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Global Institute for Agri-Tech Economics,

Food, Land and Agribusiness Management Department,

Harper Adams University

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

Global Institute for Agri-Tech Economics (GIATE)
Food, Land & Agribusiness Management Department
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Laurens Klerkx

Knowledge, Technology and Innovation Group, Wageningen University, Hollandseweg 1

6706KN Wageningen, Netherlands

Abstract

In this keynote presentation for the Adopting Agri-Tech Innovations session at the 4th Symposium on Agri-Tech Economics for Sustainable Futures, I will outline how technology adoption has been viewed from technology, individual and system-oriented perspectives. Looking at strengths and weaknesses of the different approaches, and their complementary, I will show how these approaches may inform different sorts of readiness in view of the adoption of (potentially) transformative agri-tech innovations, such as precision farming technologies and robotics. Drawing on recent frameworks, and illustrated with some examples, I will argue that having a broad consideration of different sorts of readiness of the technology, individual user, regulatory and enabling environment can help to better grasp and navigate the complexity of agri-tech innovation adoption processes. The presentation will conclude with some reflections on what contemplating different sorts of readiness implies for innovation systems, in terms of organizing and supporting technology design and development, and its wider dissemination and scaling into farming practice.

Presenter Profile

Laurens Klerkx Laurens Klerkx is Full Professor of Agrifood Innovation and Transition at the Knowledge, Technology and Innovation Group of Wageningen University, The Netherlands, of which he has been part since 2002. He obtained his PhD from the same university and is an expert in the field of (agricultural) innovation studies, doing social science research and teaching and supervision (at Bachelor, Master and PhD level). Laurens (together with colleagues and his team of PhD students and postdocs) has done research in many countries, such as The Netherlands, England, New Zealand, Vietnam, Tanzania, Kenya, Ghana, Chile and Mexico. Throughout his career, Laurens has (co-)authored and published more than 120 articles in international peer reviewed journals. His work informs policy makers, through contributions to policy and practice-oriented publications and direct engagement through invited presentations with organizations like the World Bank, the European Commission, the Food and Agricultural Organization of the United Nations (FAO), the Organization for Economic Cooperation and Development (OECD), and the United Nations Commission for Trade and Development (UNCTAD). Furthermore, he frequently interacts with practitioners through presentations and workshops on systemic perspectives on innovation and the implications for research and development professionals.

Laurens is, editor-in-chief of the Journal of Agricultural Education and Extension, editor of Agricultural Systems, associate editor of Agronomy for Sustainable Development and a member of the editorial board of the International Journal of Agricultural Sustainability. He is a member of the steering committee of the International Farming Systems Association, member of the Science Advisory Panel of AgResearch Ltd (New Zealand) and has held several advisory positions for several research and innovation programmes and projects in Europe, New Zealand, Australia, and Latin America.

Adoption potential of digital and automation technologies in smaller-scale livestock farming

Andreas Gabriel and Johanna Pfeiffer

Digital Farming Group, Institute for Agricultural Engineering and Animal Husbandry, Bavarian State Research Center for Agriculture (LfL), Ruhstorf a.d. Rott, Germany.

Abstract

Media reports in Germany convey the impression that digitalization has already made its way onto almost all farms. However, a recent online survey on the adoption of digital technologies on Bavarian farms clarifies that the reality is different in the small-scale agricultural context of Bavaria. The farmer survey yields a total of 2,390 fully completed and analysable questionnaires, of which 1,376 participants were livestock farmers. Of these, 888 operate in dairy production with an average herd size of 48 cows. With information on firmographics, socio-demographics, and adoption behaviour for seven selected digital technologies for livestock farming, it is possible to analyse adoption rates depending on herd size and common technology combinations. Results show that Bavarian livestock farms cannot be described as exceedingly digitalized but show interest in investing within the next years in technologies such as automatic milking systems, barn cameras or barn robotics. For example, on many dairy farms, automatic milking systems are an entry technology that triggers the use of other robotic or digital technologies. Herd size, type of housing (tethering vs. loose housing), and professionalization (full-time vs. part-time operations) are decisive for the diffusion of technologies. However, there is future potential for small-scale agriculture to become more digital if a quick return on investment can be achieved for the new technologies or the necessity of a technical transformation is reinforced by changing regulatory frameworks.

Keywords

Adoption rates, dairy farming, digital technologies, livestock farming, online survey, small-scale agriculture

Presenter Profiles

Andreas Gabriel joined the Institute for Agricultural Engineering and Animal Husbandry in 2018. With his experience in empirical social research, his work in the Digital Farming Group focusses on investigating social acceptance of digital technologies and their adoption in agricultural practice.

Johanna Pfeiffer is a researcher at the Institute for Agricultural Engineering and Animal Husbandry, Bavarian State Research Center for Agriculture. Her focus is on the comprehensive assessment of digital technologies for dairy farming. In particular, she works on animal welfare, social and economic aspects of animal sensors for dairy farming.

