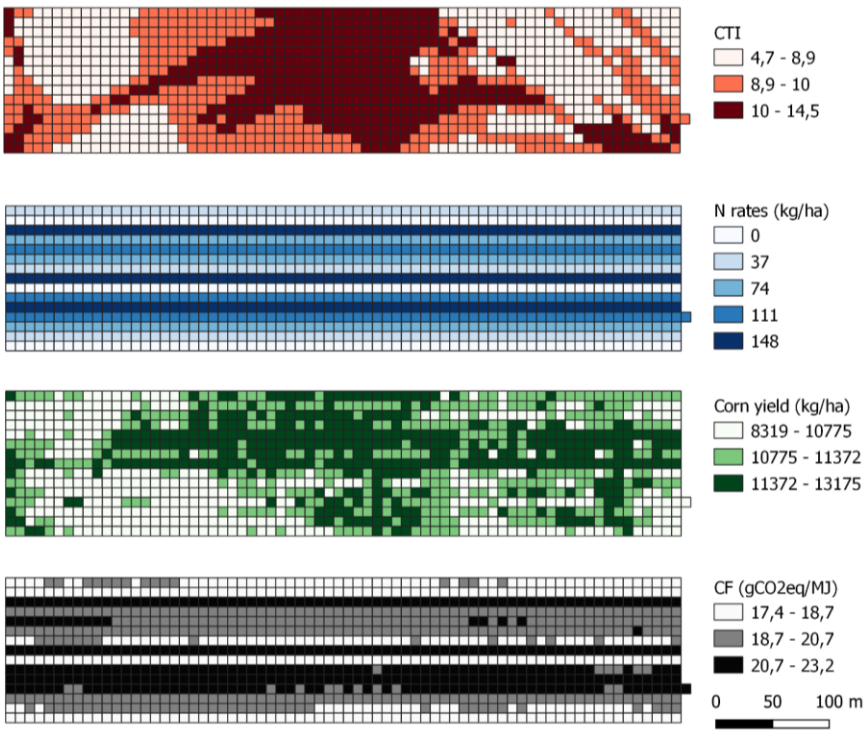

Figure 2: Topographic index (CTI), strip fertilisation nitrogen (N) rates, corn yields and corn bioethanol carbon footprint (CF) values at a site-specific scale in a typical field of the area.

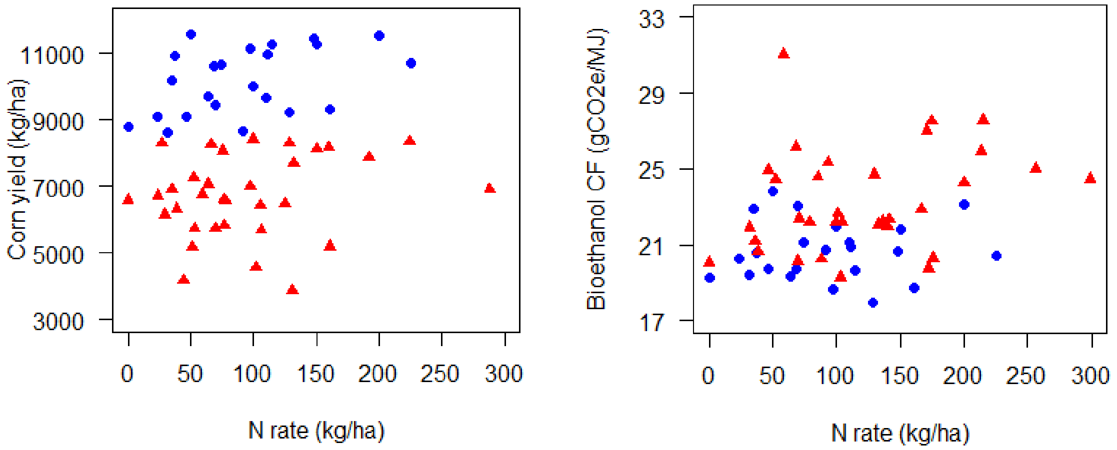

Figure 3: Scatter plot of median corn yield and median bioethanol CF for each nitrogen rate, considering data from 18 field trials. Blue circles: wet seasons. Red triangles: dry seasons.

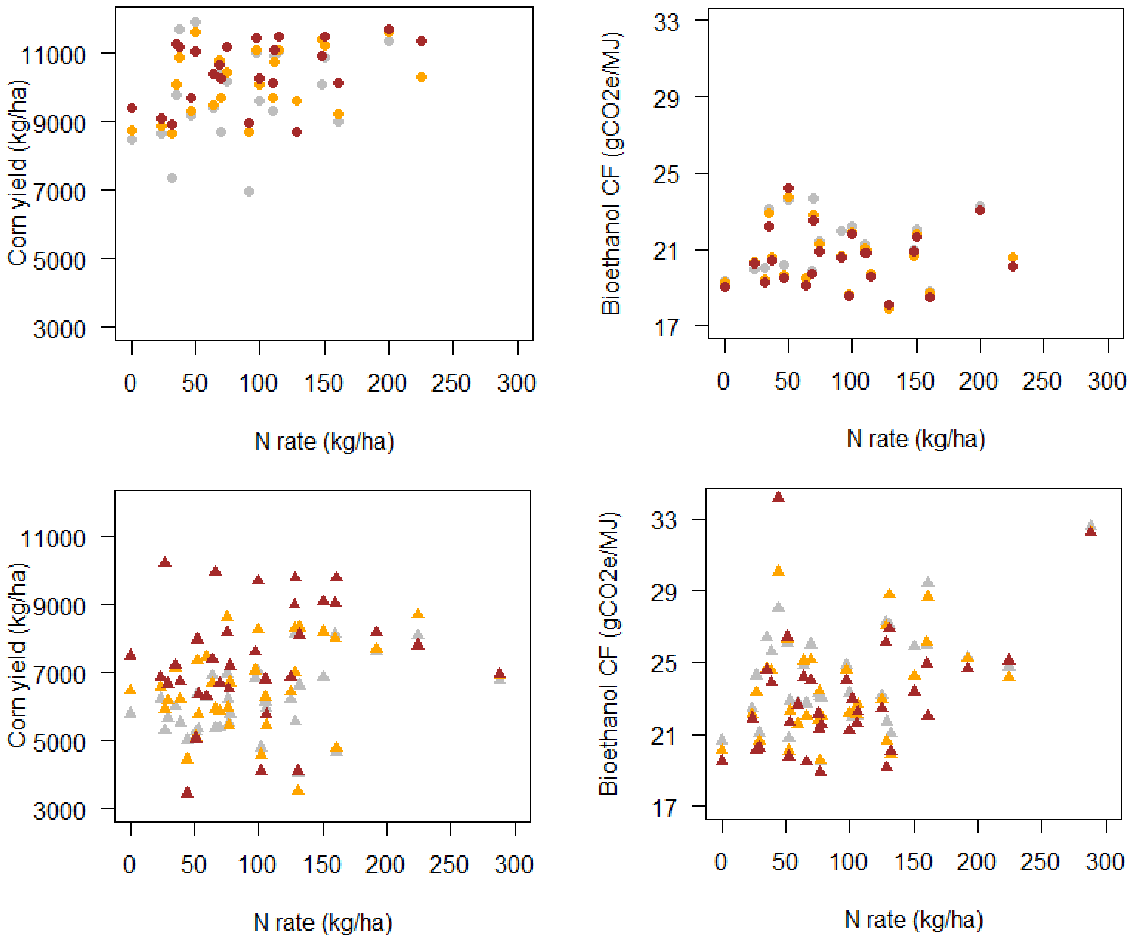

Figure 4: Scatter plot of median corn yield and median bioethanol CF for each nitrogen rate, considering data from 18 field trials. Circles: wet seasons. Triangles: dry seasons. Grey: high zone. Orange: middle zone. Brown: low zone.

Discussion and conclusion

The resulting maps are a very useful tool as CF data can be related with yield and fertilisation data, as well as with topographic and climatic conditions in order to analyse the spatial and temporal variability of CF within and among fields. As opposed to a single CF value per field, assessing the CF at a site-specific scale allows us to explore the within-field variability caused by different input rates, its interaction with environmental factors and crop yields. Furthermore, it allows us to consider the CF as an indicator in the definition of PA strategies.

A wide variety of studies around the world have demonstrated a negative correlation between crop yield and its CF (Yan et al., 2015; Arrieta et al., 2018; Zhang et al., 2018; Zhang et al., 2021). This relation is affected by the use of inputs. As the use of inputs increases, so does the yield, reducing the associated CF (Zhang et al., 2018, Zhang et al., 2021), until reaching a threshold. Above this threshold, the addition of more inputs does not increase the crop yield, which can result in a higher CF (Yan et al., 2015). Therefore, it is relevant to calculate the CF at a site-specific scale to optimise the fertilisation rate with PA.

Due to the date of the experiment data available, we do not focus on the value of the CF itself, but we do highlight the functionality of the LCA methodology to calculate a site-specific corn bioethanol CF and its potential optimisation with PA technologies. By analysing the relation between nitrogen fertilisation and corn bioethanol CF with spatial statistics, in the next steps of the current research project we expect to assess if the CF responds differently to the addition of nitrogen fertilisation in seasons with different rainfall and across different management zones. Moreover, we expect to include the function that best represents this relation as an objective function in multiobjective optimization problems. This approach will allow the determination of the optimum nitrogen fertilisation rate with which, simultaneously, CF is minimum and agricultural yields and economic returns are maximum.

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Exports of Banana from Costa Rica to the UK: economic model, marketing standards and waste

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Abstract

Banana is a very popular tropical fruit commodity mostly produced by small farmers and farmer organizations. Farmers tend to specialize in its production as part of a cash crop for export economic model and in the process become locked in, thus dependent. The banana trade wars conflict between US traders and the EU resulted in benefiting consumers for lowering prices at retail level and large banana trading corporations for expanded market access. However, farmers ended up losing due to, one the one hand, declining prices at farm gate, increasing cost of production and ever demanding product quality standards imposed by food retailers. Due to the exploratory nature of the topic, Rapid Evidence Assessment (REA) was chosen as methodology to collect and collate published data from key databases. In recent years, farmers in many banana producing and exporting countries have not been able to invest in the crop which has consequently had an impact on the overall product quality. Therefore, in addition to strict product marketing standards and lower produce quality it is estimated that 2.27 million metric tonnes of the fruit have been wasted in Cost Rica alone. This is the equivalent of the total banana exported quantity from the country to the UK. Wasted fruit is usually dumped on the land or rivers further contributing to greenhouse gas emissions. Estimations on the nutrition loss resulting from waste indicate that the energy content could feed 202.4 million people for one day or the entire Costa Rican population for 38 days considering an intake of 2,000Kcal/person/ day. Considering a more circular approach, waste valorisation actions are needed to revert the loss of resources. Developments in bio-engineering have the potential to utilize compounds found in banana leaves, fingers and peels with application in food manufacturing. These can improve food product functionality, shelf-life and nutrition, not to mention the overall economic and environmental gain in avoiding produce going to waste.

Keywords

Waste valorisation, Banana, Bio-engineering

Presenter Profile

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Determinants of use of Climate Smart Technology in Agriculture: Evidence from Household data

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Abstract

The objective of this paper is to explore the determinants of the use of climate smart agriculture technology (CSAT) among agrarian households of Odisha, India. The effect of climate change and the consequent unpredictability of weather patterns make agricultural production vulnerable. It calls for a solution wherein it is required to transform the existing agricultural practices to make it more efficient, more productive and less prone to climate change. So, the farm inputs should be more adaptive that can be ushered in by adopting CSAT by the practitioners. It is a smart agriculture process that minimizes the negative effect of climate change on agricultural production and contributes towards sustainable agricultural system. The result of the Fractional and Beta regression reveals that higher the level of social capital, higher is the intensity of the use of CSAT by the households. The use of CSAT is less in households that are female headed and belong to the scheduled tribes in comparison to the households that are male headed and belong to the scheduled castes. However, the households having knowledge about the technology use it more than the households with no knowledge of CSAT. The households who think that CSAT is not women-friendly use the technology more in comparison to households that think that women do not have the skills to use the technology. The intensity of the use of CSAT is higher for households where the female takes agricultural decisions. Further, the use of CSAT is less in families where land is owned by the male members only. This calls for institutional arrangements to ensure wider usage of social capital, land ownership by the female members and their economic empowerment by providing them better wages and livelihood so that agrarian households will be interested to use CSAT in agriculture that can ultimately cater to the growing demand of food.

Keywords

Climate Smart Agriculture Technology, Sustainable Agriculture, Land Ownership, Fractional and Beta Regression.

Presenter Profiles

Dr Dukhabandhu Sahoo has expertise and specialisation in the field of Economics with more than 20 years of extensive Research and Teaching experience in Applied Econometrics, Industrial Economics, Environmental Economics, Development Economics & Social Sector Economics with Public Policy. He also has specialization in Program Management, Coordination, Research, Consultancy, Market survey, and Data Management (design, collection, analysis, and presentation). Dr Sahoo has in-depth experience of estimation and forecasting through econometric models for quantitative and qualitative variables, interpretation and presentation in policy and research reports, journal articles, and books.

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Introduction

The growth in world population between now and 2050 will be around one-third of the current population, and the present agricultural system needs to be transformed to meet the increasing food demands of the growing population. For the expected rise in demand, the increase in agricultural production should be 60% by 2050 (FAO, 2013). However, the effect of climate change and the consequent unpredictability of weather patterns make agricultural production vulnerable that calls for a solution wherein it is required to shift the existing agricultural practices to make it more efficient, more productive and less prone to climate change. So, the farm inputs should be more adaptive that can be ushered in by adoption of climate smart technology (CST) by the practitioners. It is a smart agriculture process that minimizes the negative effect of climate change on agricultural production and contributes towards sustainable agricultural system. However, despite the enormous advancements in agricultural research and development, CST usage has remained low in developing countries like India; one probable reason could be apprehension of the end users towards the possible adverse effects of such technologies. Additionally, due to their inability to recognize and support ongoing, interactive social learning and innovation processes that help farmers manage the changing complexity in their farming systems, traditional top-down and linear processes of generating and transferring agricultural innovations to end users have shown limited progress in promoting technology adoption (Kilelu, Klerkx, and Leeuwis 2013; Lundy, Gottret, and Ashby 2005).

According to recent research, in order to successfully adopt CST and practices, researchers and development practitioners must take into account agricultural systems approach innovations, which encompass all social and economic activities related to the creation, dissemination, adaptation, and use of new technical, institutional, and organizational knowledge and resources for the benefit of all stakeholders (Adekunle and Fatunbi 2012; Hall 2005; Hall et al. 2006). The idea of innovation platforms (IPs), which are increasingly seen as possible catalysts for promoting smallholder market participation, inclusive agricultural innovation, and knowledge transfer in agriculture, is an important idea in the agricultural systems approach (Adekunle and Fatunbi 2012; Schut et al. 2017). The IPs can assist the creation of social networks to stimulate the mobilization of resources necessary to boost adoption and diffusion of agricultural technology and knowledge through active interactions and learning among actors (Schut et al. 2017). Building such networks is in line with theory and research that acknowledge social capital[1] as a significant resource that people may use to address issues in their daily lives (Obaa and Mazur 2017; Small 2009).

Though the concept of social capital was introduced in 1916, it was linked to economic growth and development in the 1902 (Lollo, 2012). Social capital was expected to facilitate the formation of platform to achieve economic development (Putnam, 1993). However, there is no convergence on the definition of social capital among the thinkers (Chou, 2006; Sabatini, 2007; Karanja et al., 2016), leading to non-clarity of the concept. However, networks, norms, and trust in social interactions are typically cited in literature as characteristics of social capital, which facilitate collaboration and coordination of people to achieve desired goals and mutual gain (Narayan and Cassidy, 2001; Putnam, 1993). The non-clarity of the concept makes it more difficult to measure it quantitatively. Despite the challenges associated with defining and

[1] *For a detailed definition of social capital, see Claridge 2004*

measuring social capital, numerous research has advanced the notion that its primary contribution is to ease information flow among people, which may promote adoption processes (Läpple and Van Rensburg, 2011; Ramirez, 2013; Micheels and Nolan, 2016). According to Pannell et al. (2006), adoption is a learning process that involves gathering knowledge and developing practical skills. Additionally, adding to the discussion of the social nature of learning, Eastwood et al. (2012) note that adoption of technology is only the tip of the iceberg in terms of future changes in management practices and adoption of new technologies, with networks and trust serving as primary drivers of this dynamic. Despite the obvious benefits of this interaction, it can also have unfavourable outcomes, such as when poor performance of the technology used by some farmers results in a widespread rejection of the technology among the community. Agurto-Adrianzen (2009) also found that rural families tended to respond more forcefully to a new technology's poor performance than to one that performed well.

A good number of literatures has acknowledged the role of climate smart technology adaptation in agriculture to improve the productivity (e.g., Chhetri et al. 2017 s; Mwongera et al. 2017; Senyolo et al. 2018; Patle et al., 2020; Daum, 2023; Zougmoreet et al., 2016; Kiani et al. 2022; Sayed, 2022; Rosenstock et al. 2022; Amertet et al. 2023; and Bhavani et al., 2023). Similarly, studies have also explored the factors determining the use of CST (e.g. Tanti, 2022 has discussed the institutional and social factors in addition to other factors).

The technology adaptation in agriculture is broadly studied with a standard utility model where farmer's characteristics (human capital) and farm structure (physical capital) are the main determinants (Foster and Rosenzweig, 2010; Abdulai et al., 2011; Abdulai and Huffman, 2014; Wossen et al., 2015). Such studies ignore the fact that individual decisions are entangled with the societal structure (Oreszczyn et al., 2010). Further, this complex social structure shapes institution that accommodates holistic (physical, economic, and cultural) environment of the individuals. As discussed earlier, since adaptation of CSAT is a behavioural decision to be taken by the adopters, the factors related to social capital are significant in the decision-making process related to adoption. However, it is unclear how various elements of social capital combine to determine the producer's behaviour. Understanding these connections may provide insight into the social capital variables that can influence decision-making processes and lead to a particular behaviour. This statement raises two queries. What is the connection between social capital and how farmers use technology, and how are different aspects of social capital related to one another? Therefore, one needs to develop a social capital framework (SCF) to understand the holistic impact of all forms of capital on the adaptation of technology especially the CST in the light of changing farm behaviour due to the challenges of climate change. The present study is an endeavour towards this goal. The rest of the paper is organized as follows: the following section discusses methods and analytical framework of the study along with the research design. The third section discusses results of the study while the last section concludes the study with policy implications.