Introduction

The adoption of digital livestock farming technologies

Livestock farmers in mid- and western Europe have access to an increasing number of market-available applications. A broad range of digital technologies serves both as decision-making support tools and to improve more efficient processes in crop and livestock production (Paustian & Theuvsen 2017). The share of users of precision agriculture in general in developed countries varies widely among countries (Lowenberg-DeBoer & Erickson 2019), and sporadic on regional level (Pfeiffer et al. 2021; Schimmelpfennig & Ebel 2016; Llewellyn & Ouzman 2014). Adoption rates also vary regionally depending on the prevailing regional production intensity and operational structures (Eastwood & Renwick 2020; Gargiulo et al. 2018).

Adoption of digital dairy farming technologies is mainly driven by a desire for relief from physical labour and for support in herd management, especially in larger herds (Dela Rue et al. 2019; Gargiulo et al. 2018). Consequently, there are technologies that serve primarily to automate a process as well as technologies that are primarily intended to collect data of individual cows (Dela Rue et al. 2019). The milking robot is, however, a good example of a simultaneous fulfilment of both purposes. In the case of automatic milking systems, farmers are opting for the use of such systems due to increased working time flexibility (Straete et al. 2017) and accompanying improvements in animal welfare through better monitoring of dairy farm operations (Vik et al. 2019; Latvala & Pyykkönen 2005). The number of dairy farms using automatic milking systems has increased worldwide over the last two decades (De Koning 2010). While adoption rates in Finland, UK and Canada were reported to be below 10 %, Denmark, Sweden, Iceland, the Netherlands, and Norway had adoption rates of 10 to 30 % (Sigurdsson et al. 2019; Vik et al. 2019; Barkema et al. 2015).

Further studies on the adoption of digital technologies in dairy farming showed a great relevance of automation technologies such as automatic drafting and plant and yard washing in New Zealand and Australia. The study by Gargiulo et al. (2018) also revealed a significant increase in the adoption of digital technologies with increasing herd size in Australia. Data capturing technologies such as sensors on the dairy cow for oestrus detection or health monitoring have, however, only played a minor role in these countries so far (Dela Rue et al. 2019, Gargiulo et al. 2018). This can be explained by their low-cost pasture-based farm systems, accompanied by large herd sizes (see Dela Rue et al. 2019). Adoption studies conducted in the United States (Borchers & Bewley 2015), Switzerland (Groher et al. 2020) and Germany (Pfeiffer et al. 2021) showed that data capturing technologies are already playing an increasing role in these countries. The surveyed dairy farmers in these countries stated that in particular technologies for automated collection of data on the milking process (daily milk yield, milk components) and individual animal behaviour and condition (e.g., activity and rumination) are in use on their farms.

Digital technologies in small-scale livestock production

Small-scale agriculture is a loosely used term and defined differently in different regions of the world (Bosc et al. 2013). It is used in multiple respects for smallholder agriculture in developing countries with less than two hectares of farmland and directly connected to family farming (Graeub et al. 2016). The FAO defines the term as “family and farm business are linked, co-evolve, and combine economic, environmental, social, and cultural functions.” (FAO 2013, p. 2). In Europe, small-scale agriculture is used in a different context as the average EU-

28 farm size in 2016 was 16.6 ha, although 85 % of farms do not even meet this threshold (Eurostat 2019). In Germany, the national average farm size is around 60 ha, whereas farms in Bavaria, the south-eastern federal state of Germany, only own 35 ha on average (StMELF, 2020). Being characterized by smaller structures in contrast to regions especially in the north and east of the country, Bavaria has more than 100,000 farms, thus representing almost one third of all farms nationwide (StMELF 2020). The small-scale agricultural sector in Bavaria is additionally characterized by frequent operation as family farms and comparatively low degrees of specialization.

About two thirds of the farms in Bavaria have at least one other source of income (StMELF 2020). In addition to the production of agricultural products (e. g., field crops, feeding production, animal husbandry), alternative businesses of energy, forestry, services for other farmers or municipalities, processing and direct marketing of agricultural products, and agro-tourism provide additional revenues for 53 % of Bavarian farms (Destatis 2021). Nonetheless, animal husbandry remains an important source of income for Bavarian farmers as almost three out of four farms in Bavaria operate livestock production, including 27,500 dairy cow farmers and around 4,500 pig farmers. The profitability of dairy production in Germany as a whole is estimated at around 40,000 Euros per annual work and family work unit (EC, 2021). This means that labour profitability is significantly lower than in countries such as Denmark, the Netherlands, Italy or Ireland. In terms of income per cow, Germany has the second highest income in the EU behind Italy.

Aim of the study

A lack of scientific research on adoption rates of digital technologies in dairy farming, combined with an existing variation in market-available technologies (see e.g., Stachowicz and Umstätter 2020) and farm conditions, highlights the requirement for further in-depth adoption studies. However, knowledge about adoption rates of digital livestock and dairy farming technologies and farmers' interest in future investment is of high importance for many stakeholders involved in the sector, pointing the scientific community towards identifying research needs, providing feedback to the industry on farmers' (future) interest in their technologies, and thus supporting farmers on their way to digitalizing their enterprises. In general, expectations of stakeholders in the dairy industry are that digitalization will offer opportunities for farmers, animals, and the environment through animal-friendly, competitive, and sustainable production. For example, the use of automation and sensor systems enables farmers to reduce labour requirements and improve management of monitoring of herds (Borchers &Bewley, 2016; Eastwood et al., 2012).