Methods

Data, Sampling, and Analytical Framework

In the study, a combination of multi-stage simple random sampling and judgmental sampling techniques was used. The households directly and/or indirectly involved in agriculture and/or allied activities are the units of observation. Therefore, the present study has used primary data collected from the households (selected through proper sampling technique) to elicit relevant conclusions. Thus, the present study has used primary data collected from the rural agrarian households of Odisha, India during October 2019. Odisha is situated on the East Coast of India along the Bay of Bengal and shares its borders with Jharkhand to the North, West Bengal to the North-East, Chhattisgarh to the West, and Andhra Pradesh to the south. It encompasses an area of 155,701 sqkms. The State is bestowed with diverse climatic conditions and has a coastline extending to 480 kms. The climate is predominantly tropical, characterized by high temperature, high humidity, medium to high rainfall, and mild winter. The average normal rainfall is 1451 mm per annum, of which 75-80% is received during June to September (Agri Odisha, 2022a). Despite high rainfall, natural calamities like drought, flood, and cyclones visit the state quite frequently. Primary data were collected through a self-administered semi-open questionnaire, which was specifically developed for this study. Before data collection, a pilot survey was undertaken to validate the questionnaire.

Universe of the study

The study is carried out in Odisha, one of the states of Eastern India. The state of Odisha is divided into ten Agro-climatic Zones (ACZs, given in Table 1) as per different agro-climatic parameters, therefore each ACZ is unique and different from the other. Since, the objective of this study is to understand the association of social capital and use of climate smart agricultural technology, it is required to have representation of agrarian households from all ACZs.

Sampling methods

Based on the climate, annual rainfall, and soil type, each ACZ includes different numbers of revenue districts or part thereof. Each ACZ can be considered as a homogeneous group and thus a stratum. Therefore, to have a proper representation of the ACZs, some districts were selected through proportional sampling method, e.g., since the North Western plateau ACZ consists of two districts, namely, Sundargarh and Deogarh, only one district, i.e., Sundargarh was selected in the sample, whereas four districts, namely, Cuttack(P), Nayagarh, Puri, and Khurda were selected from East & South Eastern plateau in the sample. This proportional sampling would help in the proportional representation of the ACZs in the ultimate sampling process (see Table 1). Accordingly, the present study covered 17 revenue districts out of the total 30 districts of Odisha.

After selection of the districts, one revenue block (each district is comprised of some revenue blocks for administrative proposes in Odisha) from each district was selected through a simple random technique. This gave us a total of 17 blocks across ten ACZs of Odisha. From each revenue block, one Gram Panchayat (GP) was selected through the lottery method of simple random sampling technique method. After selecting GPs, two revenue villages from each GP were chosen through a combination of judgmental sampling and simple random sampling technique method. While selecting the revenue villages, the village-level socio-economic and demographic information was collected from the 2011 census database. It was observed that in some GPs, there were some villages with very few households (even less than 20). Therefore, at that stage of the sampling process, a combination of judgmental sampling and a simple random sampling technique was used so that the selected village has at least 30 households directly and/or indirectly involved in agriculture and/or allied activities. Additionally, while selecting the villages, the distance of the village from the GP office was considered. One village nearer to the GP and another farther from the GP office were selected. This criterion was considered during the selection of the villages as it is assumed that the villages nearer to the GP office (office from where different policy interventions are controlled and/or regulated, and through which extension services are provided to the farmers) may reap the benefit of government policy interventions and extension services better than the villages far away from the GP office (Singer-Prebish hypothesis, center-periphery relation). Thus, the present study covered a total of 34 villages (two villages from each GP). After selecting the villages, the details on the socio-economic and demographic profiles of the households were collected from the 2011 census data. Additionally, discussions were held with the village heads and the Sarpanch (elected representative of the GP) to supplement the household information of the 2011 census data. From each village, 30 households were selected through judgemental sampling technique so that different levels of the size of landholding, asset, income, education, sanitation infrastructure as well as caste and religion are properly represented in the selected sample households. Thus, in total, the present study has 1020 sample households for data collection and analysis (30 households each from 34 villages). However, after careful screening and cleaning of data, the effective sample size is 1001.

Analytical Framework

The present study has identified eighteen (18) different types of climate smart agriculture technology (CSAT) practices adopted by the farmers of Odisha. Therefore, a CSAT adaptation index (CSATAI) is developed to understand the intensity of the use of CSAT by a farming household. The CSAT practices are: *1. Seed variety; 2. Pest control; 3. Fertilizer use; 4. Soil test; 5. Row planting; 6. Irrigation; 7. Composting; 8. Marketing; 9. Access to credit; 10. Insurance; 11. Tractor; 12. Power tiller; 13. Seed sowing machine; 14. Sprayer; 15. Weeding machine; 16. Crop-cutting machine; 17. Fan; 18. Storage facility*. The CSATAI is calculated by using the method of weighted arithmetic mean (the weights being uniform) and is defined as:

$$\mathrm{CSATAI} = \frac{\sum_{1}^{18} I_i}{18}.$$

Possession and/or adaptation of any technology by the household is assigned the value "1" and non-possession is "0". The household having all the technology will have CSATAI =1 and having no indicators will have CSATAI =0. Thus, the value of CSATAI will lie between 0 to 1, i.e.,$(0 \leq (\mathrm{CSATAI}) \leq 1)$. For the empirical estimation purpose, however, there is an issue of the Dependent Variable (DV) being a fraction. In the present case, the Regression equation would be like this:

$$\mathrm{CSATAI} = (IV)\beta + \varepsilon\text{...........(1)}$$

Where "ε" is the error term and is assumed to be satisfying all the assumptions of CLR technique, IV is the matrix of all independent variables including intercept, intercept dummy, and slope dummy and β is the vector of regression coefficients. Here, the population assumption under CLR should be:

$$E(\mathrm{CSATAI}) \sim Normal\left((IV)\hat{\beta}, \sigma_{\varepsilon}^{2}\right)\text{......... (2)}$$

where "σ_{ε}^{2}" is $Var(\varepsilon)$. This normality assumption of "CSATAI" is not reasonable as it is a ratio. This gives rise to two types of the problem; firstly, the problem of heteroscedasticity, which implies the variance is smaller near the extreme values. The second problem is with respect to the asymmetry of the distribution violating the normality assumption. Therefore, it is more appropriate to use a regression model that assumes that the dependent variable follows a continuous distribution with supporting the value between zero and one. In the literature,

Table 1: Sampling Process (Source: Agri Odisha, 2022b)

1st Stage	2nd Stage					3rd Stage	4th Stage	5th Stage	6th Stage	7th Stage
State	**ACZs**					**Selected District**	**Blocks (One block from each district)**	**GPs (One GP from each block)**	**Villages**	**Households**
	ACZs	**Climate**	**Mean annual rainfall (in mm)**	**Soil type**	**District(s)**					
Odisha	North Western plateau	Hot & moist	1648	Red & yellow	Sundargarh, Deogarh	Sundargarh	Rajgangpur	Laing	Two villages from each GP	30 HH from Village (Total 1020 HH, but effectively 1001 HHs are studied here)
	North Central plateau	Hot & moist	1535	Red loamy	Mayurbhanj, Keonjhar (Except Anandapur)	Keonjhar	Ghatagaon	Patilo		
	North Eastern coastal plateau	Hot & moist sub-humid	1568	Alluvial	Balasore, Bhadrak, Jajpur (except Sukinda), Anandapur	Bhadrak, Jajpur (except Sukinda)	Dhamnagar; Jajpur	Dalanga; Khairabad		
	East & south eastern plateau	Hot & humid	1449	Coastal alluvial saline (near the coastline)	Cuttack(P), Jagatisighpur, Kendrapara, Puri, Khurda, Nayagarh, Ganjam(P)	Cuttack(P), Puri, Nayagarh, Khurda,	Narasinghpur; Kakatpur; Nayagarh; Khurda	Jayamangala; Kakatpur; Khuntabadha; Khurda		
	North Eastern ghat	Hot & moist sub-humid	1597	Laterite and brown forest	Ganjam(P), Gajapati, Rayagada, Kandhmal, Boudh(P)	Boudh(P), Ganjam(P),	Charichhak; Sheragoda	Purunakatak; Mahupada		
	Eastern ghat high land	Warm & humid	1522	Red mixed red & yellow	Koraput(P), Nabarangpur(P)	Koraput(P)	Semiliguda	Pitaguda		
	South Eastern ghat	Warm & humid	1522	Red, mixed red & black	Malkangiri, Koraput(P)	Malkangiri	Mathili	Mathili		
	Western undulating	Warm & moist	1527	Black, mixed red and black	Kalahandi, Nuapada,	Kalahandi	Golamunda	Sinapali		

					Nawarangpur (Dabugaon)					
	West-central table land	Hot & moist	1527	Red, heavy textured colour	Bolangir, Subarnapur, Boudh(P), Sambalpur, Bargarh, Jharsuguda	Jharsuguda, Bargarh	Jharsuguda; Bargarh	Badmal; Khuntapalli		
	Mid Central Table land	Hot & dry sub-humid	1421	Red loamy, laterite mixed red & black	Dhenkanal, Angul, Cuttack(P) & Sukinda	Dhenkanal, Angul	Kankadahad; Pallahara	Bam; Rajdang		
Purposive	**Purposive**					**Proportional Stratified Sampling**	**Simple Random Sampling**	**Simple Random Sampling**	**Judgmental Sampling and a Simple Random Sampling**	**Judgmental Sampling and a Simple Random Sampling**

Note: P stands for part of the district.

such regression models are now available, known as the Beta regression model (Paolino, 2001; Kieschnick & McCullough, 2003; Ferrari & Cribari–Neto, 2004; Cepeda & Gamerman, 2005). Following Carrasco et al. (2014), the beta regression model for the present study is specified, estimated, interpreted, and discussed as:

$\mathrm{CSATAI} = (IV)\beta + \mathrm{u}$.........(3)

where $E(\mathrm{CSATAI}) \sim Beta\left((IV)\hat{\beta}, \sigma_{\mathrm{u}}^{2}\right)$ and $u \sim N\{0, \sigma_{\mathrm{u}}^{2}\}$. Additionally, the fractional regression model as suggested by Papke and Wooldridge (1996) is estimated to compare the results. Further, the marginal effect of the independent variables is interpreted and compared. Estimation will be done through statistical software STATA 13.0 edition (StataCorp, 2013; Bruin, 2006). Table 2 presents the descriptions of the dependent and independent variables used in the study.

Table 2: Descriptions of Variables with reference category

Variables	Descriptions	Nature of variables
Dependent Variable: Climate Smart Agriculture Technology Adaptation Index (CSATAI)		
Climate Smart Agriculture Technology Adaptation Index (CSATAI)	Weighted Arithmetic Mean (WAM) of the 18 CSAT practices (*1. Seed variety; 2. Pest control; 3. Fertilizer use; 4. Soil test; 5. Row planting; 6. Irrigation; 7. Composting; 8. Marketing; 9. Access to credit; 10. Insurance; 11. Tractor; 12. Power tiller; 13. Seed sowing machine; 14. Sprayer; 15. Weeding machine; 16. Crop-cutting machine; 17. Fan; 18. Storage facility*	Ratio, $0 \leq (\mathrm{CSATAI}) \leq 1$
Independent Variables		
Level of Social Capital (LSC)[1]	Four levels of Social Capital Index (SCI) score. The SCI is created by the Principal Component Analysis (PCA) from eight (8) aspects of social behaviour in 5-point likert scales (for the technical aspect of PCA, see Kumar, et. al., 2007). The PCA generated SCI then is standardised so that 0≤ SCI≤1. The aspects include the frequency of; *mobile use, attending social, cultural, religious, economic, political meeting(s), watching television in a group and visit of the relatives to the household*.	Categorical Lower=SCI≤0.25 Moderate=0.251≤ SCI≤0.50 Higher=0.501≤ SCI≤0.75 Highest= SCI≥0.751
Agriculture Expenditure Index (AEI)	It is the Total Agriculture Expenditure of a household divided by the maximum Agriculture Expenditure among all the households	Ratio 0≤ AEI ≤1
Caste Category (Caste)	Caste the household head belongs	Qualitative; Reference category: SC

[1] The operational definition of social capital here is "it's a multidimensional qualitative social network that can affect the behavioral decision of an individual and/or household to reap economic benefits."

	to? 1. Scheduled Caste (SC), 2. Scheduled Tribe (ST), 3. Other Backward Caste (OBC), 4. Others (includes upper caste/forward category)	Dummy, 1=ST, 0=Otherwise Dummy, 1= OBC, 0=Otherwise Dummy, 1=General, 0=Otherwise
Age (AG)	Age of the household's head (In years)	Quantitative
Family Type (FT)	It includes 1. Joint family (JF), 2. Nuclear family (NF)	Qualitative; Reference category: Nuclear family (NF)
Gender (Gen)	Gender of the head of the household. 1. Male, 2. Female	Qualitative; Reference Category= Male Dummy, 1= Female, 0=Otherwise
Sanitation index (SI)	Sanitation Index (SI) of the entire household. It is constructed by considering eight (08) indicators (I) of sanitation and they are 1) living in a pucca house; 2) availability of toilet facilities; 3) availability of bathroom facilities; 4) availability of purified drinking water facilities; 5) frequency of using soap for bathing purpose; 6) use of phenyl to clean bathroom, toilet, and surface; 7) use of hand wash; and 8) use of any detergent to clean utensil.	Ratio. The SI is calculated by using the method of weighted arithmetic mean (the weights being uniform) and is defined as:$SI = \frac{\sum_1^8 I_i}{8}$. Possession of an indicator by the household is assigned the value "1" and non-possession of the indicator is "0". The household having all the indicators will have SI=1 and having no indicators will have SI=0. Thus, the value of SI will lie between 0 to 1, i.e.,$(0 < (SI) < 1)$.
HDI of the household (HHDI)	Human development index of the household. It is computed by taking the weighted arithmetic mean (the weights being uniform) of three indicators. Firstly, the total health expenditure[1] (total family expenditure on health during last one year); secondly, the total education expenditure (total family expenditure on education during last one year); and thirdly the total income (income from primary occupation plus income from secondary occupation by during last one year). To calculate the dimension indices (DI) of health, education, and income, minimum and maximum values/goalposts are chosen.	Ratio. The DI are calculated as: $DI = \frac{Actual\ value - Minimum\ value}{Maximum\ value - Minimum\ value}$ And the HDI is constructed as: $HDI = \sum DI_i/3$, i= Health, Education, and Income. The value of HDI will lie between 0 to 1, i.e., $(0 \leq (HDI) \leq 1)$.
Knowledge about the CSAT (KCSAT)	Knowledge about the CSAT by the household	Qualitative; Dummy, 1=Yes, 0=No
Level of Education (LEDU)	Level of education the head of the household has completed.	Qualitative; Reference category: Illiterate Dummy, 1= primary (7^{th} or less),

[1] *The collected data on the health expenditure is the Curative Health Expenditure of the households which means with poor health this expenditure will increase. The households had some Preventive Health Expenditure, the information of which is used to compute the Sanitation Index. Thus, to make the HDI directly related to the health dimension, 1-the Standardized Health Dimension is used to calculate the HDI.*

		0=Otherwise Dummy, 1= secondary (8th to 12th), 0=Otherwise Dummy, 1= higher (above 12th), 0=Otherwise
Land Index (LANDI)	It is the Total Land owned by a household divided by the maximum Land owned among all the households	Ratio 0≤ LANDI ≤1
Reasons for females not using CSAT (RFCSAT)	What are the reasons for females not using CSAT? 1. Not Women-friendly, 2. No adequate skill 3. Socio-cultural reasons	Qualitative Reference Category= Women using CSAT
Gender wise agricultural decisions taken (GAD)	Who takes the decision on agriculture in the household? 1. Male, 2. Female, 3. Both Male and Female	Qualitative; Reference Category= Male Dummy, 1= Female, 0=Otherwise Dummy, 2= Both, 0=Otherwise
Gender-wise Land ownership of the household (GWL)	Who owns the land in the household? 0.Noland 1. Male, 2. Female, 3. Both Male and Female	Qualitative; Reference Category= Noland Dummy, 1= Male, 0=Otherwise Dummy, 2= Female, 0=otherwise Dummy, 3=Both, 0=Otherwise

Results and Discussion

As mentioned earlier, the total effective number of households for the study is 1001. The summary statistics of all the variables described in Table 2 are presented in Table 3. Perusal of Table 3 reveals that the mean score of CSATAI, LSC, AEI, SI, HDI, and Land index is 0.464, 0.370, 0.052, 0.393, 0.074, and 0.038 respectively, which is comparatively low. However, the average score of the households on the knowledge about CSAT is 0.818. This implies that a fairly good number of households have ideas about climate-smart agricultural technology. But the low adoption rate of the CSAT may be due to other factors.

In fact, the cross-tabulation of LSC reveals that in case of the households having higher LSC, the level of CSAT is more whereas most of the households using CSAT have a lower AEI (Table 4). In Table 5, it is found that the households where the head of the household's age is less than 60 years, the intensity of use of CSAT is higher than households with heads above 60 years of age. Similarly, the households with nuclear family structure uses CSAT more than the ones with joint family structure. Further, families with males as the head of the households adopt more CSAT than families headed by female members.

The cross-tabulation of caste category and sanitation index is presented in Table 6. It shows that the OBC households have a high level of CSAT followed by SC and ST categories. Further, households where the SI ranges from 0.251-0.500, the level of CSAT is more in comparison to households having other levels of sanitation. Moreover, in Table 7, it is found that most of the households having low HHDI have more levels of CSAT. This implies that these households are improving their position in order to increase their level of CSAT.

The households where the male takes agricultural decisions have a higher level of CSAT while the households having knowledge about the CSAT have a lower level of CSAT. Table 8 shows that percentage of households having a higher level of education have more levels of CSAT while most of the households using CSAT have a lower land index. In addition, the households where the reason for females not using CSAT is inadequate skill, have a higher level of CSAT (Table 9). Most of the households with male land ownership have a higher level of CSAT.

Table 3: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
CSATAI	1001	0.464	0.221	0.055	0.889
LSC	1001	0.370	0.174	0.000	1.000
AEI	1001	0.052	0.072	0.000	1.000
Caste	1001	2.278	0.933	1.000	4.000
Age	1001	45.663	11.629	17.000	84.000
Joint Family	1001	0.671	0.470	0.000	1.000
Gender	1001	0.879	0.326	0.000	1.000
Sanitation Index	1001	0.393	0.192	0.018	1.000
HHDI	1001	0.074	0.068	0.001	0.694
KCSAT	1001	0.818	0.386	0.000	1.000
Level of education	1001	5.614	3.965	0.000	15.000
Land Index	1001	0.038	0.105	0.000	0.998
RFCSAT	1001	1.531	0.821	0.000	3.000
GAD	1001	1.544	0.839	1.000	3.000
GWL	1001	1.156	0.504	0.000	3.000

Table 4: Cross-tabulation of level of CSAT with level of social capital and level of agricultural expenditure (%)

Level of CSAT	Level of Social Capital					Level of Agricultural Expenditure				
	0-0.250	0.251-0.500	0.501-0.750	0.751 & above	Total	0-0.250	0.251-0.500	0.501-0.750	0.751 & above	Total
0-0.250	12.39	9.89	0.30	0.00	22.58	22.48	0.00	0.00	0.00	22.58
0.251-0.500	15.18	24.38	3.80	0.00	43.36	42.46	0.60	0.00	0.00	43.36
0.501-0.750	1.20	10.29	4.70	0.30	16.48	16.08	0.40	0.00	0.00	16.48
0.751 & above	0.20	4.90	10.29	2.20	17.58	17.48	0.10	0.00	0.00	17.58
Total	28.97	49.45	19.08	2.50	100	98.50	1.10	0.10	0.30	100
Pearson $chi^2(9)$ = 459.412***; Kendall's tau-b = 0.523; ASE = 0.019						Pearson $chi^2(9)$ = 13.308; Kendall's tau-b = 0.013; ASE = 0.021				

Note: *** denotes 1% level of significance

Table 5: Cross-tabulation of level of CSAT with age, family type, and gender (%)

Level of CSAT	Age			Family Type			Gender		
	≤ 60 Years	> 60 Years	Total	Joint	Nuclear	Total	Female	Male	Total
0-0.250	12.39	10.19	22.58	5.59	16.98	22.58	1.60	20.98	22.58
0.251-0.500	28.87	14.49	43.36	15.38	27.97	43.36	5.39	37.96	43.36
0.501-0.750	10.19	6.29	16.48	6.19	10.29	16.48	1.30	15.18	16.48
0.751 & above	10.69	6.89	17.58	5.69	11.89	17.58	3.80	13.79	17.58
Total	62.14	37.86	100.00	32.87	67.13	100.00	12.09	87.91	100.00
Pearson $chi^2(9)$ = 8.876**; Kendall's tau-b = -0.029; ASE = 0.030			Pearson $chi^2(9)$ = 9.724**; Kendall's tau-b = -0.057; ASE = 0.028			Pearson $chi^2(9)$ = 23.093***; Kendall's tau-b = -0.098; ASE = 0.029		

Table 6: Cross-tabulation of level of CSAT with caste category and level of Sanitation Index (%)

Level of CSAT	Caste category					Level of Sanitation Index				
	SC	ST	OBC	General	Total	0-0.250	0.251-0.500	0.501-0.750	0.751& above	Total
0-0.250	4.00	12.29	5.19	1.10	22.58	9.49	7.09	5.59	0.40	22.58
0.251-0.500	13.49	6.49	21.28	2.10	43.36	12.09	14.29	15.88	1.10	43.36
0.501-0.750	3.60	3.30	7.69	1.90	16.48	3.60	8.59	4.30	0.00	16.48
0.751& above	5.79	3.00	7.29	1.50	17.58	3.00	6.39	7.79	0.40	17.58
Total	26.87	25.07	41.46	6.59	100	28.17	36.36	33.57	1.90	100
Pearson chi^2(9) = 151.287***; Kendall's tau-b = 0.071; ASE = 0.026						Pearson chi^2(9) = 59.166***; Kendall's tau-b = 0.129; ASE = 0.027				

Note: *** denotes 1% level of significance.

Table 7: Cross-tabulation of level of CSAT with level of HHDI, Gender wise agricultural decision (GAD), and Knowledge about the CSAT (%)

Level of CSAT	Level of HHDI					Gender wise agricultural decision (GAD)				Knowledge about the CSAT		
	0-0.250	0.251-0.500	0.501-0.750	0.751& above	Total	Male	Female	Both	Total	Yes	No	Total
0-0.250	22.48	0.10	0.00	0.00	22.58	14.39	2.60	5.59	22.58	7.09	15.48	22.58
0.251-0.500	41.86	1.50	0.00	0.00	43.36	32.07	2.60	8.69	43.36	8.19	35.16	43.36
0.501-0.750	15.78	0.70	0.00	0.00	16.48	12.19	0.80	3.50	16.48	2.10	14.39	16.48
0.751& above	16.58	0.80	0.20	0.00	17.58	9.69	2.90	5.00	17.58	0.80	16.78	17.58
Total	96.70	3.10	0.20	0.00	100.00	68.33	8.89	22.78	100.00	18.18	81.82	100.00
Pearson chi^2(9) = 16.900***; Kendall's tau-b = 0.087; ASE = 0.025						Pearson chi^2(9) = 32.692***; Kendall's tau-b = 0.030; ASE = 0.029				Pearson chi^2(9) = 52.056***; Kendall's tau-b = 0.208; ASE = 0.026		

Note: *** denotes 1% level of significance.

Table 8: Cross-tabulation of level of CSAT with level of education and level of Land Index (%)

Level of CSAT	Level of education					Land Index				
	Illiterate	Primary	Secondary	Higher	Total	0-0.250	0.251-0.500	0.501-0.750	0.751& above	Total
0-0.250	4.10	8.49	9.29	0.70	22.58	22.38	0.00	0.00	0.20	22.58
0.251-0.500	5.89	16.18	18.18	3.10	43.36	42.76	0.10	0.10	0.40	43.36
0.501-0.750	3.30	6.29	5.29	1.60	16.48	16.28	0.10	0.00	0.10	16.48
0.751& above	2.70	5.49	7.49	1.90	17.58	17.18	0.00	0.00	0.40	17.58
Total	15.98	36.46	40.26	7.29	100.00	98.60	0.20	0.10	1.10	100.00
Pearson chi^2(9) = 18.576***; Kendall's tau-b = 0.040; ASE = 0.027						Pearson chi^2(9) = 6.303; Kendall's tau-b = 0.029; ASE = 0.029				

Note: *** denotes 1% level of significance.

Table 9: Cross-tabulation of level of CSAT with RFCSAT and GWL (%)

Level of CSAT	Reason for females not using CSAT					Gender-wise land ownership				
	Women using CSAT	Not Women-friendly	No adequate skill	Socio-cultural reason	Total	No land ownership	Male	Female	Both	Total
0-0.250	4.00	7.39	8.59	2.60	22.58	0.00	19.38	1.80	1.40	22.58
0.251-0.500	3.60	9.49	27.57	2.70	43.36	0.00	41.56	0.30	1.50	43.36
0.501-0.750	2.30	5.00	6.29	2.90	16.48	0.30	14.59	0.50	1.10	16.48
0.751& above	2.80	8.09	6.39	0.30	17.58	0.20	13.49	2.30	1.60	17.58
Total	12.69	29.97	48.85	8.49	100.00	0.50	89.01	4.90	5.59	100.00
Pearson chi^2(9) = 102.693***; Kendall's tau-b = -0.061; ASE = 0.029						Pearson chi^2(9) = 69.092***; Kendall's tau-b = 0.052; ASE = 0.035				

Note: *** denotes 1% level of significance.

Table 10 presents the results of both Beta and Fractional probit regression models. Since the direction of the marginal effect is same in both the regression models with slightly different magnitudes, the result of one model (Beta regression) can be interpreted. The households having moderate, higher, and highest LSC relative to lower LSC increases the CSATAI by 0.121, 0.331, and 0.438, respectively. This implies that at a higher level of social capital, the intensity of the use of CSAT is higher. Thus, we can conclude that promoting social capital among agrarian households can intensify the use of CSAT among farmers.

The households belonging to the ST category reduce CSATAI by 0.080 compared to the households belonging to the SC category. This implies that the tribal households in Odisha that are marginalised from the main land have a lower intensity of use of the CSAT. Additionally, the female-headed household reduces the CSATAI by 0.041 in comparison to the male-headed household. This result highlights the gender bias in the use of CSAT in Odisha. One probable reason could be that the CSAT used in Odisha may not be conducive for the women to use it in practice. The SI and HDI were considered as the human capital determinants of use of CSAT. The result reveals that sanitation index and HDI of the households increase the CSATAI by 0.131 and 0.461, respectively, implying there by better human capital raises the use of CSAT among agrarian households. Similarly, the households having knowledge about the CSAT increase the CSATAI by 0.089. This result could be an indication of confirmation bias in the model.

Perusal of Table 10 also reveals that the level of education has nothing to do with the use of CSAT. Similar conclusion is also drawn for the agricultural expenditure and age of the head of the household. Surprisingly, the land index that is a major natural and/or physical capital for the agrarian households also does not affect the decision of the household to use CSAT. However, the households who stated not women-friendly as the reason for females not using modern equipment have higher CSATAI compared to the households who stated other reasons such as: women with inadequate skills or other socio-cultural reasons. On the contrary, the households stating no adequate skills relative to women using CSAT as the reason for females not using modern equipment have lower CSATAI. This implies that if we can promote CSAT that is women friendly, then the agrarian households may be inclined to use CSAT. The households where female takes agricultural decision has higher CSATAI by 0.068 than the households with male agricultural decision maker. Besides, for households where male members are the owner of the land the CSATAI decreases by 0.233. On the other hand, where females are the owners of the land or both the female and male are the owners of the land, then the CSATAI increases by 0.184 and 0.190, respectively. Such phenomena highlight the role of women and their contribution in using the CSAT in Odisha, India.

Table 10: Regression results

Dependent Variable: CSATAI	**Beta Regression**		**Fractional Probit Regression**	
Independent Variables	Coefficient (Std. err.)	Marginal effect Delta-method (Std. error)	Coefficient (Std. err.)	Marginal effect Delta-method (Std. error)
Level of Social Capital (LSC)				
0.251-0.500	0.527***	0.121***	0.309***	0.116***
	(0.060)	(0.013)	(0.028)	(0.011)
	{0.000}	{0.000}	{0.000}	{0.000}
0.501-0.750	1.415***	0.331***	0.869***	0.330***
	(0.077)	(0.017)	(0.045)	(0.016)
	{0.000}	{0.000}	{0.000}	{0.000}
0.751 and above	1.962***	0.438***	1.272***	0.459***
	(0.132)	(0.024)	(0.085)	(0.025)
	{0.000}	{0.000}	{0.000}	{0.000}
AEI	0.201	0.045	0.093	0.034
	(0.196)	(0.044)	(0.120)	(0.044)
	{0.305}	{0.305}	{0.439}	{0.439}
Caste				
ST	-0.359***	-0.080***	-0.238***	-0.087***
	(0.081)	(0.018)	(0.040)	(0.015)
	{0.000}	{0.000}	{0.000}	{0.000}
OBC	-0.033	-0.008	-0.045	-0.016
	(0.061)	(0.014)	(0.034)	(0.012)
	{0.587}	{0.588}	{0.186}	{0.186}
General	0.075	0.017	0.018	0.007
	(0.101)	(0.023)	(0.059)	(0.022)
	{0.453}	{0.452}	{0.755}	{0.755}
Age (AG)	0.002	0.000	0.001	0.001
	(0.002)	(0.000)	(0.001)	(0.001)
	{0.328}	{0.328}	{0.250}	{0.250}
Joint Family (JF)	0.093	0.021	0.005	0.002
	(0.062)	(0.014)	(0.030)	(0.011)
	{0.137}	{0.134}	{0.871}	{0.871}
Gender	-0.182**	-0.041**	-0.118***	-0.043***
	(0.076)	(0.017)	(0.046)	(0.017)
	{0.017}	{0.017}	{0.010}	{0.010}
SI	0.589***	0.131***	0.276***	0.101***
	(0.144)	(0.032)	(0.078)	(0.028)
	{0.000}	{0.000}	{0.000}	{0.000}
HHDI	2.069***	0.461***	1.206***	0.440***
	(0.407)	(0.090)	(0.227)	(0.082)
	{0.000}	{0.000}	{0.000}	{0.000}
KCSAT	0.400***	0.089***	0.240***	0.087***
	(0.090)	(0.020)	(0.045)	(0.016)
	{0.000}	{0.000}	{0.000}	{0.000}
Level of Education (LEDU)				
Primary	-0.040	-0.009	-0.063	-0.023
	(0.090)	(0.020)	(0.042)	(0.015)
	{0.655}	{0.655}	{0.136}	{0.137}
Secondary	-0.028	-0.006	-0.034	-0.012
	(0.104)	(0.023)	(0.044)	(0.016)

	{0.788}	{0.788}	{0.441}	{0.441}
Higher	0.044	0.010	-0.018	-0.006
	(0.144)	(0.032)	(0.067)	(0.025)
	{0.759}	{0.759}	{0.791}	{0.791}
Land index (LANDI)	0.169	0.038	0.067	0.024
	(0.146)	(0.032)	(0.102)	(0.037)
	{0.246}	{0.245}	{0.514}	{0.650}
Reasons for females not using modern equipment (RFCSAT)				
Not women-friendly	0.192**	0.043**	0.113**	0.041**
	(0.091)	(0.020)	(0.054)	(0.020)
	{0.034}	{0.034}	{0.034}	{0.034}
No adequate skills	-0.244***	-0.054***	-0.142***	-0.052***
	(0.077)	(0.017)	(0.048)	(0.017)
	{0.002}	{0.002}	{0.003}	{0.003}
Socio-cultural reasons	-0.208	-0.046	-0.048	-0.018
	(0.159)	(0.035)	(0.065)	(-0.018)
	{0.191}	{0.186}	{0.454}	{0.454}
Gender-wise Agricultural decisions taken (GAD)				
Female	0.303***	0.068***	0.145**	0.053**
	(0.102)	(0.023)	(0.064)	(0.023)
	{0.003}	{0.003}	{0.024}	{0.024}
Both	0.098	0.022	0.058*	0.021*
	(0.061)	(0.014)	(0.034)	(0.013)
	{0.109}	{0.111}	{0.091}	{0.091}
Gender-wise Landownership (GWL)				
Male	-1.073***	-0.233***	-0.706***	-0.250***
	(0.165)	(0.033)	(0.114)	(0.037)
	{0.000}	{0.000}	{0.000}	{0.000}
Female	0.852***	0.184***	0.575***	0.202***
	(0.195)	(0.400)	(0.134)	(0.045)
	{0.000}	{0.000}	{0.000}	{0.000}
Both	0.879***	0.190***	0.620***	0.218***
	(0.192)	(0.400)	(0.132)	(0.044)
	(0.000)	{0.000}	{0.000}	{0.000}
Constant	2.099***		0.013	
	(0.073)		(0.156)	
	{0.000}		{0.934}	
Number of observations	1,001		1,001	
Wald chi^2 (25)	1009.77***		1169.57***	
Log pseudolikelihood	482.33863		-637.78699	
Pseudo R^2			0.0774	

Note: *, **, and *** denote 10%, 5%, and 1% levels of significance, respectively. Standard error and p-value are given in () and {}, respectively.

Concluding remarks and policy implications

To summarise, it can be said that the intensity of the usage of CSAT increases in tandem with the level of social capital that is present. Therefore, we are able to draw the conclusion that increasing the amount of social capital among agrarian households can increase the use of CSAT among farmers. Further, CSAT is utilised by the tribal households in Odisha that are cut off from the mainland to a lesser extent than the other households in the state. In addition, the CSATAI is reduced by 0.041 points when comparing the female-headed home to the male-headed household. This result demonstrates the gender bias that exists in the use of the CSAT in the state of Odisha. One of the possible explanations for this is that the CSAT that is utilised in Odisha is not conducive for usage by women in practice. Further, CSAT adoption rates are higher among agrarian households with better human capital that calls for providing better sanitation and other facilities for these households. In a similar vein, families with at least one member being familiar with the CSAT result in a 0.089-point gain in the CSATAI that implies that if we want the households to use CSAT then we need to popularise it among the users. The intensity of use of CSAT is higher for households where female takes agricultural decision and families where land is owned by the male members only, the use of CSAT is less. This calls for institutional arrangements to ensure wider usages of social capital, land ownership by the female members and their economic empowerment by providing them better wages and livelihood so that agrarian households will be interested to use CSAT in agriculture that ultimately can cater to the growing demand of food.

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Keynote: Sustainability and circular economy perspectives

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Presenter Profile

Konstantinos Tsagarakis is a Professor of "Economics of Environmental Science and Technology" in the School of Production Engineering and Management at the Technical University of Crete. He holds a degree from the department of Civil Engineering of the Democritus University of Thrace, a BA degree from the Department of Economics of the University of Crete and a Ph.D. Degree in Public Health from the School of Civil Engineering from the University of Leeds, UK. His research interests include: circular economy, technical–economic project evaluation; environmental and energy economics; public health economics; environmental and energy behavior; big data; online behavior; environmental performance of firms; quantitative methods. He is Specialty Chief Editor in Circular Economy Section Frontiers in Sustainability, Associate Editor in Water Policy and Healthcare Analytics, and Subject Editor in Sustainable Consumption and Production.

Meat Waste-Safety-Traceability Prototype for Supermarkets & Restaurants deploying blockchain & meat quality index

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Extended Abstract

Meat traceability aspect has been addressing concerns on food safety and other allied issues. Properly structured meat supply chain can handle concerns of meat quality, source and the entire process from farm to plate increasing stakeholder satisfaction. In fact, an efficient meat supply chain would certainly reduce wastage and contamination. Recording and transferring relevant information across all the nodes holds the key here.

Traditionally Radio Frequency Identification Devices (RFID), Barcode readers and isotopic technologies have been used. The same can be extended to meat wastage data as well. The major area to address is, extension & standardization of information and readiness of use from both supermarket and restaurant perspectives. Concerns such as food safety-adulteration, wastage can be addressed by an apt traceability system. Therefore, corporations are looking out for an efficient and scalable system to accommodate these three interlinked problems in the long run.

We propose a blockchain based meat supply chain for solving such a complex yet real world problem. Blockchain, a distributed digital ledger which can record transactions in sequential multiple series of blocks can be extremely useful. This being a decentralized system no single entity is there for the safekeeping, thus ensuring security. The cardinal aim of this research is to identify and deploy a suitable blockchain based prototype model for both supermarkets and restaurants, addressing waste-safety-traceability parameters in the meat supply chain. First, this would ideally be implemented for restaurants & supermarkets for ensuring quality meat products through regulated standards of storage and handling. As we know that blockchain typically offers safety-reliability-standardisation and cost-effectiveness when implemented properly.

We discuss a mathematical construct here to arrive at an index for meat quality complying with standards mentioned by the regulators. Underlying product has been Beef over here; further, we provided a reference measurement (scale-based) while gathering fundamental parameters from the past studies on Beef at a global level(Bansback, 2014; Cornforth, D. and Hunt, 2008; Delmore, 2007; Frank et al., 2019; Voges, et al., 2007).