The aim of our study is to determine the adoption rates of digital technologies in livestock and dairy farming in the smaller-scale agricultural context of Bavaria. The second aim is to analyse the dependence of technology adoption rates on herd size. In order to be able to support the digital transformation of agriculture (e.g., through funding, technical consulting, or product development), it is also important to determine common combinations of digital technologies used in agricultural practice and to identify structural barriers for implementing individual technologies.

Methods and data collection

An online survey of Bavarian farmers provides database for capturing the current level of use of digital technologies on Bavarian farms. Questionnaire structure and content were initially compiled based on existing questionnaires of PA adoption farmer surveys from the USA, UK, and Denmark (Erickson et al. 2017; DEFRA 2020, Danmarks Statistik 2018), and adapted to the situation of Bavarian agricultural practice. An initial revision of the questionnaire concept was carried out with experts from agricultural research, extension, and government agencies. This resulted in a preliminary version of the questionnaire, which was carried out in a Germany-wide pre-test employing a pre-quoted sampling procedure at the end of 2019 (n=591) (Gabriel et al. 2021). An extended pre-test was relevant, among other things, to define the terminology and classification of specific technologies for farmers. Studies in German-speaking countries have shown that terminology has an influence on the understanding of digitalization in agriculture (Reissig 2020), and unclear formulations themselves impact the acceptance of technologies (Schukat et al. 2019). The resulting findings regarding comprehensibility and technical implementation were used to adjust the questionnaire for the main survey in Bavaria. The final questionnaire comprised distinct question groups querying initially respondents' socio-demographics and farm structures (firmographics), followed by information on their use of and future investment plans for 31 selected digital technologies in crop and livestock farming. The structure of question groups and questions was adaptive, conditioned by the previously given answers of the respondents. This made it possible to design the questionnaire in a compact and user-friendly manner. Farmers who specialize in livestock farming or dairy farming, for example, were only confronted with the respective technologies during the survey process.

The entirety of Bavarian farms was accessed via the support and funding platform of the Bavarian State Ministry of Food, Agriculture and Forestry (StMELF), which is available online to all farmers, as applications for EU agricultural subsidies in Bavaria are submitted exclusively via this platform within a fixed period each year. The application period and access to the funding application platform in 2020 was possible from mid-March to mid-May (with an extension period until mid-June). The link to the survey was prominently displayed in the application portal together with introductory information explaining the purpose of the questionnaire, so that every applicant had the option to participate in the survey. In addition, after submitting the application form, a further reference to the survey was made through a pop-up window for each user. The survey link was available throughout the 89 days of the funding application period (including the extension period) and was accessible to the target population of 103,552 Bavarian applicants in 2020. Additional dissemination of the survey link via other media was omitted in order not to bias the probability of access. The use of cookies in the survey system (LimeSurvey V3.22, Hamburg, Germany) prevented multiple completion of the survey interviews.

A total of 3,739 participants started the questionnaire, of which 2,458 completed the seven consecutive groups of questions. Thus, the dropout rate was 34.3 %, with four out of five of the dropouts terminating participation early after the first few questions. The data set of complete responses was checked for plausibility (answer consistency) and quality (total response time). The final data set of 2,390 complete questionnaires could be used for analysis with SPSS Statistics 26 (IBM, Armonk, NY, USA). For the descriptive results illustrated in this paper, the total sample was reduced to livestock farmers including all kinds of livestock enterprises (dairy, beef, pigs and sows, poultry; n=1,376). Additionally, respondents operating dairy farms (n=888) and the subset operating loose housing systems (n = 540) could be analysed separately. Farmers' responses from the first two question groups of the questionnaire (1: socio-demographics and firmographics; 2: use of and future investment plans) were used to analyse current technology adoption rates, future investment plans, and technology combinations on Bavarian animal husbandry and dairy farms in particular.

Results

Sample description

Bavarian agriculture is still dominated by sole proprietorship (94 %, Destatis 2018), which is also reflected in the results of the subsample of livestock farms (Table 1). More significant differences can be seen in the ratio of part-time to full-time farms, as the sample contains a significantly higher share of full-time farms (64 %) than in official statistics for the total agricultural sector in Bavaria (38 %; StMELF 2020).

The type of operation plays a crucial role on farmers' motivation to use specific technologies (Mittenzwei & Mann 2017). Organic livestock farm managers participated in the survey proportionately more often (16 %) than the actual share of organic livestock farms in Bavaria, which is significantly below 10 %. Dairy farms in the sample are characterized with larger herds than official statistics indicate for the Bavarian average of about 40 cows for dairy production (StMELF 2020). In Bavaria, 37 % of dairy farms keep their animals tethered (status of 2020) which is also reflected in our sample (share of farms with tethering: 33 %). As use of digital technologies on farms operating tethering is limited compared to loose housing farms, information on housing type is decisive for the adoption of digital technologies.