Proposed Blockchain Model

Proposed model captures data from various nodes, processes them through the blockchain and evaluates it. Model takes into consideration refrigeration, packaging, storage time; out of which prototype explains parameter considered for shelf life in three stages (open shelf life, before cooking, after cooking, are depicted as panels namely A, B & C respectively). This is a customisable model for food safety, security, wastage and traceability for specific situations (data sources, regulatory authorities, climatic conditions etc.).

The proposed model can be explained in four steps:

STEP 1: First, data has to be captured from specific stakeholders who are involved in this process either through sensors or manually. The producers (butchers & meat processing people) can input the data through a mobile application. Pictures of every stage can be captured and stored in the same application. This will generate a hash in the first block of the blockchain. The authenticity certificate (by regulators) has to be added to the block as well. photograph and authenticity certificates can be cross checked against the original reporting in the blockchain. Moreover, date of production and ID of the producer should be hashed and stored as well. Apart from this all intermediaries have to add dates and product specifications including quantity to the blockchain on receipt of the product. Each package can be traced back to the source by RFID or QR code. Various other measures such as temperatures has to be tagged on the first block as well(Hilten et al., 2020; Kamath, 2018; Patel et al., 2023). There are three Panels in consideration (A and B are for supermarkets in 0specific as they indicate open shelf-life and before cooking; whereas, B and C are for restaurants as they illustrate before cooking with after cooking). We propose a public-permissioned single ledger with pre-selected participants can be implemented(Jeppsson & Olsson, 2017; Varghese et al., 2019).

STEP 2: Procuring & standardising the boundary values of the proposed MQI Index is specific for different categories of meats. Five major cuts of Beef, clustered into three clusters (serving as many as eleven end products at restaurants) have been considered as per various regulatory authorities. The shelf lives at open, before cooking and after cooking are procured from UK standard of FSA studies. As we know, shelf lives vary with the storage/transit temperature. Further, all shelf lives are converted into standard hours (day). We've assigned the weightages in an inverse order (highest weightage for the least number of days of storage). The total weightage for a product is 1. This is a generalised model to fit any type of meat (having definite shelf life).

STEP 3: We used curve estimation to identify correlation between shelf life and respective weightages for all the three Panels (Open Shelf-Life, before Cooking & after cooking). Since, weightages are derived from existing literature, therefore, curve fitting is crucial to bridge the gap between theory & practice.

STEP 4: We finally could create the index (MQI) incorporating the boundary applying minimum and maximum values into the curve fit correlations. Thus, we derive specified range (using an algorithm), inside which the food can remain consumable, however not outside.

Keywords

Meat waste, meat safety, meat traceability, meat quality index.

Presenter Profile

Bikramaditya Ghosh is an Erasmus+ Professor of Finance and Analytics. He has a proven track record in publication with several noted articles to his credit. His research areas are Agri-Finance, Green Finance, Behavioural Finance & Financial Econometrics.

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The Role of Agriculture in Economic Growth of the European Union and Its Resultant Climate Change Implications

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Abstract

This study explores the relationship between agriculture, economic growth, and climate change in the European Union (EU) from 2000 to 2019. Using proxies for each variable, the research employs cointegration and causality tests to assess their dynamic interconnections. Results indicate long-run relationships and causal links, emphasising the agricultural sector's continued contribution to economic growth and its climate change implications. The study's findings offer valuable insights for policymakers, economists, and business personnel, supporting sustainable policies and greener economic development in the EU. Future research opportunities lie in further investigating these complex interrelationships to promote a more sustainable future.

Keywords

EU agriculture, GDP growth, climate change, TFP, causality.

Presenters profile

Hitheesha Cattamanchi, a recent graduate from Harper Adams University, Newport, Shropshire, UK, holds an M.Sc. in International Agribusiness and Food Chain Management, majoring in International Business Economics and Strategic Management for International Agribusiness and other insightful modules. With a passion for global agriculture and its dynamic nature, the author embarked on the current research. Aspiring to contribute significantly to the global agricultural sector, she aims to promote sustainable farming practices and innovative agricultural production technologies for a cleaner and greener future. Her unwavering dedication to agriculture fuels her commitment to achieving impactful advancements in the industry.

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Introduction

Agriculture, historically a significant driver of economic growth, has experienced declining contributions to the European Union's (EU) economy in recent years (Dammers and Keiner, 2006). This decline coincides with rising concerns about food security and the environmental impact of the agricultural sector (Bertoni *et al.*, 2018). As such, this research aims to comprehensively explore the economic dimension of agriculture and its interplay with climate change in the EU, during the period from 2000 to 2019. The study seeks to bridge the gap between these crucial aspects and shed light on the sector's impact on the economy, potential for sustainable growth, and challenges posed by climate change. Understanding the intricate connections between economics and the environment in agriculture can provide insights to inform policy decisions such as in case of the Common Agricultural Policy (CAP) and pave the way for a more sustainable future.

Objectives

The main objectives of this research are to examine the relationships between the agricultural sector, economic growth, and climate change in the EU by evaluating the long-run relationships among them, by employing their proxies/representative variables such as agricultural Total Factor Productivity (TFP), EU GDP growth, and greenhouse gas (GHG) and CO_2 emissions. Lastly, drawing insights on their interlinkages by investigating the causality between the variables, identifying the direction and strength of the relationships.

In order to achieve the objectives of this research, the research methodology is chosen in a way that it aids in addressing the research problem which is identified in the current research as the lack of literature that collectively addresses the issue of the declining importance in the EU economy, heavy investment in agriculture with limited economic growth role raises questions on its effectiveness for sustainable development, considering high emissions. Additionally, the lack of an overarching proxy/representative of the agricultural sector also limits the ability to quantify the role/contribution of the sector to the economic growth.

Methodology

This research adopts a positivist ontological perspective and employs a quantitative research design by employing secondary data. The data is collected from reliable sources, including the USDA ERS (USDA ERS, 2022), The World Bank (The World Bank, 2023), and the OECDiLibrary (OECD, 2023). The chosen time frame of 2000-2019 ensures the relevance and generalisability of the results, providing policy implications for current scenarios.

The empirical analysis to assess the causal linkage between the variables in question is performed through a three-step systematic process. Firstly, the Im, Pesaran and Shin (IPS) (Im, Pesaran and Shin, 2003) unit root test is carried out to check for stationarity in the dataset which might lead to spurious results, followed by which is the Johansen's cointegration test (Johansen, 1988) to assess the long run relationships among the variables. The final test carried out on the variables is the Dumitrescu Hurlin (DH) panel causality test (Dumitrescu and Hurlin, 2012) which is a model for non-causality based on the granger causality test. The EViews software which is widely used for econometric testing is employed to carry out the tests. In order to carry out the tests, the logarithmic values (LN) of data are computed which would aid in further analysis.

Results

The results of the IPS test upon the indication of unit roots (non-stationarity) in the individual datasets in level, the test was run once again however by employing first differenced data. The results of the first differenced datasets have proved that the datasets are free of unit roots, thereby making them suitable for further analysis. Moving on, Johansen's cointegration test has indicated the presence of cointegration among all the variables that were assessed in pairs, thereby implying that these variables are related in the long run. Lastly, the granger causality test was carried out to assess the factor of causality among the variables and also the direction of causality. The test was carried out on the variables that were once again assessed in pairs. The results indicated that there was presence of causality among the variables though the direction was varied. LNTFP was found to granger cause all the other proxies (LNGDP, LNGHG, and LNCO2) in a unidirectional manner. On the other hand, the direction of causality between LNGDP and climate change proxies (LNGHG and LNCO2) was bidirectional, with these proxies granger causing each other.

Discussion and Conclusion

Utilising the first differenced stationary data, the Johansen's cointegration test results signify that the agricultural sector, economic growth, and climate change exhibit a long-run relationship, offering valuable insights into the agricultural sector's contribution to economic growth and its implications on climate change. The findings support the argument that the agricultural sector remains linked to economic growth in the recent years (2000-2019). Furthermore, the cointegration between the proxies of the agricultural sector and climate change provides evidence of implications associated with climate change during the study period. It strengthens the main argument of the study that the agricultural sector's activities may contribute to climate change within the EU.

The analysis of causality offers valuable insights into the interrelationships among the variables, providing a comprehensive understanding of the dynamic relationships between the agricultural sector, economic growth, and climate change in the EU. The presence of Granger causality suggests that changes in the agricultural sector's productivity (TFP) have implications for economic growth and climate change factors during the period of analysis of this current study (2000-2019).

The presence of Granger causality is a crucial finding that this research had aimed to explore. The established causal relationship indicates that the agricultural sector has indeed caused economic growth during the period of this study. Addressing the secondary research problem, the analyses consistently point to the agricultural sector's contribution to regional economic growth and its associated climate change implications. The cointegration test confirming long-run relationships among the variables, along with the established causality, validates the assumptions of this study. The use of sectoral TFP as an overarching proxy for agriculture has been instrumental in providing a comprehensive representation of the entire industry, enabling this research to achieve its objectives effectively.

To validate the results, inferences are drawn from various individual studies that explored similar variables. This research's outcomes can be successfully compared to the work of Katircioglu, (2006), Tiffin and Irz, (2006), Baer-Nawrocka, (2016), and Popescu, (2017) in assessing the relationship between the agricultural sector and economic growth, as well as Lapinskienė, Peleckis and Radavičius, (2015), Zafeiriou and Azam, (2017), Kulyk and Augustowski, (2020), and Makutėnienė et al., (2022) in examining the link between the agricultural sector and climate change (emissions). Although these studies used different representative variables and methodologies, the similarity in scope and aims allowed for meaningful comparisons.

Managerial/policy implications

For policymakers, economists, and business personnel, this study offers conclusions on the agricultural sector's continued contribution to EU's economic growth. Furthermore, understanding climate change implications supports the pursuit of CAP goals and necessary policy changes for sustainable development in the EU. The recent time focus (2000-2019) adds relevance and relatability to the study's outcomes.

Academically, this research contributes by exploring interrelationships between the variables, inviting further explanatory analysis by researchers in different domains.

Scope for future research

The scope for future research is wide-ranging, with opportunities to expand on the current study's findings and delve deeper into the complexities of the interrelationships between the agricultural sector, economic growth, and climate change. Through insightful and comprehensive investigations, researchers can contribute to shaping sustainable policies and promoting greener economic development in the EU.

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An assessment of the trade impact of the Ukraine war on the environment: the case of oilseed rape

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Abstract

The environmental effect of the Ukraine war has been studied mainly from the point of view of physical destruction. However, little is known about the effect of the war on the trade system, and how this affects the environment. The objective of this research is to contribute to filling this gap by proposing a novel approach that measures the impact of the complexities of international trade and the environment. It consists of incorporating two different models into a single approach: the Life Cycle Analysis (LCA) model for environmental assessment; and the International Agri Food Trade Network (IAFTN) model for trade simulations under imperfect competition. The proposed approach was employed to simulate quantitatively the possible environmental impact of the Ukraine war on the trade system using oilseed rape (OSR) as a study case. The results revealed that a decrease in the production of OSR in Ukraine is accompanied by a reduction in environmental pressure in this country. However, environmental damage is exported and transmitted to other countries in the trade network system. This suggests that mitigating environmental strategies should be designed cooperatively in order to reduce the negative trade side effects of the war at the global scale.

Keywords

Ukraine war; International Trade and the Environment; International Agri Food Trade Network; Life Cycle Analysis; Oilseed Rape.

Presenter Profile

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The influence of the war on Ukrainian Grain export

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Extended Abstract

Ukraine is one of the world's top agricultural producers and exporters and plays a critical role in supplying oilseeds and grains to the global market. More than 55 percent of Ukraine's land area is arable land. Agriculture provides employment for 14 percent of Ukraine's population. Agricultural products are Ukraine's most important exports. In 2021 they totalled $27.8 billion, accounting for 41 percent of the country's $68 billion in overall exports (USDA, FAS). Before the war in Ukraine, agriculture accounted for 10% of GDP in 2021, 86 million tons of grains and legumes were harvested in 2021 (Ministry of Agrarian Policy and Food of Ukraine, 2019 – 2022). Ukraine is a key exporter of these range of products: 1st place in world exports sunflower oil (4.6 million tons); 3rd place in the world export of rapeseed (2.7 million tons); 4th place in the world export of barley (5.7 million tons); 6th place in the world export of corn (24.7 million tons) (FAO, Ukrstat). Ukraine is the world's seventh-largest wheat producer and is forecasted to be the fifth-largest exporter for the 2021/22 marketing year. In 2021, Ukrainian wheat exports were valued at $5.1 billion, with Egypt, Indonesia, Turkey, Pakistan, and Bangladesh as the primary destinations (FAO, Ukrstat). Before the beginning of the war, the main flow of grain for export passed through the seaports of Mykolaiv, Odesa and Chornomorsk. By sea in 2021, Ukraine exported 49.5 million tons of grain out of 51.2 million tons. No more than 2–5% of the total volume was transported by land (by rail or road transport) (Ukrstat).

However, the full-scale invasion of the Russian Federation on the territory of Ukraine led to the blocking of grain exports through closed sea lanes, the mining of approaches to ports and the dominance of the Russian fleet in the Black Sea. The blockade of seaports led to a significant reduction in exports: from 6-7 million tons per month to 1.5-2 million tons.

The entire agricultural sector also suffered damage. Losses of available cultivated areas - over 25%, irrigated lands – over 70%, berries - about 25%, gardens - 20%. About 5% of agricultural land was damaged. Infrastructure facilities: agricultural, warehouse, transport, energy, and processing industry suffered significant destruction. There was an increase in the cost of production due to the increase in the prices of fertilizers, fuel and seeds (FAO, Ukrstat).

Since February, the ports of Odesa and Odesa region ("Pivdenniy" port), Chornomorsk, Bilhorod-Dnistrovskyi, Mykolaiv ("Olvia" port) have been closed. The ports of Kherson, Mariupol, Berdyansk and Skadovsk have been captured by the invaders. At least 100 ships were blocked in the Black Sea ports. (N. Iveruk, 2022). After a month of war, in March 2022, according to information from various sources, from 200 to 370 thousand tons of grain, and in April 2023 - 1 million tons were exported from Ukraine by joint efforts. Thus, Ukraine was able to export no more than 20% of pre-war indicators (N. Iveruk, 2022).

The EU member states reached agreements on the diversification of export routes from Ukraine, which consisted in combining the maximum possibilities of rail and road transport,

river ports of Ukraine and seaports of other countries for grain export. Ukrzaliznytsia (Ukrainian railway company) announced its readiness to urgently organize the delivery of agricultural products by rail to the borders with Romania, Hungary, Slovakia, and Poland.

As a result, grain and oilseeds exporters began to frantically look for other options and turned to exporting their products through the western land borders and ports on the Danube River (Reni, Izmail, Kiliia, and Ust-Danube). Chaos on the western borders at railway crossings quickly began to grow because of the number of stalled grain wagons. In addition, lines of trucks tens of kilometers long, especially on the Ukraine-Poland border, had formed (I. Mykhaylov, 2022).

The four ports on the Danube River have limited capacity (about 600,000 tons per month of commodities shipped to barges that transfer grain and oilseeds to the nearby Romanian Port of Constanta for further transportation), and they were quickly flooded with the flow of trains and trucks filled with grain (I. Mykhaylov, 2022).

There were many reasons for the bottle necks at the borders (C. Hebebrand, 2023).There are different scales of railways in Ukraine and its Western European neighbours. The cargo either must be transshipped from Ukrainian wagons to European ones or wheel sets must be changed. There are limited capacities at border crossings to transship cargo or to change wheel sets. There are different dimensions of Ukrainian and European wagons, so Ukrainian wagons with the changed wheel sets can run on very limited European routes. There are different allowed weights of trains. While Ukrainian trains can weigh 5,400 tons in some European countries the weight of trains must not exceed 2,700 tons. Because of this, in some cases grain had to be divided and an additional set of documents had to be provided. There are limited rolling stock and throughput of the European railroads. There are limited capacities of the grain terminals on the Baltic Sea. Bureaucratic delays at the border associated with customs clearance, border inspection, and phytosanitary and veterinary control. In contrast, to exporting grain by sea only one set of certificates is required for the entire cargo. When exporting grain by rail, it requires one set of certificates per wagon or truck.

However, setting up new logistics required time and additional funds (experts claimed that the cost of new logistics has increased 4 times), and even where it is possible to install it, the possibilities of transporting Ukrainian grain are limited (a maximum of 600,000 tons of grain per month) (N. Iveruk, 2022).

Since the beginning of the war, the increase in logistical costs was largely due to rail transportation within Ukraine, this was influenced by tariffs for the use of wagons, the speed of transportation and a number of other factors. According to individual estimates, after the start of the war, logistical costs solely for the use and transportation of Ukrainian grain carriers increased to $ 85 per ton (calculated on the average transportation distance and average standard speed), or 4.5 times. Forwarding services and other logistical costs in Ukraine can range from 10 to 40% of additional cost. Together with the transshipment of grain and the cost of logistics outside of the Ukraine, the logistics component in the price of grain can reach up to $180-200/t (compared to $30-40/t before the start of the war) (Agroportal, D. Luvch. 2022).

The blocking of grain in Ukrainian ports has led to an intensive increase in world prices for wheat, and therefore for food products. Thus, in March, global food prices increased by almost 12.6%.

The Black Sea Grain Initiative was signed on July 22 in Istanbul and provides measures for the unblocking of three Ukrainian ports (Odesa, Chornomorsk and Pivdenny) for the export of Ukrainian agricultural products. Since then, over 900 ships full of grain and other foodstuffs have left three Ukrainian ports: Chornomorsk, Odesa and Yuzhny / Pivdennyi.

At the same time, in order to preserve the competitiveness of Ukrainian grain producers, it is important to solve the problems related to internal railway transport. Decisions that may be introduced by the Government include the revision of the tariff system, reduction of the cost of using grain trucks, Improvement of the transportation planning system, demand monitoring system (to avoid a shortage of wagons) and subsidizing Ukrainian agricultural producers. With the Russian-Ukrainian war entering its second year, prices of grains, fertilizers, and other agricultural commodities have reduced somewhat from their early post-invasion highs, and supply disruptions have moderated. (C. Hebebrand, 2023).

Taking into account the above, we note that in these conditions, the industry of grain storage and export is influenced by many factors and the main task remains unchanged to ensure the export of grain from Ukraine with the lowest costs while maintaining quality.

As a result, the conducted study summarized the problems faced by the agriculture of Ukraine, namely the branch of grain storage and export with the beginning of the Russian invasion. Lessons on improved infrastructure may be important in other regions of the world. Open trade is key in ensuring food security in the face of war. Investment in sustainable food systems needs to be increased at the country level. As was mentioned above some decisions (tariff system, reduction of the cost) should be introduced by the local Government. Enhancing flexibility in the sources for food, feed, and agricultural inputs is essential.

Keywords

Grain products, Ukraine, export, Ukrainian- Russian war, global food security.

Presenter Profile

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Valorisation of Poultry Litter: A socio-environmental cost-benefit comparison of traditional land application and anaerobic digestion

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Abstract

Traditional land application of poultry litter (PL) as a fertiliser has led to numerous environmental issues, including eutrophication and soil acidification. An alternative valorisation option is, therefore, sought. Anaerobic digestion (AD) of PL is an emerging field that shows promise and benefits from both energy and fertiliser production. This study aimed to compare the economic, environmental, and social costs and benefits of land application and AD of PL using a modified economic life cycle assessment (LCA) approach. Using economic data from literature and industry reports, a model for each method was created to calculate key economic markers, including net present value (NPV). LCA was incorporated into the model with the environmental emissions of each method being calculated for Global Warming Potential (GWP), Acidification Potential (AP), Freshwater Eutrophication (FE), Photochemical Ozone Potential (POP), and Particulate Matter Formation Potential (PMFP) impact categories. The social value of these impact categories was applied to the emissions data to calculate a socio-environmental cost (or benefit) for each method. Using Monte Carlo simulation, the model shows that AD performs worse when focusing purely on the economic category with an NPV of £707.17 per tonne of PL, compared to £1838.36 per tonne for land application of fresh PL. However, when factoring in the environmental costs, both methods generated a negative NPV. However, AD is shown to be less environmentally damaging than direct land application with an NPV of -£1354.17 per tonne of PL compared to -£5788.34 for direct land application. Furthermore, the model showed that it is possible to optimise the AD process to generate a positive economic and socio environmental NPV, through operational control of biogas and energy production. Further research is needed in this area to determine the optimal parameters to operate a PL mono-digestion AD process for economic and socio-environmental gain.

Keywords

Poultry litter, Valorisation, Life Cycle Assessment, Techno-economic

Presenter Profile

Deborah Hall is a PhD researcher at Harper Adams University, Shropshire, focusing on the valorisation of poultry litter through the use of anaerobic digestion.

Introduction

Greenhouse gas (GHG) emissions from poultry litter (PL) are of significant concern. The high nitrogen concentration in PL, and its volatilisation through conversion to ammonia gas (NH_3), has notable detrimental effects on the environment due to its involvement in the production of acid rain (Choi and Moore Jr, 2008). When ammonia enters the atmosphere and condenses, the resultant rainwater has a higher pH, giving it a greater ability to dissolve sulphur dioxide (Nahm, 2005). The sulphur dioxide and ammonia form into ammonium sulphate, and, when entering the soil, oxidise and release sulphuric and nitric acids (Pote and Meisinger, 2014). In addition, the volatilisation of ammonia significantly increases the atmospheric fallout of nitrogen, which adds to the eutrophication of waterbodies (Nahm, 2005). Cabrera *et al.* (1993) explain that up to 50% of the nitrogen within PL is emitted as either ammonia or nitrous oxide gas, particularly when PL is land spread. This loss of nitrogen not only reduces the value of the fertiliser, but also has notable impacts on the atmosphere. Forster *et al.* (2007) states that the global warming potential (GWP) of nitrous oxide is around 300 times that of carbon dioxide (298 kg of CO2-equivalents per kg). Methane is reported to have a global warming potential 24 times higher than carbon dioxide (Forster *et al.,* 2007). Ahn *et al.* (2011) estimates that 62 megatons of CO_2 equivalents of methane and nitrous oxide have been emitted globally from animal manures since the start of the industrial age.

Good PL management is, therefore, a necessity, from environmental, economic, and nutrient recycling viewpoints. The traditional use of PL has been land application to recycle nutrients, predominantly N, P and K (Lorimor and Xin, 1999). Due to the high costs associated with transportation, the majority of fresh PL is spread within a 5km radius of the poultry production facility. Furthermore, until recently, application rates were calculated to meet the N requirement of the crop, which often results in an elevated and unnecessary P application. This means that much of the land surrounding intensive poultry facilities have reached their agronomic and regulatory threshold for soil P. This threshold means that the farmer gains notable agronomic benefits with higher crop yields, whilst excess P (and N) is leached into nearby watercourses and impacts water quality (Harmel *et al.*, 2009). Therefore, it is necessary to adopt an improved assessment of PL usage and processing within agro ecosystems to determine optimal applications for soil health, agricultural yield, and water quality. This assessment also needs to consider the economic impact of utilising PL as a fertiliser or diverting its use into biomass for energy production.

To reduce the economic and environmental impact of waste disposal options for PL, an alternative option to land spreading, which has been considered more frequently over recent years, is the valorisation of this waste stream. There are numerous strategies for poultry manure valorisation currently described in the literature. These include composting of PL (Vandecasteele *et al.* 2014), thermal energy recovery using pyrolysis (Kim *et al.* 2009), combustion (Lynch *et* al. 2013) and gasification (Palma and Martin, 2013) or biological energy recovery through the use of technologies such as anaerobic digestion (AD) (Rao *et* al, 2013). This research will complete a social cost benefit and life-cycle comparison between traditional land spreading of PL with AD coupled with energy recovery technology.

Aim and Objectives

The primary aims and objectives of this research are shown in Table 1; in brief the research compares the use of AD with combined heat and power (CHP) energy recovery and organic fertiliser production with traditional land spreading of PL; this includes an assessment of economic viability and social and environmental impact evaluation.

Primarily, the theoretical system is modelled using baseline data from previously published literature along with calculated data from Ecoinvent and includes a 'hot spot' analysis assessment to determine the significant parameters within the foreground system that have the largest social and environmental impacts. In the sensitivity analysis, some of these parameters are varied to determine their effect on the overall results. As previously explained, the system has been expanded to include background processes to allow for the impact of energy and materials recovery from the waste to be considered; this includes the production of inorganic fertiliser through the production and use of digestate, along with the displacement of fossil fuel produced electricity and heat energy using CHP energy recovery.

Ideally, site-specific data would be used for the foreground processes; however, the use of AD for PL valorisation is a relatively new and complex topic with limited practical application; therefore, theoretical and average data from the literature has been used. As Heijungs and Guinée (2007) caution that LCA studies sometimes produce conflicting results, all assumptions made in this research are described as succinctly as possible to enable a reproduction of the analysis. The study focuses on five LCA impact categories that have been chosen due to their environmental significance. These are global warming potential (GWP) as an indicator of climate change and greenhouse effect; acidification potential (AP) as an indicator of the production and impact of acid rain; freshwater eutrophication (FE) as an indicator of the eutrophication impact of nitrate and phosphate leaching into freshwater; photochemical ozone potential (POP) from the emission of NOx and the creation of photo-smog, and particulate matter formation potential (PMFP) from the emission of small particulate matter ($PM_{2.5}$) and its effect on human health. These impact categories are internationally accepted through ISO 14044 recommendations (ISO, 2006). A 100-year time horizon assessment has been used as per the IPCC recommendations.

Table 1. Project aims

Aim	Purpose
Assess Economic Viability	Determine the economic feasibility of anaerobic digestion as a valorisation method compared to traditional land spreading
Environmental Impact Evaluation	Evaluate the potential environmental benefits and drawbacks of each option in terms of emissions and eutrophication
Social Cost-Benefit Analysis	Perform a comprehensive social cost-benefit analysis (SCBA) to capture both economic and social implications of each method

Table 2. Project objectives

Objective	Purpose
Cost Analysis	a. Calculate the initial investment costs for AD, including construction, equipment, and setup expenses. b. Estimate operational costs for AD, considering OPEX and maintenance costs c. Compute the net present value (NPV), benefit-cost ratio (BCR), and payback period for AD and land spreading.
Environmental Impact Assessment	a. Quantify emissions from AD and traditional land spreading. b. Estimate the social cost of emissions using appropriate valuation methods. c. Assess the cost of eutrophication caused by nitrate and phosphate leaching and compare it across different methods.
Sensitivity Analysis	a. Conduct sensitivity analyses to assess the impact of changing key parameters on the economic indicators and environmental outcomes.

Methods

Whilst there are numerous strategies that have been developed and presented in the literature that attempt to integrate LCA into process design and optimisation frameworks, the majority of these are within the chemical process design field. Indeed, Grossmann and Guillén-Gosálbez (2010) stated that the major limitation of LCA application to process systems is the lack of systematic methodology for melding the LCA impacts with good economic performance. This was largely addressed by the multi-objective optimisation approach presented by Gerber, Gassner and Marechal (2011), which focused on environmental, economic, and thermodynamic impacts on life cycle performance. However, these authors were focused on just one product, that of electricity from biowaste. In this study, two products are considered: energy and organic fertiliser production. As such, a modified LCA and techno-economic approach have been used.

The economic evaluation follows a cost-benefit analysis approach. This model focuses on the estimate of capital and operational costs and the associated calculation of the net present value, benefit cost ratio and payback period. The estimate of capital costs is based on equipment and installation cost estimates provided by IRENA (2012). A financial spreadsheet was designed and utilised to incorporate the costs and benefits of each valorisation method. The capital cost was estimated based on the required digestor size to treat the total mass of feedstock (20,000 tonnes of PL). A dynamic interest rate function is applied to appropriately discount future cash flows considering changing economic conditions. A constant salvage value is considered for the AD to account for asset value at the end of its life. Net present value (NPV) and benefit-cost ratio are calculated using time series data and dynamic interest rate. The formula for calculating NPV is as follows:

$$NPV = \frac{R_t}{(1+i)^t}$$

where NPV = Net present value; R = net cash flow at time t; i = discount rate and t = time of the cash flow.

Benefit cost ratio (BCR) is calculated as follows:

$$BCR = \frac{\sum_{t=0}^{n} \frac{CFt\ [Benefits]}{(1+i)^t}}{\sum_{t=0}^{n} \frac{CFt\ [Costs]}{(1+i)^t}}$$

where CF = cash flow; i = discount rate; n = number of periods; and t = time of the cash flow. OPEX costs incorporate the annual running costs of the plant and are split into fixed and variable costs. Fixed costs include labour, scheduled maintenance, routine component replacement and insurance, whilst variable costs include non-biomass fuel costs, unplanned maintenance, equipment replacement and incremental servicing costs. These OPEX costs are estimated using estimates provided by IRENA (2012). All costs are presented on a 2023 basis and the main financial assumptions are tabulated in Section 3.

For the environmental impact, a modified LCA approach has been utilised. Clift (2013) explains that life cycle assessment (LCA) is one of the most significant and widely utilised tools for assessing and comparing the environmental impact of alternative technologies. The tool enables the quantification of energy and materials within a complete supply chain, or life cycle, of services or goods, whilst also identifying wastes and/or emissions from these life cycles (Azapagic *et al*., 2003). Furthermore, Azapagic *et al.,* (2003) explain that LCA enables the identification of system 'hot spots', which are the areas that exert the most significant impacts on the environment, thereby enabling the modification of systems to more sustainable approaches. However, from this it is necessary to determine a rational approach to allocate the environmental costs or impacts of each of the processes. This allocation issue has been debated by Clift *et al*. (2000) and Heijungs and Guinée (2007) but ably clarified by Eriksson *et al.* (2007) who support the broadening of the system boundaries to account for the environmental benefits of recovered resources whilst including the avoided burdens associated with conventional systems. An avoided burden is effectively a saved impact that arises from the reuse, recycling or energy generation from waste and is generally subtracted from the categorised impacts to generate a reduced overall environmental impact. This is the approach that is applied throughout this research. As such, 'foreground' and 'background' processes are initially identified as per the Integrated Waste Management approach defined by Clift *et al.* (2000). The 'foreground' processes are those that are directly influenced by study-based decisions, whilst the 'background' processes are those that interact with the foreground processes through the supply or receipt of energy or materials.

There is always an element of uncertainty with LCA, particularly when theoretical, rather than site specific, data are used. For this study, average data is used that has been obtained and collated from previously published, peer-reviewed literature. In addition, calculated emission data published by Ecoinvent has been used where available.

To improve the robustness of the process, a sensitivity analysis is performed by running Monte Carlo simulations of the model's 14 variables:

These variables are:

- Biogas yield (m^3)
- Biogas potential (l/kg)
- Biogas conversion efficiency (%)
- Methane content (%)
- Total energy production (kWh)
- Electrical conversion efficiency (%)
- Heat conversion efficiency (%)
- Total electricity production (kWh)
- Total heat production (kWh)
- Parasitic load percentage (%)
- Mineral fertiliser cost (£)
- Fixed O&M costs (£)
- Variable O&M costs (£)
- Capital cost (£)

These variables were given range values that were determined from previously published literature. The results were studied under two different levels of analysis; Analysis 1 considers purely economic parameters (CAPEX, OPEX, yield, energy production, etc) whilst Analysis 2 considers all these costs plus the costs of environmental emissions (GWP, AP, FE, etc). All financial parameters were calculated over a 20-year life span, considered to be feasible for an AD plant. For the land application method, mineral fertiliser cost is the only considered variable.

For the Monte Carlo simulation, all of the variables were considered at once; therefore, multiple regression analysis was performed in order to determine the most influential variables on NPV. Limitations include reliance on input data quality, potential uncertainties due to changing economic conditions, and evolving technology performance.

Assumptions

Biogenic CO2

Emissions of biogenic CO2 are defined by the US EPA (2011) as "emissions from a stationary source directly resulting from the combustion or decomposition of biologically based materials other than fossil fuels". In line with the approach used by Christensen *et al.* (2009) and Manfredi *et al.* (2011), this research considered biogenic CO2 emissions as neutral with regards to global warming, as they are a part of the natural carbon cycle. Therefore, for the purpose of this study, the biogenic carbon within the organic matter (PL or digestate) is sequestered into the soil and removed from the atmosphere, therefore its characterisation factor from organic sources is considered to be zero throughout the study.

Transportation

As this research is following a comparative LCA approach, processes that are identical within each alternative are omitted as they are not considered to impact on the overall results (Finnveden, 2008). This includes the transportation of PL between stages, from the PL house to the storage tank or stockpile and from here to the field. The cost of spreading of the PL and digestate is also valued equally, despite potentially different distances being covered from stockpiles and the treatment plant. As explained by Patterson *et al*. (2011), the environmental impact of transportation distances on LCA results is arbitrary and therefore is unlikely to impact on the overall result.

System expansion for electricity, heat and fertiliser production

To ascertain the impact of the background process, it is necessary to apply a system expansion approach. This involves the identification of the type and quantity of the product, i.e., energy and digestate / organic fertiliser, that is replaced by the technology (Fruergaard and Astrup, 2011). Consequential LCA studies often use marginal technology data and are focused on the significances of policy or broader changes; conversely, attributional LCA studies are used to describe a proposed or specific current process and often use average technology data to calculate the avoided burdens linked with the system expansion (Fruergaard *et al.*, 2009). As this research focuses on a specific, though assumed, process, it is a form of attributional analysis, thereby allowing the use of average data for organic fertiliser and energy production to be used.

The avoided burdens of electricity and heat export to the National Grid have been collated from data presented by Evangelisti *et al*., (2014) and utilises an average UK mix of technologies and fuels. The results of the avoided burdens per kWh of energy produced (heat and electricity) are shown in Table 3 and reported for four of the five environmental impact categories considered (no data was reported for particulate matter formation).

Table 3. Avoided burdens per kWh of energy for substitution of heat and electricity produced (Evangelisti et al, 2014).

Impact category	National Grid mix UK	Thermal energy natural gas
Global warming potential (kg CO_2 eq)	0.167	0.004
Acidification potential (kg SO_2 eq)	0.00058	0.00001
Photochemical oxidant potential (kg NOx eq)	0.000032	0.000001
Nutrient enrichment (eutrophication) potential (kg NO_3 eq)	0.00051	0.000008

In order to calculate the avoided burdens through the substitution of PL or digestate as an organic fertiliser on inorganic fertiliser production and use, the nutrient availability to the crops has been used. Inorganic fertiliser substitution has been discussed previously in the literature (Bernstad and la Cour Jansen, 2011; Moller *et al.*, 2009). Moller *et al*. (2009) supported the use of average burden calculations for the production of N, P and K fertilisers. As such, for the purpose of this study, average data from a fertiliser life cycle assessment by Skowroñska and Filipek (2014) has been used, as shown in Table 4. Table 5 shows the economic LCA values per kg of each gaseous emission for each impact category.

Table 4. Avoided burdens associated with digestate or PL use compared to inorganic fertiliser (from Skowroñska and Filipek, 2014).

Parameter	Unit	Avoided burden
GWP	kg CO_2 eq/kg fertiliser produced	1.79
AP	kg SO_2 eq/kg fertiliser produced	6.07
FE	kg PO_4 eq/kg fertiliser produced	0.53

Table 5. Economic LCA values for each environmental impact category.

LCA Values	GBP (£)
1kg CO2 eq	0.11
1kg SO2 eq	7.99
1kg PM2.5	31.96
1kg PO4 eq	4.31
1kg NMVOC eq	4.58

Use of digestate as a replacement fertiliser

Whilst digestate is a by-product from AD, its use as a substitute for inorganic fertilisers is becoming more mainstream. For the purpose of this study, it is assumed that all produced digestate is spread on the land as a fertiliser with the quality of the digestate mirroring that of the feedstock. This follows the method proposed by Moller *et al.* (2009) whereby it is assumed that the AD process results in no net loss of nitrate, phosphate, or potassium. Application of the digestate and PL as organic fertiliser has been assumed on a rate of 120:60:40, N:P:K, respectively, which is considered suitable for standard maize cultivation and complies with the use of agricultural fertilisers within the UK (UK Government, 2008).

Case study scenario

Tables 6 – 9 provide the data and source of assumptions and values used in the model along with the theoretical farm situation. Table 6 describes the theoretical farm situation, detailing volume of PL, NPK application rate, electricity and heat usage in the poultry house along with key parameters that are included or omitted from the study.

Table 6. Theoretical Farm Situation

Assumption	Value	Notes
Poultry litter quantity	20,000 tonnes	Broiler poultry farm housing 14,500 birds
Land application radius	5km	Surrounding land of 6250 hectares
NPK application rate	120:60:40	Standard maize cultivation
Electricity consumption	20,341 kWh/yr	For poultry unit operations
Heat consumption	140,000 kWh/yr	For poultry unit operations
Scale of valorisation options	Small-scale on-farm technology	Technologies built on farm premises

Transportation and emissions, excluding spreading costs	Not included	Transport between farm and field considered to be similar for each method so not included
GHG Emissions from poultry unit	Not included	Assumed to be the same for both methods
Cost and emission differences	Calculated	Between fertiliser / digestate / and PL applications
Economic analysis		
Spreading costs	£10.15 per tonne	Literature values range from £9.76 /t (Vervoort and Keeler, 1999) to £10.54 /t (Huijsmans *et al.,* 2004) adjusted for inflation and exchange rate.