Additionally, socio-demographic characteristics of the surveyed farmers depict the situation in the mostly family-run farms (Table 1). The distributions of age classes, gender, and level of agricultural education in the sample deviate only slightly from the data of the Bavarian statistics on the agricultural sector (Destatis 2018). The sample reveals a typical domination of male operators of Bavarian farms with more than 90 %. There are deviating distributions between the sample and official statistics regarding the age categories of the farm managers. In particular, the two highest age classes (50-59 years; 60 years and older) are much more strongly represented in the sample, while the age class from 40 to 49 years is proportionately underrepresented. An additional question for farmers older than 49 years about the arrangement of their succession reveals that six of ten farms are still confronted with an unclear situation. This aspect is of particular importance, as older managers without successors tend to resist investments, e. g. in disruptive technologies, and to reduce rather than increase production intensity (Huber et al. 2015; Troost & Berger 2016). However, a relationship between succession situation and adoption rate of digital farming technologies has not yet been demonstrated clearly (Paustian & Theuvsen 2017).

Table 1. Survey sample description of livestock farms (n = 1,376)

	Variable	Category	Frequencies abs.	rel. (%)
Farmo-graphics	Type of operation	Full-time	878	63.8
		Part-time	498	36.2
	Type of production	Conventional	1,133	83.8
		Organic	219	16.2
	Legal form of company	Sole proprietorship	1,222	89.2
		Partnership	147	10.7
		Others[a]	1	0.1
	Production categories[b]	Beef cattle (avg. 46 animals)	420	30.5
		Dairy cows (avg. 48 animals)	888	64.5
		Fattening pigs (avg. 325 animals)	190	13.8
		Breeding sows (avg. 89 animals)	60	4.4
		Fattening poultry (avg. 3,019 animals)	32	2.3
		Laying hens (avg. 231 animals)	231	16.8
		Others	208	15.1
	Housing type (only dairy farms; n=888)	Tethering	291	32.8
		Loose housing	540	60.8
		Others/mixed types	57	6.4
Socio-demo-graphics operator	Gender	Female	95	6.9
		Male	1,276	92.7
		Diverse	5	0.4
	Age	under 20 years old	1	<0.1
		20 - 29 years old	94	6.8
		30 - 39 years old	256	18.6
		40 - 49 years old	362	26.3
		50 - 59 years old	471	34.2
		60 years and older	192	14.0
	Farm education level	Skilled worker	414	30.1
		Agricultural master	323	23.5
		Agricultural technician	79	5.7
		University degree (agricultural programs)	73	5.3
		BiLa[c]	177	12.9
		Others[d]	310	22.5
	Succession arranged[e]	Not at all or situation unclear	397	59.9
		Yes, succession has been arranged	266	40.1

[a] e. g., partnership (legal company); cooperative; public limited company
[b] multiple answers possible; percentage of cases
[c] BiLa = Bavarian vocational training program for part-time farmers (state-supported; one-year training)
[d] Indications: business economist; mechanical engineer; banker; agricultural school; none; etc.
[e] answers from participants older than 49 years (n=663)

Technology adoption rates in livestock farming

For each of the seven queried digital technologies for animal husbandry, respondents were asked about their current use and whether they planned to invest in the short term (within 1 year) or medium term (with next five years). In addition, respondents were asked to indicate which of the technologies they use was acquired first and which is currently used most intensively on the farm (Table 2).

Table 2. Digital technologies in livestock farming and their shares of entry and intensive use

Digital technologies in animal husbandry	Cat.[a)]	in use	Entry technologies		Most intensively used technology	
		in % of category	abs.	*in % of users*	abs.	*in % of users*
Barn cameras	1	17.1	74	31.5	59	25.1
FMI (e.g., herd management software)	1	16.5	38	16.7	53	23.3
Behaviour monitoring sensors	1	12.4	21	12.4	38	22.4
Automatic milking system	3	15.2	72	53.3	121	89.6
Feed pushing robots	2	7.2	15	19.2	14	17.9
Slat cleaning robots	2	7.2	12	15.4	13	16.7
Automatic forage supply	2	3.0	10	30.3	12	36.4

[a)] Categories: 1= livestock farming (n=1,376); 2= beef and dairy (n=1,087); 3= only dairy(n=888)

It is apparent that low-cost digital technologies are most popular. Barn cameras have already been purchased and used by 17 % and farm management information software for livestock farming by more than 16 % of the farms in the sample. These two technologies are followed by behaviour monitoring sensors (including e.g., pedometers and rumination sensors) and automatic milking systems, which are in use on 12 % and 15 % of dairy farms surveyed, respectively. The use of slat cleaning robots, feed pushing robots and automatic feeding systems is rather limited at 7 %, and 3 %, which may be attributed to the fact that these technologies are comparatively younger and thus have been on the market for a shorter time.

There are differences between the surveyed digital technologies in terms of whether they are the first technology used on a farm. While farm management information systems for livestock farming such as herd management software, and behaviour monitoring sensors are not the common entry into digitalization, many farmers are getting on board with barn cameras and automatic milking systems. The fact that for more than half of automatic milking systems adopters, this very high-cost digital technology was the first on their farm shows that many farmers are assessing the financing risks and benefits of getting started with digitalization. More than half of the farmers using automatic milking systems have adopted this very expensive digital investment as their first digital technology on their farm. This fact indicates that investment in digital technologies is not purely a financial consideration, but is also intended to fulfil the required functional purposes. Studies from Denmark and Holland found economic impacts and identified important thresholds with regard to time after investment (four years) and number of cows (45) above which automatic milking systems become more profitable than conventional milking systems (Hansen et al. 2019, Gazzzarin & Nydegger 2014, Floridi et al. 2013). At least the average rate of 48 cows per farm in the Bavarian sample seems to account for this as well.

Impact of herd sizes on adoption rates

A possible use of digital technologies is relatively limited for farms with tethered housing compared to loose housing farms. Consequently, more digital technologies are used on loose housing farms than on tie-stall housing farms. This is because structural conditions of stables with tethering are not or only partially suitable for many digital technologies (e.g., automatic milking system). Furthermore, tethering farms have smaller herds on average, which makes some digital technologies more difficult to implement economically. However, an influence of herd size on the adoption rates of digital technologies can also be seen when analysing exclusively the farms with loose housing in the sample (Figure 1). The adoption rates of all technologies are higher on farms with at least 50 cows compared to farms with less than 50 cows. Looking at farms with loose housing, farms with less than 50 cows show adoption rates of up to 17 % for farm management information systems, while farms with at least 50 cows show adoption rates of up to 43 % (behaviour monitoring sensors).

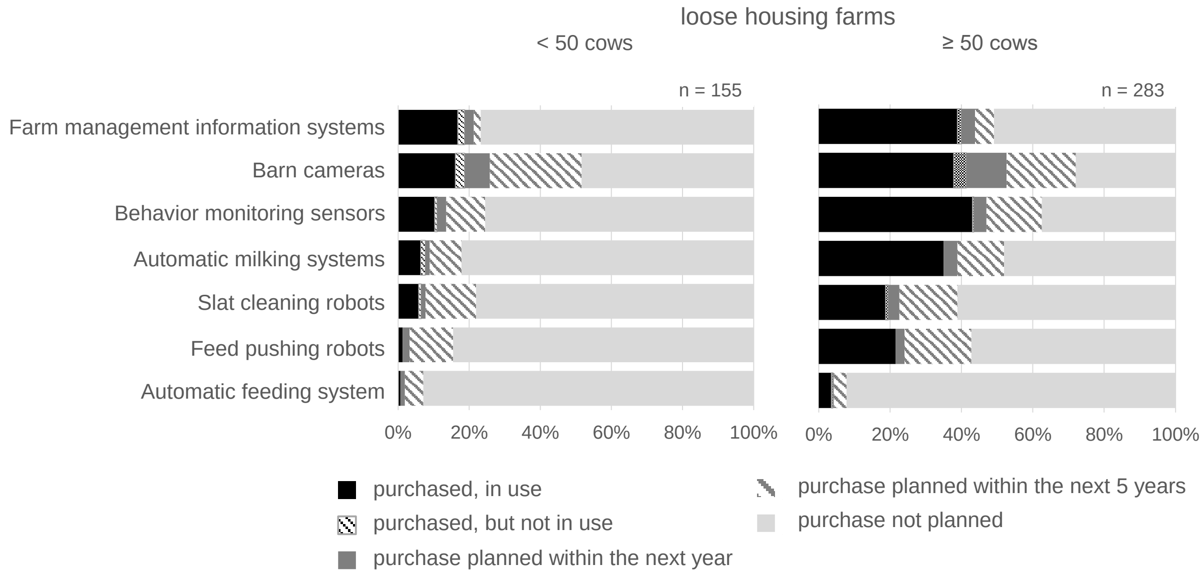

Figure 1. Adoption rates of selected digital dairy farming technologies on loose housing dairy farms with less (left) and more (right) than 50 dairy cows

The extent to which technology adoption rates depend on herd size of loose housing dairy farms surveyed is shown in Figure 2. For the commonly used barn cameras and farm management information systems, a steady increase in adoption rate with herd size is illustrated. Compared to the other technologies, barn cameras and farm management information systems are also applied on small farms (herd size ≤ 20). Although automatic milking systems and behaviour monitoring sensors are already in use in herds with ≥ 20 cows, a clear increase in their adoption rates is shown at herd sizes between 60 and 70 cows. In the case of automatic milking systems, this can be explained by its optimal capacity at this point. As behaviour monitoring sensors are often purchased together with an automatic milking system, their adoption curve assimilates to that of automatic milking systems. Slat cleaning robots show a more pronounced increase in the adoption curve at a herd size of 40 cows, and feed pushing robots at a herd size of 50 cows, followed by a steady increase at larger herd sizes. In general, there is a clear positive effect of herd size on adoption rates of all digital dairy farming technologies analysed. Only the two low-cost solutions, barn cameras and farm management information systems, are already adopted on farms with very small herds.