Table 7 outlines a number of assumptions for each of the valorisation methods that were considered likely to impact emissions within the model.

Table 7. Assumptions for Different Valorisation Methods

Assumption	Land spreading	Anaerobic digestion
Energy source for poultry house (Electricity	National Grid	CHP
Electricity cost	£0.34 per kWh	
Energy source for poultry house (Heat)	LPG	CHP
Heat cost	£0.10 per kWh	
Poultry litter storage	Field windrow	Bunded, covered tank
Maximum storage period	6 months	N/A

Table 8 details the digestor size and assumed hydraulic retention time used for the case study.

Table 8. Anaerobic Digestor Assumptions (fixed)

Assumption / Calculation	Value	Reference / Notes
Digester size calculation	Size (m^3) = Flow rate (m^3) x Hydraulic retention time (days)	
Flow rate	125 m3/day	Assumption: Given maximum daily feedstock flow rate
Hydraulic retention time	40 days	Mahdy *et al.,* 2020
Digester size	5000m3	

Table 9 provides the variable ranges that are included in the Monte Carlo simulation for the model sensitivity analysis.

Table 9. Anaerobic Digestor Assumptions (variables)

Assumption / Calculation	Value	Reference / Notes
Capital cost	£4,188,990 - £9,934,275	IRENA, 2012
OPEX	Range 2.1-7% of installed cost	IRENA, 2012
Biogas potential	Range 88 -226 l/kg fresh weight.	Jurgutis *et al.,* 2020
Biogas production efficiency	45 - 60%	
Methane content of biogas	48 - 62%	Assumption
Electrical conversion efficiency	30 - 50%	
Heat conversion efficiency	30 - 50%	
Parasitic load (electricity)	Range 4% - 31.4% of the electrical energy production	Gikas, 2014; Murphy and Power, 2006; Murphy and Thamsiriroj, 2013; Walker *et al*., 2017
Parasitic load (heat)	22.65% (Range 15% - 30.3%) of the heat energy production	Aui, Li and Wright, 2019; Walker *et al.,* 2017

Results

Analysis 1. Economic Analysis

The average net present value (NPV), benefit cost ratio (BCR), payback period and modified internal rate of return for the two options were calculated from a purely economic viewpoint and are recorded in Table 10. Figure 1 shows the NPV range for the two methods calculated through Monte Carlo analysis. Comparison of key financial parameters between land application and AD are shown in Figure 2.

Table 10. Net Present Value (NPV) for 1 tonne of poultry litter (economic comparison)

Valorisation Method	NPV (£/t)	BCR (return per £ invested)	Payback period	MIRR (%)
Land spreading	1838.36	12.55	n/a	n/a
Anaerobic Digestion	707.17	1.63	5.34	6.86

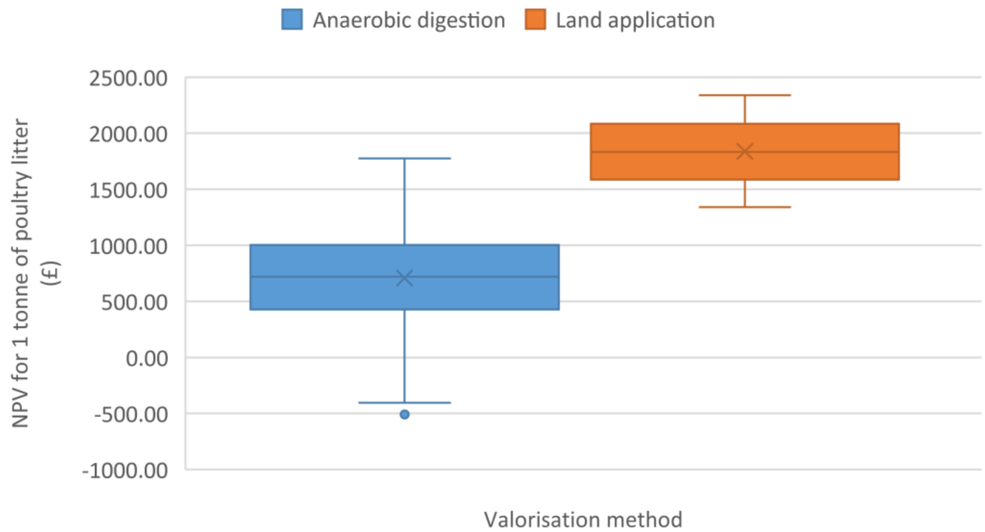

Figure 1. Sensitivity analysis results comparing NPV values for anaerobic digestion and land application.

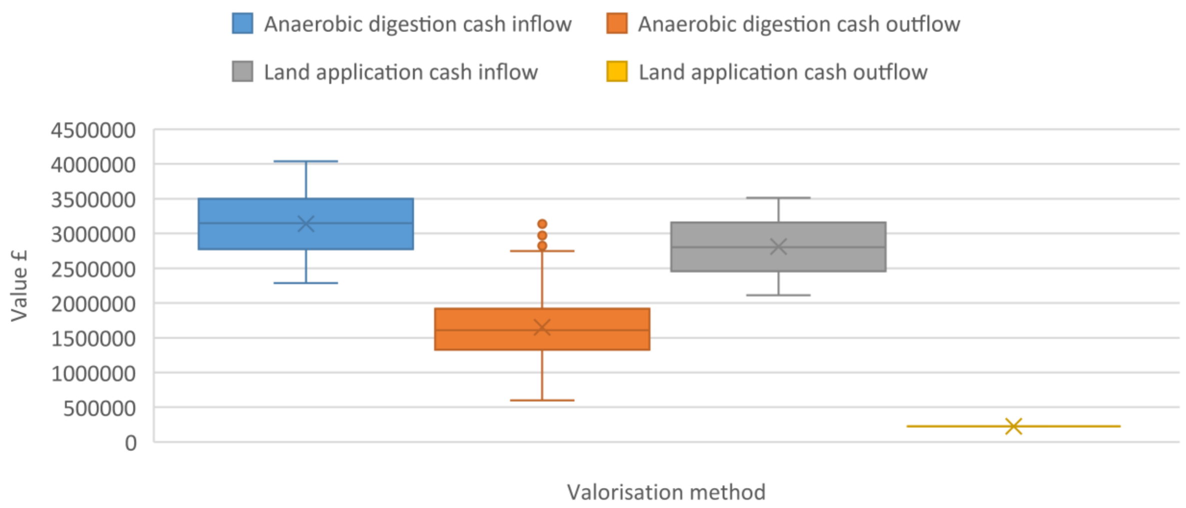

Figure 2. Comparison of the cash inflow and cash outflow of anaerobic digestion and land application.

Analysis 2. Economic and environmental analysis

Average NPV and BCR were calculated for both methods using the Monte Carlo simulation. Due to the negative results, payback period and MIRR are not calculated. Table 11 presents the results.

Table 11. Net Present Value (NPV) and BCR for 1 tonne of poultry litter (economic and environmental comparison)

Valorisation Method	NPV (£)	BCR (return per £ invested)
Land spreading	- £5788.34	0.33
Anaerobic Digestion	-£1354.17	0.74

The avoided burdens of fertiliser (4687 tonnes) and heat used (140,000kWh) and electricity produced (average 3648416.8kWh) were subtracted from the environmental emissions data to calculate and compare overall environmental costs for each method (Figure 3). In Figure 3, negative figures denote a net environmental gain when comparing each method against the use of equivalent mineral fertilisers and through National Grid electricity and heat substitution from the AD.

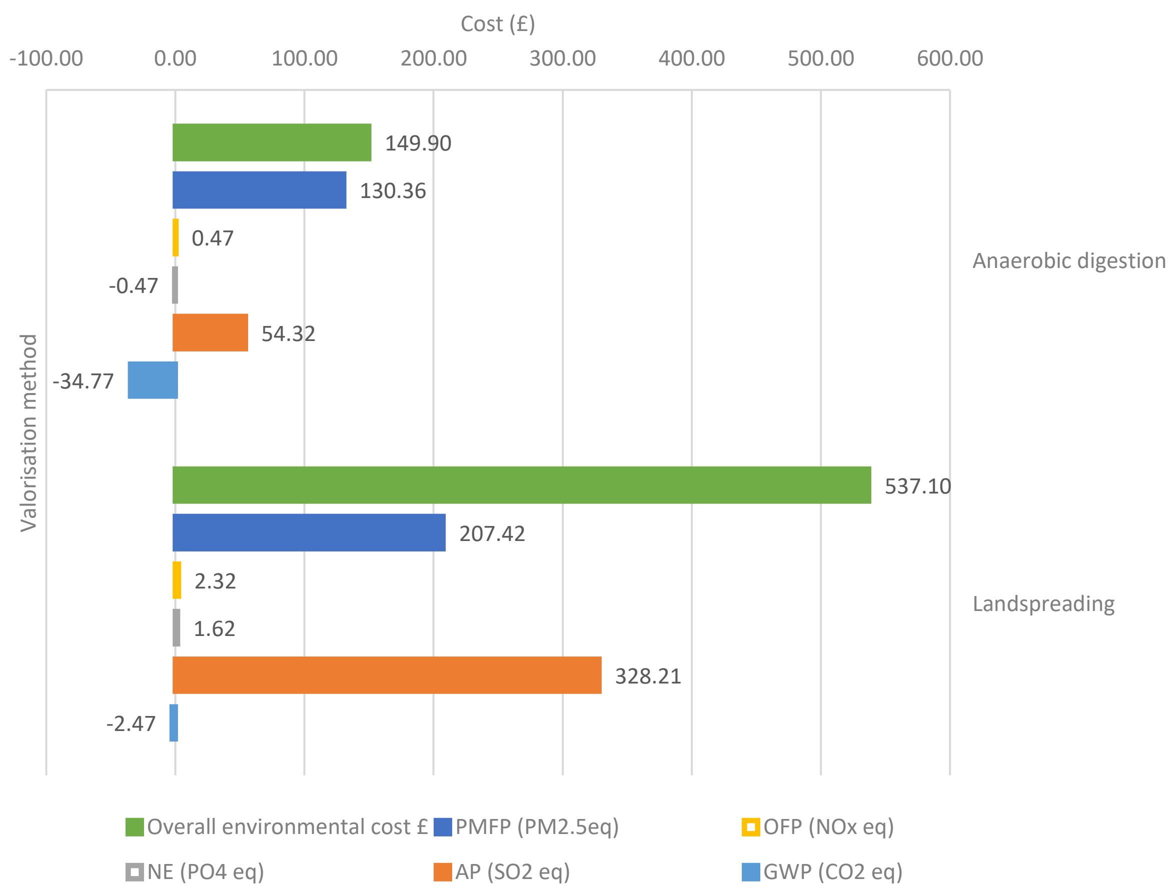

Figure 3. Environmental cost comparison between land application and anaerobic digestion per tonne of poultry litter

The mean, standard deviation, min, and max data were collated from the Monte Carlo simulations of all ten variables and analysed alongside the NPV, BCR and payback period. This sensitivity analysis utilised all collated data, therefore, was focusing on the overall costs of each method, inclusive of environmental costs. Figure 4 shows the NPV comparison from this sensitivity analysis.

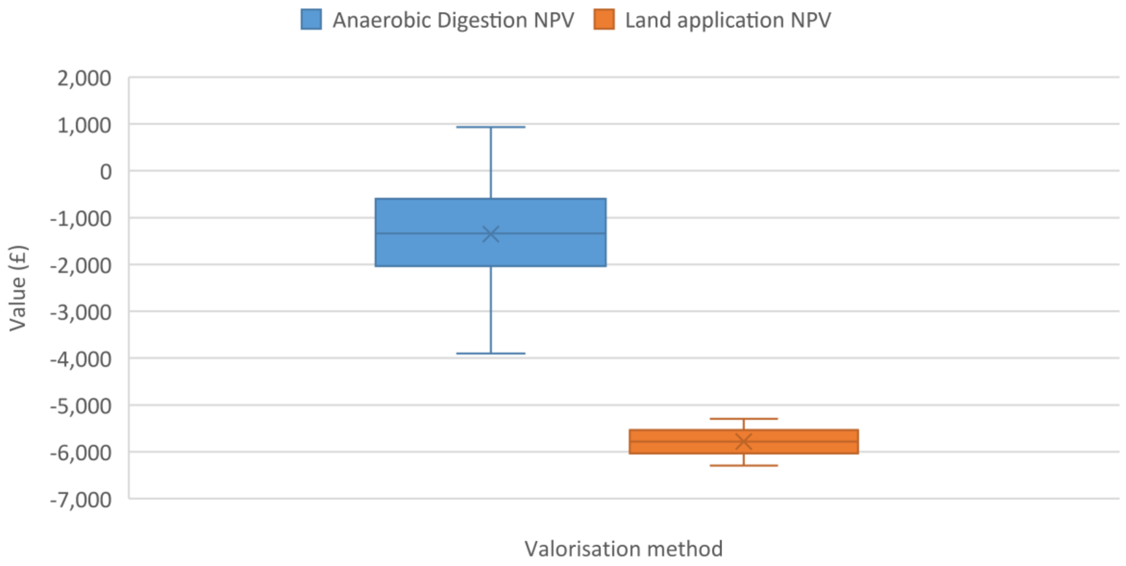

Figure 4. NPV comparison between AD and land application from Monte Carlo sensitivity analysis

This comparison displayed expected results, with the AD option showing a higher, therefore better, NPV than that of traditional land application. Whilst the comparison between the two options is notable, the range within the AD NPV is worthy of further investigation. A negative NPV value was expected from this analysis, as the emissions from the construction of the AD plant and associated operational emissions will have negative impacts on the environment; however, the sensitivity analysis showed that in certain scenarios, a positive NPV was gained. By ranking the data sets using NPV value, and selecting all of those with a positive NPV, further analysis was undertaken.

Multiple regression analysis was carried out to determine the relationship between NPV and the independent variables. The correlation matrix is shown in Table 12.

Table 12. Multiple regression analysis – Correlation matrix (pearson)

	NPV	Biogas Potential	Biogas efficiency	Methane content	Electrical conversion	Heat conversion	Parasitic load value	Mineral fertiliser cost	Biogas yield	Total energy production	Fixed O&M Cost	Variable O&M cost	Capital cost	Total electricity	Total heat production
NPV	1	-0.1701	-0.1152	-0.1883	0.02732	-0.1294	-0.0288	0.27831	-0.2376	-0.3456	-0.3034	-0.2981	-0.1966	-0.2049	-0.3177
Biogas Potential	-0.1701	1	-0.2671	-0.278	0.10736	-0.0349	-0.2422	0.23951	0.81004	0.65647	-0.1387	-0.1015	0.04585	0.5145	0.42507
Biogas efficiency	-0.1152	-0.2671	1	-0.0356	-0.0073	0.12687	-0.3824	0.06564	0.34463	0.33524	0.09169	-0.0614	-0.1143	0.20128	0.31594
Methane content	-0.1883	-0.278	-0.0356	1	0.04353	-0.0381	0.00404	0.20108	-0.2944	0.2638	0.21191	-0.097	0.09162	0.17673	0.14199
Electrical conversion efficiency	0.02732	0.10736	-0.0073	0.04353	1	0.07198	-0.2231	0.22982	0.10275	0.11987	0.14258	0.1088	0.09557	0.767	0.15055
Heat conversion efficiency	-0.1294	-0.0349	0.12687	-0.0381	0.07198	1	-0.129	-0.1127	0.04269	0.01397	-0.024	0.17942	0.05872	0.07491	0.73087
Parasitic load value	-0.0288	-0.2422	-0.3824	0.00404	-0.2231	-0.129	1	-0.0585	-0.4555	-0.4655	-0.0979	-0.0766	0.03548	-0.4588	-0.4129
Mineral fertiliser cost	0.27831	0.23951	0.06564	0.20108	0.22982	-0.1127	-0.0585	1	0.2795	0.394	0.36008	0.05256	-0.1597	0.40494	0.19779
Biogas yield	-0.2376	0.81004	0.34463	-0.2944	0.10275	0.04269	-0.4555	0.2795	1	0.84165	-0.0833	-0.1273	-0.0218	0.62414	0.60643
Total energy production	-0.3456	0.65647	0.33524	0.2638	0.11987	0.01397	-0.4655	0.394	0.84165	1	0.0407	-0.1876	0.01934	0.72345	0.68678
Fixed O&M Cost	-0.3034	-0.1387	0.09169	0.21191	0.14258	-0.024	-0.0979	0.36008	-0.0833	0.0407	1	0.04273	-0.0977	0.11633	0.01501
Variable O&M cost	-0.2981	-0.1015	-0.0614	-0.097	0.1088	0.17942	-0.0766	0.05256	-0.1273	-0.1876	0.04273	1	0.08229	-0.0297	0.00791
Capital cost	-0.1966	0.04585	-0.1143	0.09162	0.09557	0.05872	0.03548	-0.1597	-0.0218	0.01934	-0.0977	0.08229	1	0.08189	0.06677
Total electricity production	-0.2049	0.5145	0.20128	0.17673	0.767	0.07491	-0.4588	0.40494	0.62414	0.72345	0.11633	-0.0297	0.08189	1	0.55749
Total heat production	-0.3177	0.42507	0.31594	0.14199	0.15055	0.73087	-0.4129	0.19779	0.60643	0.68678	0.01501	0.00791	0.06677	0.55749	1

By plotting the absolute correlation coefficients on a tornado chart, the variables with the strongest influence can be determined (Figure 5).

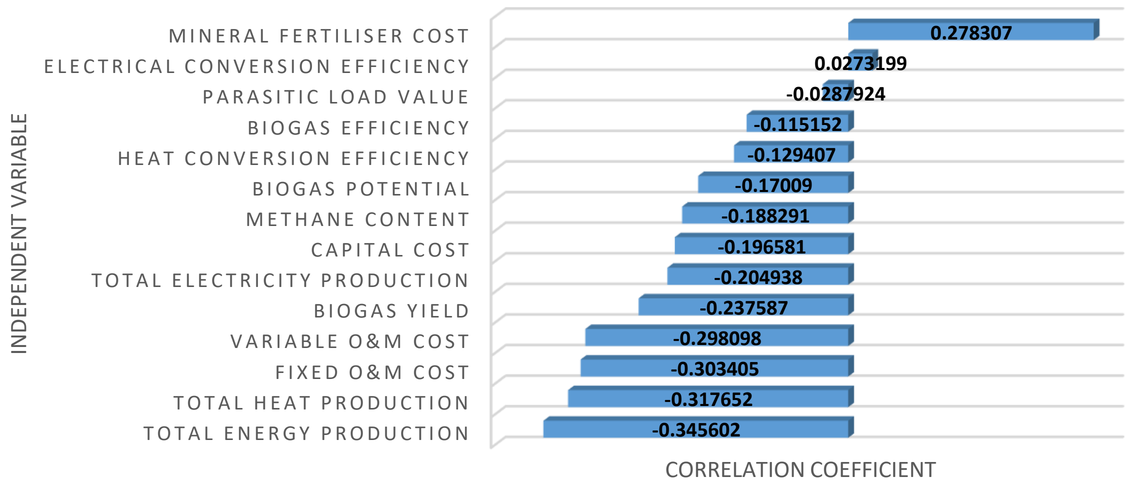

Figure 5. Correlation coefficients for the 14 independent variables and their influence on NPV.