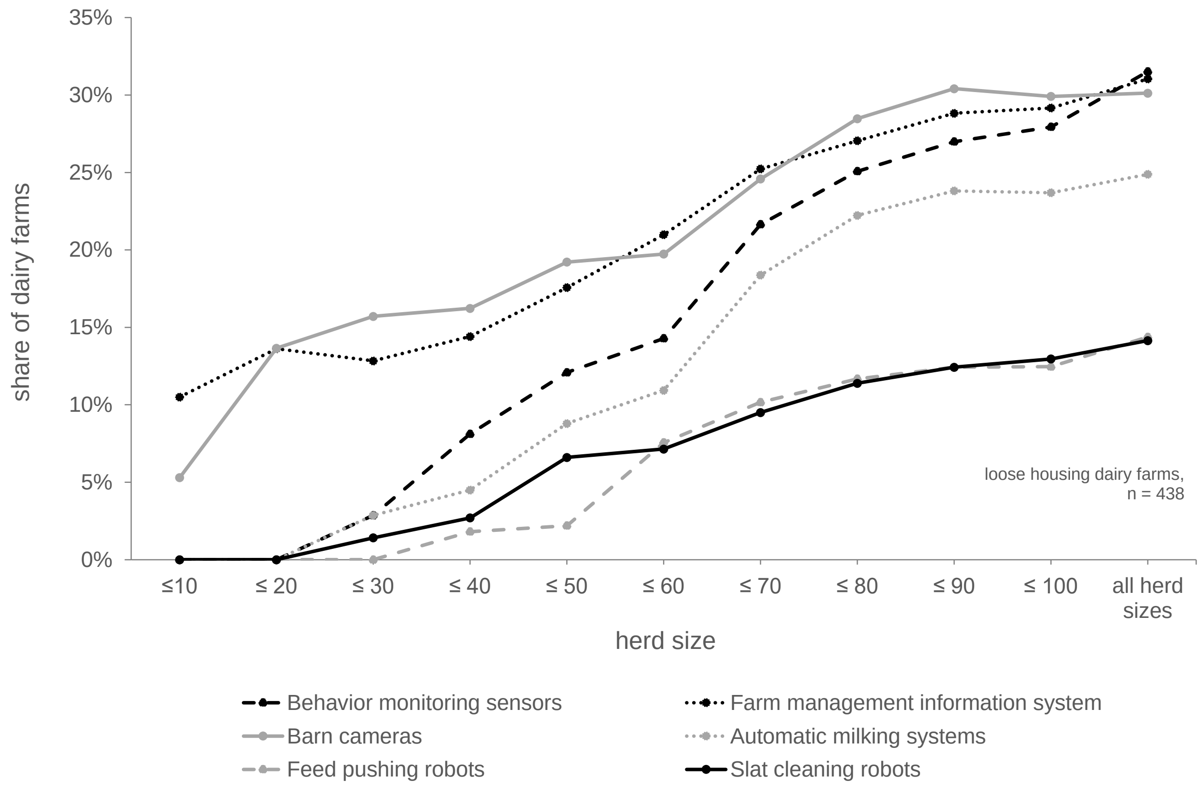

Figure 2. Adoption rates of digital dairy farm technologies depending on herd size

Potential short and medium-term technology combinations

The Bavarian livestock farmers surveyed were also asked about their investment plans within one year and within the next five years. Based on these estimates, we can assess the current frequency of technology combinations in use as well as at two points in the future. Although the future combination frequencies are based solely on farmers' assessments, trends in livestock farming can be identified as to what other technologies adopters of commonly used technologies are at least thinking about (Figure 3). The figure shows the combinations with other technologies if at least 10 % of the users also currently use them. The indicated average period of use of the selected digital technologies in livestock farming refers to the time of the survey in spring/summer 2020.

In dairy farms, the use of automatic milking systems stands out as an entry scenario (see also Table 2). On the one hand, this cost-intensive technology is very often the farmer’s entry into digitalization. On the other hand, it is often followed by other digital technologies for animal husbandry. In many cases, adopters of automatic milking systems also use behaviour monitoring sensors (80 %), barn cameras (58 %) and farm management information systems (57 %). A higher proportion of farmers that already use farm management information systems and behaviour monitoring sensors think about investing in cameras if they do not already use them anyway. There are high frequencies of multiple combinations with other barn robotics such as slat cleaning robots and feed pushing robots. For future development, the relevance of compatible systems for the adoption of digital farming technologies is evident (Yoon et al. 2020). If compatibility and reliability of the systems are ensured, the sequential expansion of digital equipment in livestock production can be accelerated.

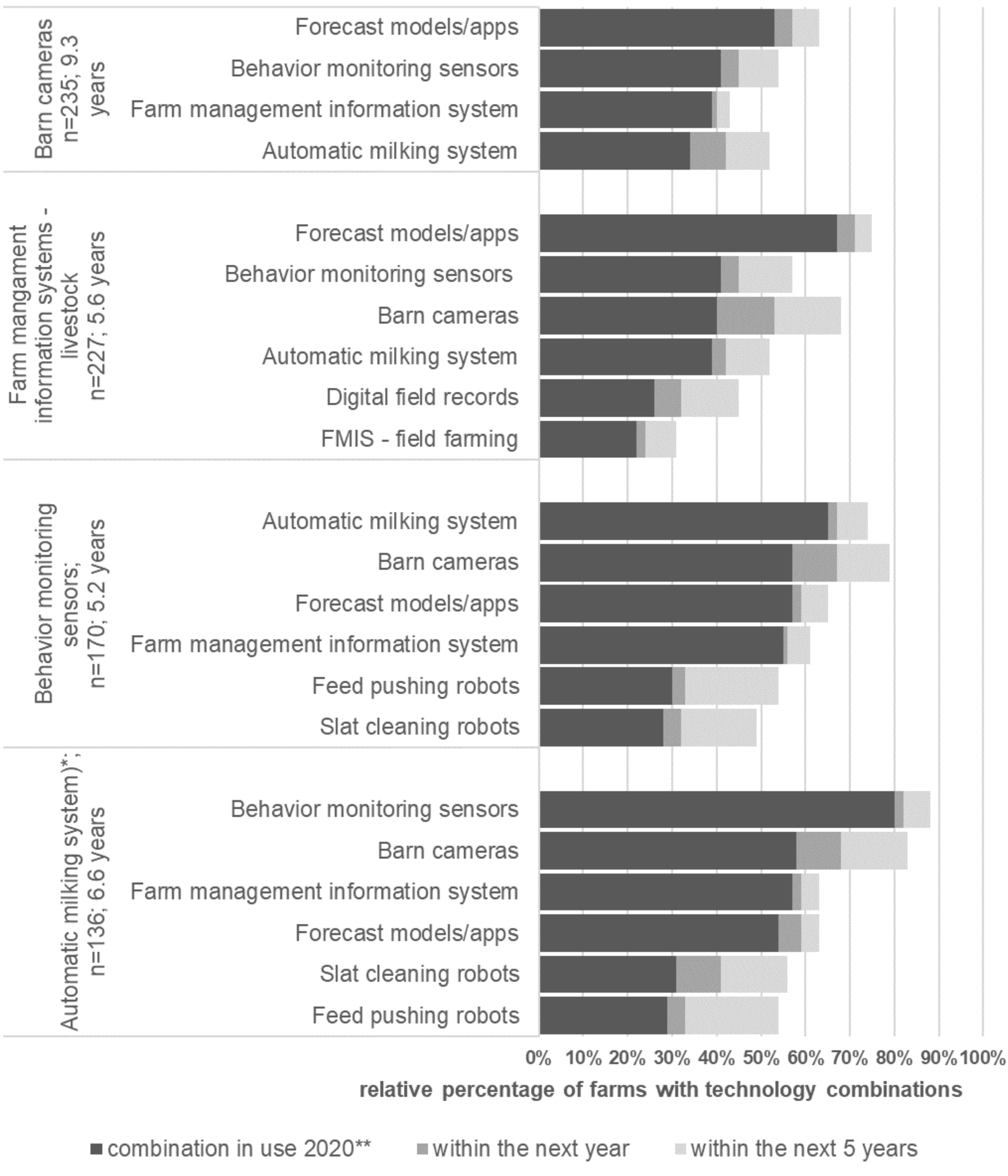

Figure 3. Current and potential short (within next year) and medium-term (within the next 5 years) digital technology combinations in livestock farming

Note: Selection of technologies used by at least 10 % of farmers from the relevant production category (n=absolute number of farms; indication of the average time since use of the technology in years) * only dairy farms; ** time of survey March-June 2020.

Discussion and conclusion

Conducting a farmer online survey, reliable data on the use of digital technologies on farms in Bavaria was collected for the first time. Results reveal that livestock and dairy farming in this smaller-scale farming region cannot be described as 'exceedingly digital'. Digital technologies with high adoption rates are low-cost barn cameras and farm management information systems, but adoption rates do not exceed 17 %. The figures for the overall livestock farming sample also show that digital technologies such as barn robotics are being used more frequently, especially in dairy farming. On many dairy farms, automated milking systems are an entry technology that trigger the use of other robotics or digital technologies. If the stated future planning of systems users in the sample is to be believed, the use of cleaning or feeding robots will double on these farms in the coming five years.

However, digital transformation is still a question of company size and type of operation. More than one third of livestock farmers in the sample are part-time farmers. Not operating a farm as main occupation lessens motivation, capital access and time to invest in specific technologies (Mittenzwei & Mann 2017). In some cases, additional off-farm income might be expected to increase capital available to invest and adopt technologies (Schimmelpfennig & Ebel, 2016). Detailed information on financial possibilities of Bavarian part-time farmers was not included in this survey, but should be considered in future research. In addition, each technology is effective for specific optimal herd sizes, some technologies are only interesting for the farmers from a specific size. In the case of automatic milking systems, this can be explained quite well, as the maximum utilization of the systems and most effective use of milking stands is achieved at herd sizes of 60 to 70 animals. If the herd size is below this threshold, the digital milking stand is not optimally utilized. If the number of cows is larger, considerations must be started for installing a second system.

Low-cost technologies such as barn cameras and farm management information systems are also used more frequently on farms with smaller herd sizes (under 50 animals) than more cost-intensive technologies such as barn robotics. Economic aspects of profitability and cost-benefit ratio continue to play a major role in investment decisions (Borchers & Bewley 2015). But also, the simplicity and ease of use of a technology are important when deciding whether to implement a technology. Especially for farmers of smaller or part-time farms, new technologies must be easy to understand and easy to use. Groher et al. (2020) came to similar conclusions for the use of digital technologies in Swiss dairy farming, which is quite comparable to the situation in Bavaria due to the high number of smaller farms with small herd sizes. Easy-to-use technologies and compatible tools integrated into milking technology, for example, are also favoured in the neighbouring country, while expensive robotics show very little application in Switzerland (with adoption rates between 2 and 6 %).