Discussion

Table 10 provided the NPV, BCR, payback period and MIRR for AD compared with traditional land application from a purely economic viewpoint. The payback period of 5.34 years for the AD plant is similar to the findings of Kabir *et al*. (2015) and Orive *et al.* (2016), who reported <8 years and 6.7 years, respectively, in their techno-economic assessments of AD performance. Whilst neither of these studies considered PL as a feedstock, the digestor size and feedstock volume are comparable to the scenario described in this study. In addition, the NPV of £707.17 per tonne of feedstock is comparable to that reported by Li *et al.* (2021) ($972.7 per tonne of feedstock) but far higher than those reported by Li *et al*. (2020) ($75 per tonne feedstock). However, the latter study compared 2 systems in 3 different scenarios, all of which were purchasing a lower methane potential feedstock, therefore, resulting in low gas production and low product sale revenue. Both aforementioned studies focused on small-scale, on farm AD plants, suggesting they are directly comparable with our study.

When including the environmental costs, the NPV of both AD and land application became negative, suggesting that neither option is economically and environmentally viable. This finding is supported by Bora *et al*. (2020) in their comprehensive LCA and TEA study focusing on multiple valorisation options for PL. There are, however, several key differences between this study and that of Bora *et al.* (2020). Firstly, the Bora study uses a real scenario in the USA, rather than a theoretical UK scenario. Secondly, the volume and composition of the PL differ considerably in our study, thereby altering the required digestor size, capital and operational costs, biogas yield and associated energy production. Furthermore, Bora *et al*. (2020) did not use PL as a direct AD feedstock but used hydrothermal liquefaction as a pretreatment step.

The five environmental impact categories considered in the LCA component of this study have varying influence on the economic feasibility of the valorisation methods. There is an overall difference of £387.20 per tonne of PL between AD (£149.9) and land application (£537.1), with particulate matter formation and acidification potential exerting the most influence with values of £207.42 and £328.21, respectively, for land application, and £130.36 and £54.32, respectively, for AD. These high values were expected for the traditional land application approach, due to high ammonia and hydrogen sulphide emissions during land application. There is a notable difference in these environmental impacts when comparing land application to AD, with a reduction of £49.42 and £273.89 per tonne of PL for particulate matter formation and acidification potential, respectively. However, despite the reduction, these two impact categories are still relatively high in AD and are the main contributors to the economic infeasibility of the scenario. With 1kg of particulate matter and 1 kg of sulphur dioxide being priced at £31.96 and £7.99, respectively, they are the two highest costing impacts out of the five considered. In order to understand the reasons for this, one needs to recognise the notable levels of hydrogen sulphide and ammonia that are emitted during the degradation of biomass during the AD process. Ammonia is easily oxidised to NO_2, then hydrated to nitric acid, whilst hydrogen sulphide is oxidised to SO_2 then hydrated to sulphuric acid, thereby both contributing the acidification potential. With regards to particulate matter formation, again ammonia is key as $PM_{2.5}$ constitutes high levels of ammonium ions formed when ammonia gas reacts with NO_x and SO_x in the atmosphere. These levels can be reduced in AD through the upgrading of biogas to biomethane by implementing membrane separation, or water scrubbing, followed by the use of a thermal power plant. This process would effectively lower the ammonia and hydrogen sulphide emissions to levels that are on a par with natural gas.

Within AD, the GWP impact is also of note with a negative value, suggesting that AD has a positive impact on the environment. This negative figure is largely due to the avoided burdens of both fertiliser production and electricity production afforded by the use of AD. Indeed, whilst the GWP impact costs for AD amount to £12.82 per tonne of PL, the avoided burdens through energy and fertiliser productions amount to £47.59 per tonne of PL, thereby resulting in an enviro-economic gain of £34.77.

With regards to the small number of positive NPV results arising from the Monte Carlo simulation, results of the multiple linear regression indicated that there was a very strong collective significant effect between the Biogas Potential, Biogas efficiency, Methane content, Electrical conversion efficiency, Heat conversion efficiency, Parasitic load value, Mineral fertiliser cost, Biogas yield, Total energy production, Fixed O&M Cost, Variable O&M cost, Capital cost, Total electricity production, Total heat production, and NPV, ($F(7, 65) = 893.38$, $p <.001$, $R^2 =0.99$, $R^2_{adj} =0.99$). The individual predictors were examined further and indicated that Biogas Potential ($t = -3.256$, $p = .002$), Biogas efficiency ($t = -37.564$, $p < .001$), Methane content ($t = 59.002$, $p < .001$), Electrical conversion efficiency ($t = -13.358$, $p < .001$), Heat conversion efficiency ($t = -44.538$, $p < .001$), Parasitic load value ($t = -41.758$, $p < .001$) and Mineral fertiliser cost ($t = 2.927$, $p = .005$) were significant predictors in the model.

The tornado chart in Figure 5 showed that mineral fertiliser cost is strongly positive, suggesting that the higher the price of mineral fertiliser, the more cost-effective AD becomes. This is obvious as the average avoided financial burden of fertiliser purchase from the Monte Carlo simulation is in excess of £2.7m. Conversely, biogas potential, biogas efficiency, methane content, heat conversion efficiency, and parasitic load are strongly negative, suggesting that the more energy that is produced, the lower the NPV becomes. This is surprising; however, this may be due to higher environmental impact emissions being associated with higher energy production.

Within our study, it is assumed that there is no cost for feedstock or no financial value for the digestate fertiliser; these are scenarios that could have a significant impact on the economic feasibility of the AD plant. Furthermore, Renewable Heat Incentive payments, and other government initiatives, are also not considered. As such, further research should consider these aspects to determine the economic impact that these scenarios would have on the feasibility of AD use.

Conclusion

In conclusion, AD shows notable promise as a cost effective and environmentally beneficial valorisation option for PL. Whilst the average NPV from the Monte Carlo simulation for both land application and AD was negative, the simulation showed that it is possible to generate a positive NPV for AD with a favourable payback period through the operational optimisation of the technology. Surprisingly, the optimisation involves reducing the biogas and energy yield. Further research into this is required to fully understand the optimisation process. However, it should also be noted that the positive socio-environmental-economic NPV is also largely determined by the cost of mineral fertiliser as an avoided burden as the average cost of fertiliser needed exceeds £2.7 million and is the highest variable cost. Further research is also required to compare this valorisation method with other options, such as gasification, pyrolysis and incineration. By using the model created in this study, this comparison would provide a comprehensive socio-enviro-economic model to evaluate the costs and benefits of these valorisation methods with AD, in order to determine the optimal technology.

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Keynote: Enabling agroecology through digitalisation of agriculture

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Presenter Profile

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Cost benefit analysis of robotic weeding in vineyards: A case study from France

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Abstract

Increasing demand for food with minimal traces of chemicals is challenging viticulture to move away from chemical weeding. In France, there is increasing trend towards mechanical weeding, but it is repetitive, labour intensive, and costly to farmers. Autonomous robotic systems may help tackle the labour challenge while also providing opportunities to improve input use efficiency and minimize CO2 emission. This study provides a cost benefit analysis of robotic mechanical weeding relative to conventional practices of chemical weeding and mechanical weeding using tractor based on a case study in France. The results show that the robotic system generates a little less net present value but considerably reduces labour and fuel use compared to conventional practice.

Keywords

Chemical weeding, Conventional system, Mechanical weeding, Vineyard, France, Robot

Presenter Profile

Søren Marcus Pedersen is an Associate professor at University of Copenhagen. He works with production economics, innovation economics, adoption studies and technology assessment in the agri-food sector. His research areas include farm management information systems, irrigation systems, and precision farming versus conventional crop production.

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Introduction

Rising demand for high quality food with minimal traces of chemicals is calling for sustainable intensification of food production. In viticulture, for example, due to growing pressure towards pesticide-free weeding (Lucchi & Benelli, 2018; Jacquet, et al., 2021), mechanical weeding is considered but it involves high direct cost (mainly labour and fuel cost) to farmers when done with conventional tractor operation. In the face of increasing scarcity and high cost of labour in European agriculture, autonomous (robotic) solutions for repetitive, time-consuming and tedious field operations such as mechanical weeding could help tackle the labour challenge in European agriculture (ROBS4CROPS, 2020). Robotic applications are hoped to offer promising opportunities to improve input use efficiency (Gonzalez-de-Santos, et al., 2017), curb GHG emission (Gonzalez-de-Soto, et al., 2015), and minimize soil compaction (Duckett, et al., 2018) which potentially translates to yield gain (Shockley, et al., 2019).

An EU funded project called ROBS4CROPS (R4C) aims to develop reliable and fully autonomous robotic solutions for weeding and spraying of crop protection chemicals. Testing and further development of the robotic solutions undertakes in Large Scale Pilots (LSPs) in Greece, France, Spain and the Netherlands on real farm conditions. Farmers' groups who are actively engaged in the project run the LSPs. The R4C pilot in France is aimed to reduce environmental impact of vine growing by replacing chemical weed control in vineyards with mechanical weeding. The predominant practice of vine grape weeding in Loire-valley region of France is application of crop protection chemicals. However, with increasing pressure towards minimal pesticide use, mechanical weeding is gaining more attention. However, mechanical weeding with a tractor driver is economically not attractive (5-7 passes per year, total cost 800 € ha^{-1}). Moreover, it is difficult to attract and retain experienced tractor drivers who can operate the different weeding implements that are used. According to local LSP managers of the Robs4crops project, labour is indeed an issue for the farmers in the case study area.

Despite expectations, the costs and benefits of such robotic solutions are not yet clear. There is hence a need to provide context relevant cost-benefit estimates for farmers and stakeholders. The main objective of this study is to provide farm level cost benefit analysis of using autonomous mechanical weeding in the case study area. The costs and benefits associated with the R4C robotic weeding system were evaluated against existing practices of chemical weeding and mechanical weeding using conventional tractor.

Methods

This study employs a farm-level cost-benefit model from the farmer's perspective. Major components of the economic model include operation schedule and farm characteristics, vehicle and implement performance characteristics; agronomic, weather and labor availability constraints; investment; robot autonomy and human monitoring/supervision; labor time and transport; and input consumption. Induced effects such as soil compaction and health risk are under consideration but not included in the current results due to lack of estimates.

In the French LSP, CEOL robot, which is developed specifically for vineyards, is used. CEOL is a diesel-powered autonomous robot suited for vineyard weeding. CEOL has a length of 1.7 meter, adjustable width of 0.72-1.1m, track width of 18cm, and lifting capacity of 300 kg. Its positioning and guidance box (AGCbox) is guided by GNSS RTK with centimetre precision (AgreenCulture, 2022). It has autonomous operating speed of 6 km/hr and remote-control range of 100 meters. It is equipped with safety sensors (sensitive bumper and obstacle detection).

The current study focuses only on weeding with-in rows because CEOL is not used for between-row weeding. **Error! Reference source not found.** shows implements and robotic p latform used for the French LSP. The same implements are used for the conventional and robotic system, but the later also includes sensors, software and supporting systems needed for full functionality of an autonomous system.

Serrated disc

Inter-vine knives

CEOL robot with implements attached to it

Harrow disc

Kress fingers

Figure 1 Implements and robotic platform at French LSP

Table 1 shows an operation schedule and the implements used for each operation. Chemical weeding is done 3 times during a production season (November, March and June) with glyphosate as the main product used.

Table 1 Mechanical weeding schedule

Weeding operation	Implement used	November	February	March	April	May	June	July
Ridging	Serrated discs	1		1				
Cut weed roots	Inter-vine knives		1		1			
Hoe the soil	Harrow disc*					1		
Scrap soil surface	Kress-fingers						1	1

* Also called Lump-breaker discs

Cost estimate includes capital cost (for vehicles, implements, and sensors) and operating cost (labor, fuel, herbicide, water, transport, soft wares, and repair and maintenance (R&M). Labor hours for the robot consider 15% human operation. It is assumed that a person supervising/monitoring a robot can use 75% of the time doing other tasks (e.g., field monitoring, planning, etc).

An attempt was made to incorporate a range of relevant aspects in the estimation of costs and benefits of the systems considered. A very fundamental concept having serious implication in the cost estimation is working capacity (worked area per time unit also referred to as area capacity. It is calculated as: $AreaCap = \frac{w\ .\ s\ .\ FE}{10}$, where $AreaCap$ = area capacity (ha/h); *w*= working width; and *s*= working speed (km/h) and *FE*=field efficiency (assumed to be 70%). Transport time per hectare per operation day was calculated by dividing estimated transport time from barn to field and between fields by the farm area that can be operated per working day for the respective systems considering agronomic, labour availability and weather constraints. Annual ownership cost includes depreciation cost, interest cost, housing and insurance. Housing and insurance costs are each assumed to be 1% of vehicle purchase price. Operating cost includes cost of labor, fuel, transport, herbicide, water to make spray solution, software and utilities, and repair and maintenance costs. In line with (Maria G. Lampridi, 2019; Vahdanjoo, et al., 2023), repair and maintenance costs were estimated as: $RM_{cost} = RF_1 * \left(\frac{h}{1000}\right)^{RF_2} * PP$; where RM_{cost}=repair and maintenance cost (€); *h*=accumulated working hours of machinery (h); RF_1 and RF_2 are repair and maintenance factors; *PP*=purchase price of machinery (€). RFs used for vehicle and implements are (0.003, 2) and (0.17, 2.2), respectively.

Investment cost (vehicle and implements), assumed life time and working capacity (speed and width) of vehicles/platforms for the respective cases under comparison are provided in **Table 2**.

Table 2 Vehicle lifetime, investment cost and operating features

Parameter	Tractor chemical weeding	Tractor mechanical weeding	Robot mechanical weeding
Vehicle life time in years	15	15	10
Vehicle available hours per year	1067	1067	1000
Vehicle investment (€/unit of vehicle)	90000	90000	110000
Implements investment (€)*	14000	13050	13150
Working width (m)	4	2	2
Working speed (km/h)	8	5.75	4.5
Available (workable) hours per day for weeding operation (h)	6	8	10

*In addition to implements shown in Figure 1, the robotic system also includes sensors (speed and work quality monitoring sensors). The only implement for the chemical weeding case is the sprayer (including tank).

Net Present Values (NPV) are calculated using standard formula real discount rate of 4%. The study adopted a partial budget approach where only costs and benefits that are believed to vary between the conventional and robotic systems are considered.

Data used in the economic model were compiled from several sources: literature, R4C project internal documents, discussions with project partners (expert opinion), and historical farm account data. Most of the operation parameters (schedule, working speed and width, etc.), input consumption (labour, fuel, herbicide), investment, price (input price + crop price), yield was provided by Terrena, which is a farm advisory company implementing the R4C LSP in France. Data on accounting parameters, indicators for & regulation of socio-environment impacts and access modes to technology and know-how were compiled from a combination of literature review and expert opinion. Given that the robotic system is at an early yet promising stage of development, some of the model parameters involve uncertainties (e.g., investment cost, supervision time, work capacity). To partly account for these uncertainties, sensitivity analyses have been conducted.

The following working assumptions were made for the basic scenario:

- Apart from weeding, other management practices remain the same.
- Either chemical or mechanical weeding but not a combination
- Crop yield and quality is the same under robotic and conventional systems.
- At current state of technology (and in the coming few years), a person can remotely supervise only one robot during farming operation.
- No extra insurance and storage cost for robotic implements.

Results

The economic calculations are done for a reference farm of 30 ha with average field size of 5, and average 'field to field' and 'farmstead to field' distance of 2 km. As can be read from **Table 3**, the robotic system generates relatively higher annual NPV compared to conventional mechanical weeding (€1265 versus €1165). Labor use and fuel consumption is also considerably reduced by about 29% and 69%, respectively. The latter is due to the big difference between per hectare fuel consumption of the reference tractor and CEOL robot for the target operation (15 L versus 4 L).

Table 3 Results from basic scenario

	Measurement unit	Chemical weeding: Tractor	Mechanical weeding: Tractor	Mechanical weeding: Robot
Operation hours	h/ha/yr	1.12	8.93	10.36
Area capacity per day	ha/day	13.44	6.44	6.3
Labour use	h/ha/yr	2	10	7
Fuel consumption	L/ha/yr	20	116	40
NPV	€/ha/lifetime	13747	12772	10008
NPV per annum	€/ha/yr	1237	1149	1234

Due to the 'same yield' assumption, the difference in net benefit comes from differences in cost among the cases considered. Thus, understanding differences in the composition of cost components is important. In the case of the robotic system, ownership cost accounts for about 55% of total cost in wide contrast to conventional chemical weeding (17%). Owing to longer use hours of machinery, R&M cost accounts for a considerable share in the case of mechanical weeding. The fact that the share of R&M cost for robotic mechanical weeding compared to conventional mechanical weeding is relatively lower does not mean that R&M cost per year is lower under the robotic system. It is rather a reflection of shorter discounting period for the robot given the functional form used to calculate R&M cost which grows exponentially with the accumulated hours of machinery use. For the mechanical weeding cases, fuel cost accounts for only 5% and 14% of total cost under respectively the robotic and conventional systems, whereas the corresponding share of labour cost is about 21% and 27%. Results from sensitivity analysis (not reported in this paper) show that the relative economic attractiveness of the robotic system (as compared to conventional practice) is sensitive to changes in investment cost, working speed, fuel and labour price, among others.

Discussion and Conclusion

With possibly lower investment cost for sprayer, and few operation repetitions needed per season, chemical weeding could have significantly lower direct economic cost for farmers.

However, the growing pressure against its use (owing to social and environmental costs) is shifting attention towards mechanical weeding. This study intended to assess the potential of a robotic system to help tackle the labour challenge in an economically viable manner for farmers. Under the working assumptions and baseline data used for this study, the robotic system significantly reduces labour and fuel use compared to mechanical weeding with tractor. Relative economic attractiveness of mechanical weeding with robot (compared to conventional system) is sensitive to changes in working speed, investment cost, and prices of labour and fuel, among others.

The findings show that ownership as well as repair and maintenance costs account for a significant share of total cost for the robotic system implies that marginal reductions in investment costs for the robotic system would significantly improve its net benefit to farmers. Given the functional form and parameters used in the estimation, R&M costs appear to be high. This needs to be validated based on real R&M cost data possibly from the case study area. Further investigation is underway (in close collaboration with local partners running the R4C experiment) to gain improved data inputs especially related to the robotic system.

Further advances in sensor technologies, communication platforms, better internet connectivity on farms, etc., would create conducive environments for robotic solutions and bring about rewarding benefits for farmers and stakeholders. Long-term success of robotic systems of course depends on accessibility of complimentary services (such as robot servicing, data analytics), clear regulations and compliance regarding data ownership, context-relevant market models, etc., all calling for quality collaboration among stakeholders.

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Effects of agricultural productive services on fertilizer reduction and efficiency increase: theory and evidence from China

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Abstract

Reducing fertilizer and increasing efficiency are inevitable requirements to solve the structural contradiction of agricultural development and promote the sustainable development of agriculture. A relatively high proportion of small farmers is the basic pattern of Chinese agriculture, and small-scale and decentralized management are generally regarded as the key organizational and institutional obstacles to reducing fertilizer and increasing efficiency. This paper reveals the internal logic of organizing production resources through agricultural productive service agent to achieve the desired goal of fertilizer reduction and efficiency increase in terms of household management organization quality. Using the provincial (city and district) panel data in China from 2000 to 2020 to empirically estimate the impact of agricultural productive services on fertilizer use intensity and fertilizer application efficiency. The results show that agricultural productive services can significantly reduce the intensity of chemical fertilizer use and improve its efficiencies, which has an obvious effect of fertilizer reduction and efficiency increase. After using the instrumental variable method to overcome the potential endogeneity problem of the model, the basic conclusions still hold. Further heterogeneity analysis shows that the organization of production resources through inter-regional services does not have a significant effect on fertilizer reduction and efficiency increase. Based on these, this paper draws relevant policy implications for promoting fertilizer reduction and efficiency increase based on agricultural productive services.

Keywords

Fertilizer reduction and efficiency increase; Agricultural productive service; Agricultural cross-regional services

Presenter Profile

I am a PhD student from College of Economics and Management, Huazhong Agricultural University. I am mainly engaged in research on agricultural technology and economics, and have a certain degree of knowledge in this field. This study reveals the internal logic of organizing production resources through agricultural productive service subject to achieve the desired goal of fertilizer reduction and efficiency increase in terms of household management organization quality. It also provides reference suggestions for promoting fertilizer reduction and efficiency improvement based on agricultural productive services.

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A multi-objective optimisation analysis of autonomous mechanical weeding in arable farming

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Extended abstract

Introduction

Weed control is an essential operation in commercial agriculture. Weeds compete with crops for sunlight, air, space, moisture and nutrients, and harbour vertebrate and invertebrate pests, resulting in reduced crop yields and quality (Epee Misse *et al.*, 2020; Perez-Ruiz *et al.*, 2012; Quan *et al.*, 2022). Due to their relatively low cost and modest labour requirements, herbicides have become the most common weed control strategy in conventionally grown row crops (Griffin and Lowenberg-DeBoer, 2017; Pandey *et al.*, 2021). Despite providing economic benefits, the persistent use of herbicides bears several ecological and social risks. These include a decline in off-target plant species, contamination of soil and water resources, soil acidification, threats to workers' safety, and consumer hazards caused by herbicide residues in food (Bates *et al.*, 2012; Jacquet *et al.*, 2022; Quan *et al.*, 2022; Wei *et al.*, 2010).

A reduction in ecosystem services and the development of herbicide-resistant weed populations perpetuate herbicide use in a negative feedback loop (Bates *et al.*, 2012; Kunz *et al.*, 2018; Pandey *et al.*, 2021; Quan *et al.*, 2022; Wei *et al.*, 2010). For, example, a study by Varah *et al.* (2020) reported that resistance of *Alopecurus myosuroides*, commonly known as black-grass, has an annual cost of £0.4 billion in England. In the UK, the development and adoption of innovative weed control practices are supported by regulatory frameworks that aim to mitigate the risks associated with pesticide use. For example, the Plant Protection Products (Sustainable Use) Regulations of 2012 required the UK Government to enact a National Action Plan promoting the sustainable use of pesticides (DEFRA, 2013; UK Government, 2012). Considering the heavy reliance on herbicides of UK farmers (FERA Science Ltd, 2021), solutions such as autonomous mechanical weeding (AMW) may play a key role in the UK transition to agroecological farming. However, trade-offs with short-term profitability and other farm-level goals must be considered.

The hypothesis of this study is that, regardless of the ecological orientation of a farmer decision-maker, the replacement of herbicide broadcasting (HB) with AMW depends on the following economic factors: (i) the cost of the AMW equipment; (ii) the reduced labour needs in autonomous farming; (iii) yield penalties resulting from factors linked to the AMW system; and (iv) premium prices paid for herbicide-free crops.

Methods

To investigate the interactions between decision-maker types and the adoption of AMW on UK arable farms, the present study built a multi-objective optimisation tool based on the Hands Free Hectare Linear Programming model (HFH-LP) developed at Harper Adams University (see Lowenberg-DeBoer *et al.*, 2021). The model is based on a weighted goal programming technique (Hazell and Norton, 1986: p.88), and coded via the General Algebraic Modelling System (GAMS Development Corporation, 2023). It uses UK farm budget data from Agro Business Consultants (2022) and Redman (2022). The multi-objective HFH-LP model considers three farm-level goals, namely: ROLMRT[1], soil compaction, and greenhouse gas emissions. These goals are combined with four weed control treatment scenarios and two sets of objective function weights reflecting the economic and ecological orientation of the decision-maker. The modelled farm is a 295-ha farm located in the UK West Midlands and it is divided in 12-ha fields. 295 ha is the average farm size above 100 ha in England (DEFRA, 2022), while 12 ha is the average field size in the UK West Midlands (ESDAC, 2023). The model allocates farm resources in such a way that decision-maker utility is maximised, and constraints related to factors of production are not violated. The objective function used in the model is as follows:

$$\min G = w_1\left(\frac{G_1^-}{G_{opt}}\right) + \sum_{g=2}^{3} \frac{w_2}{2}\left(1 - \frac{G_g^-}{G_{wrs}}\right) \quad (1)$$

Where, G = the utility loss of the decision-maker to be minimised by the model; w_1 = the economic weight assigned to the ROLMRT goal; w_2 = the ecological weight assigned to the two ecological goals; G_{opt} = the maximum ROLMRT that can be achieved by the modelled farm business; G_1^- = the ROLMRT deviation from G_{opt}; G_{wrs} = the highest levels of deep soil compaction and direct GHG emissions that can be generated on the modelled farm; G_g^- = the deviations from G_{wrs} for the two ecological goals; g = goal indexes, with g = 2 for deep soil compaction and g = 3 for direct GHG emissions.

The crops included in this analysis are winter wheat, spring barley, winter oilseed rape, spring and winter field beans, and sugar beet. The equipment sets used in the four scenarios for operations other than weed control are equally divided between conventional (i.e., human-driven) and autonomous. The different weed control strategies assumed in the scenarios are: (i) conventional HB in crops other than sugar beet + AMW in sugar beet; (ii) AMW in all crops; (iii) autonomous HB in crops other than sugar beet + AMW in sugar beet; and (iv) AMW in all crops. The AMW system used is the FD20 seeding and weeding robot developed by FarmDroid Aps in Denmark (FarmDroid Aps, 2023). Decision-maker types are defined through three weight combinations i.e., $w_1 = 1$, $w_2 = 0$ (a profit-oriented farmer); $w_1 = 0.8$, $w_2 = 0.2$ (a moderately ecologically oriented farmer); and $w_1 = 0.6$, $w_2 = 0.4$ (a strongly ecologically oriented farmer).

Results and Discussion

The results of this study highlight some of the technical and economic difficulties for cereal and oilseed farmers willing to move away from HB practices. Performing AMW in narrowly spaced crops with technologies such as the FD20 is currently infeasible. Wider crop rows and the economic infeasibility of hiring labour for manual weeding follow-ups in low-value crops result in significant yield penalties. The FD20 is electrically powered and allows for herbicide-free farming. However, the reduced fuel and herbicide uses in the herbicide-free scenarios (Scenarios 2 and 4) do not compensate for the increased carbon footprint per kg of crop produced when yield penalties are considered. The ecological benefit identified in this study is the absence of deep soil compaction when using the FD20 in combination with small-scale autonomous equipment. When the FD20 is used in conjunction with large-scale conventional

[1] *ROLMRT = Return to operator labour, management, and risk taking.*

equipment, deep soil compaction is always maximum regardless of how intensively the FD20 is used. Key results for the three farm-level goals under analysis and the farmer utilities achieved across scenarios and decision-maker types are presented in Table 1.

Table 1 – ROLMRT, deep soil compaction, direct GHG emissions and farmer utility by scenario and decision-maker type

SCENARIO	ROLMRT (GBP)	Deep soil compaction (Mgkm/ farm)***	Direct GHG emissions ($kgCO_2eq$/ farm)	Utility by decision-maker type****		
				$w_1 = 1$ $w_2 = 0$	$w_1 = 0.8$ $w_2 = 0.2$	$w_1 = 0.6$ $w_2 = 0.4$
1. AMW* (sugar beet) + HB** (other crops), Conv. Eq.	43,744	1,841	19.9	42%	41%	40%
2. AMW* (all crops), Conv. Eq.	-18,060	1,841	20.7	-17%	-6%	5%
3. AMW* (sugar beet) + HB** (other crops), Auto. Eq.	105,333	0	20.1	100%	98%	95%
4. AMW* (all crops), Auto. Eq.	51,738	0	21.0	49%	57%	64%

Note: *AMW = Autonomous mechanical weeding. **HB = Herbicide broadcasting. ***Mgkm = tonne kilometre; this is a proxy for the pressure on the soil exerted by agricultural equipment; for more information on this measure, see Stoessel *et al.* (2018). ****ROLMRT, deep soil compaction, and direct GHG emissions values do not vary across the three decision-maker types except for ROLMRT and direct GHG emissions in Scenario 4. However, values for Scenario 4 only differ by a maximum of £11 for ROLMRT and 0.1 $kgCO_2eq$ for direct GHG emissions. The values shown in table are for a strongly ecologically oriented decision-maker type.

Both conventional and autonomous growers would obtain higher utility by restricting the use of the FD20 to high-value crops such as sugar beet, especially when grown for a premium market. For conventional farmers, the average level of utility obtained when adopting AMW does not appear to be sufficiently high to justify its use. The higher utility in the autonomous scenarios is mainly due to higher net returns achieved thanks to the reduced labour requirements and lower equipment costs, and because of the absence of deep soil compaction when field operations are conducted with small-sized autonomous equipment. Such a higher utility indicates that autonomous farms are more capable of absorbing additional costs for specialised equipment such as the FD20. This could be even more the case if the weeding efficacy of the FD20 was improved, fleet supervision of multiple FD20 units was legally and technically possible, and on-farm practices mitigating GHG emissions to achieve net zero were performed.

Sensitivity analyses indicate that the monetary penalties resulting from AMW in low-value crops could be recovered if the modelled farm was paid herbicide-free premiums of 37% in Scenario 2 and 21% in Scenario 4. Alternatively, the achievement of competitive production costs in the herbicide-free scenarios would require a reduction of the FD20 purchase price by more than 100%. This highlights the issue of the FD20 being a specialised piece of equipment. Spreading its cost across a wider range of field operations or using a less costly mechanical weeding tractor implement would result in substantially lower production costs.

Regardless of the ecological orientation of the farmer decision-maker, the following economic factors play a role in replacing herbicide broadcasting with autonomous mechanical weeding: (i) AMW equipment cost; (ii) lower labour requirements; (iii) yield penalties resulting from factors linked to the AMW system; and (iv) herbicide-free crop price premiums. Thus, the results of this study are in support of the declared hypothesis.

Keywords

Multi-objective optimisation; Profitability; Soil compaction; Greenhouse gas emissions; Autonomous mechanical weeding; Arable farming.

Presenter Profile

Elias Maritan is a Research Associate at Harper Adams University working under the supervision of Prof. Karl Behrendt and Prof. James Lowenberg-DeBoer. His research uses linear programming methods to analyse economic implications of autonomous farming. Maritan is currently involved in the Digitalisation for Agroecology project (D4AgEcol | https://d4agecol.eu/) co-funded by UKRI and the EU's Horizon Europe research and innovation programme.

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Consumer acceptance of grass and/or grass-derived ingredients

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Extended Abstract

The Pasture to Plate (P2P) project led by Harper Adams University (HAU) and University of Bath has received £2m funding from UK Research and Innovation/Biotechnology and Biological Sciences Research Council (UKRI/BBSRC). Over 3 years the project will investigate technology which produces food products from grass. Grassland makes up over 70% of all UK agricultural land, with substantial quantities of grass never used. At present, the only way of producing food from grass is to convert it into meat and milk by feeding it to animals. This is a very inefficient process as animals typically convert only 5% of the grass food fractions into meat and 10% into milk (total system efficiency). The overall aim of this project is to develop a chemical and biotechnological process for converting grass into a range of novel food ingredients that will replace environmentally damaging imports. As this process is ten times more efficient than producing meat, it could massively increase UK food output and has the potential to create a new multi-billion-pound UK food industry.

Fifty percent of the UK's harvestable grassland is underutilised and has the potential to produce more high protein edible material than the UK's annual, total meat, dairy, and egg production combined, in addition to providing several times more food oil than the UK currently imports. Better utilisation of grass as a food source, using the P2P approach, could increase UK food production to the point where the UK becomes a net food exporter by 2050, helping ease the impact of future disruptions to international supply chains, and helping reduce greenhouse gas emissions. The extraction process produces a wide range of edible food fractions including oils, proteins, essential vitamins, and carbohydrates. These have the potential to rapidly replace imported ingredients such as soy and palm oil in all mainstream, vegetarian, and vegan foods, dramatically reducing food miles, transport costs, fuel emissions, and the commercial incentive to destroy rainforests.

HAU will lead the social science part of this project. Assessing consumer readiness to engage with grass products in food is paramount to the success of the project. Using social life cycle assessment (LCA) and working with our industrial partners, we aim, in the short-term, to determine consumer and industry acceptance, as well as demonstrating the feasibility of these edible fractions as replacements in a range of plant-based dairy and meat substitute and other food products (Work Package 5: Social Science: Consumer acceptability and market positioning). This will include a UK-wide study on consumer attitudes to the use of grass derived food fractions as ingredients. It will also assess food industry readiness to adopt novel grass-based food ingredients, and, in a collaborative study with Saputo and our other commercial partners, evaluate which food products would be most suitable for the inclusion of grass derived food fractions as ingredients.

Consumer perceptions are key when introducing new food products to the market, especially so when novel technologies are being used (Herrera and Blanco, 2011). Evidence from previous research attempting to introduce novel technologies in food production suggests that grass for human consumption may struggle to gain positive perceptions. Exploring this further, including its application, education and marketing techniques is an important aspect of this project. This is important as research shows that encouraging people to try a novel food product for the first time is one of the biggest challenges when introducing new, unfamiliar food technologies (Manohar, Rehman and Sivakumaran, 2021). It has also been found to be beneficial to market the tastiness of a product to potential consumers to encourage them to try it for the first time rather than health benefits (Manohar, Rehman and Sivakumaran, 2021).

The food and drink industry is utilising an increasing number of alternative protein sources due to improvements in technology and the creative use of existing protein sources (NIRAS, 2023). However, consumers have been found to be reluctant to uptake plant-based alternative foods in some cases, likely due to the options currently on the market not proving that they are better than meat or animal product alternatives. This shows that there is a need for products which take into account consumers key requirements if wanting to encourage consumers to reduce meat consumption further. These requirements have been identified as healthy, environmentally sustainable, have high welfare and not overly processed/perceived to be natural.

The output from the research being undertaken in work package 5 will include a paper investigating consumer willingness and objections to the concept of grass as a food ingredient based on survey and focus group studies. An initially broad survey will gain an overview of consumer perceptions, followed by full consumer focus groups and sensory panels as the products develop. A paper surveying food industry professionals' views of the opportunities, and barriers to, the inclusion of grass fractions in food products from both a technical standpoint and also encompassing brand perceptions will be produced. This will include representative industry views from all sections of the food chain downstream of the farm. It will leverage the consortia's network of associated food manufacturing and food service businesses that may have applications for, or interest in, grass food fractions as ingredients. Later in the project, a paper on consumer acceptance of foods made with grass extracts including data from taste panels drawn from a statistically representative pool of consumers by age, gender, and dietary choices, including vegetarians and vegans, will evaluate food products incorporating the different grass-derived food fractions. This will assess acceptability of taste, odour, texture and appearance with a focus on quality and willingness to buy and consume when commercially available.

The first survey is aimed at understanding UK consumer attitudes to the use of grass-derived food fractions as ingredients in foods and their readiness to adopt novel grass-based food ingredients into their diets. The survey will assess the consumer intentions to consume / include grass-based proteins in their diet and its influencing factors. Although it is most likely that the majority of consumers eat a sufficient amount of protein, the demand for protein alternatives continues to increase as meat and animal product consumption decreases. These trends are relatively prevalent across all demographics, along with increasingly widespread health trends for high protein diets. This survey will build upon initial findings from a pilot study that found 76.2% of respondents agreed or strongly agreed that drastic changes must be made in order to feed the 2050 population. Younger participants (age 18-24) were most open to the benefits of novel food technologies however it also identified the oldest demographic (65+) had a significant interest in the sustainability of food innovations. From the while sample 41.7% of respondents were willing to try grass-derived proteins while 24.8% and 33.6% answered no and maybe, respectively. Respondents agreed with both positive and negative statements regarding grass-based foods reinforcing the notion that consumers are interested in the potential benefits of the technology but also have reservations such as digestibility and enjoyment.

The proposal for the presentation at the conference would be to present an overview of the P2P project, the plan for the social science research encompassing Work Package 5 and presentation of the data collected in the initial consumer survey of intention.

Keywords

Grass, consumer acceptability, grass-derived protein, food technology, protein alternative

Presenter Profile

Dr Helen Pittson is a Senior Lecturer in Human Nutrition at Harper Adams University. She is the work package leader for work package 5. Her work explores dietary healthy lifestyles and behaviour change in different groups. She also works in consumer behaviour particularly related to plant-based diets and alternative nutrient sources.

Dr Anne Mumbi is a senior post-doctoral researcher in the pasture to plate project at Harper Adams University. She has a background in environmental engineering and science and holds a PhD from the School of Economics and Management of Kochi University of Technology, Japan and a PhD in Environmental Engineering from Tongil University, China. Her key specialization areas and interests are risk management, economics, environmental science, water resources and social sciences. She is also involved in teaching research skills level 7 at Harper Adams University.

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