Other empirical studies analysing the use of digital technologies in regions or countries with large-scale agriculture show a correlation of technology adoption rates with herd sizes (e.g., Gargioulo et al. 2018; Eastwood & Renwick 2020). However, these surveys further found only minor differences between large and small farms when it comes to a generally positive perception of the use of digital technologies and future investment interest by the surveyed farmers. There is potential for smaller farms to digitalize more in the future if a quick return on investment of the new technologies can be achieved or the necessity of a technical change is reinforced externally, e.g., by changing regulatory frameworks for agricultural productions. In Bavaria, for example, tethering is still possible, although the political debate about it is intensifying due to growing social pressure. Most of the digital technologies do not work at all in tethering or cannot fully develop their application potential. For example, behaviour monitoring sensors can be used in tethered housing, but due to a restricted mobility of the animals, quality impairments in their alerts (e.g., oestrus, health) must be expected. Conversion of farms to other housing types such as loose housing intensifies the need for digital solutions and increases the adoption rates of digital technologies in animal husbandry and dairy livestock farming.

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Delphi forecasts for the adoption of digital technologies in Swiss outdoor vegetable production

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Extended Abstract

Digital technologies include a wide range of applications such as robots (e.g. for milking or hoeing), GPS applications (e.g. driver assistance or precision farming), or sensors (e.g. ammonia levels in barns or soil moisture), which serve various purposes. Digital technologies can help revolutionise agricultural production and tackle the increasing global challenges (e.g. climate change, water pollution, or soil degradation; Walter et al., 2017, Finger et al., 2019, Busse et al., 2014). Technology use can further help farmers optimise input allocation and thereby contribute to lower costs, increased outputs, and higher resource efficiency (Batte and Arnholt, 2003, Shockley et al., 2011). For instance, an increasing use of sensors can contribute to a better monitoring of the farm so that inputs such as fertilisers or pesticides can be applied according to needs (Walter et al., 2017). The adoption rates for digital technologies are well documented in certain states of the United States and Australia. In Europe, however, they are not yet as well explored (Paustian and Theuvsen, 2016, Barnes et al., 2019, Kutter et al., 2009).

Previous research revealed that adoption rates for digital technologies in Switzerland, as an example of a European country, differed widely across technologies and production branch (Groher et al., 2020b, Groher et al., 2020a). As a result, the current study focused on one production branch only. Specifically, we looked at outdoor vegetable farming. The agricultural area used for vegetable production has increased in Switzerland during the last decade (Zorn, 2020) and is very resource-intensive, for example in terms of pesticide and fertiliser use. At the same time, there is growing societal concern about the negative environmental impacts of agriculture, which is reflected for example in several popular initiatives launched in Switzerland since 2016, all of them addressing agricultural or food-related topics (Huber and Finger, 2019). Digital technologies offer a possible solution for these challenges and may have the potential to reduce negative environmental impacts of agricultural production.

Focusing on outdoor vegetable farming in Switzerland, the present study followed three main objectives. First, it aimed to identify the most promising technologies and applications. The second aim was to obtain a forecast on the future development of the adoption of digital technologies based on the assessments of various experts. The third aim was to identify drivers and barriers of technology adoption. To investigate these research questions, we chose the Delphi method as an established tool to obtain high quality experts' responses.

Most Delphi studies share four main characteristics (Anderhofstadt and Spinler, 2019, von der Gracht, 2012, Rowe and Wright, 2001). First, the experts are anonymous and their identity remains unknown to the expert panel, thus avoiding that one or few experts dominate the consensus process. Second, a series of rounds offers the experts the possibility to adapt their statements and reconsider their opinion. Third, experts receive controlled feedback which

summarises the results of the previous rounds (Hsu and Sandford, 2007). Finally, as a fourth characteristic, feedback is provided to the experts as a statistical group response, usually including measures of central tendency (e.g., mean, median).

Potential experts for the Delphi study were selected across Switzerland based on their recognised knowledge of and familiarity with vegetable production and digital technologies in agriculture. Additional individuals were contacted based on snowball sampling from the approached experts. For the selection, we put a special focus on professional and geographical diversity (Mauksch et al., 2020, Häder, 2014). We selected a total of 34 suitable experts and in accordance with Busse et al. (2014), organised them into five expert groups. The groups were formed based on the experts' professional background as follows: farmers/contractors, input suppliers, intermediates, research, and advisory.

In Round 1 of the Delphi, open-ended questions were used to collect expert opinions. These were transformed into close-ended questions for Round 2, where controlled feedback was provided to the experts. Experts were given two weeks to complete the survey, before non-responders were reminded to participate and given another week to do so. Twenty-six experts participated in both rounds, resulting in an overall response rate that was comparably high with 76%.

Based on the experts' qualitative responses, we identified GPS and RTK technology as, in the experts' view, most promising technologies for outdoor vegetable farming. Next, experts mentioned robots and autonomous machines. The popularity of robots is supported by recent research from Germany, which found that 22.6% of the surveyed farmers were planning to invest in field crop robots within the next five years (Spykman et al., 2021). While robots and autonomous machines can bring significant benefits in terms of working hours or physical labour reductions, an increased use of robots and autonomous machines, however, creates new challenges such as legal and safety issues. For instance, in the European Union, it remains unclear who is accountable for damages caused by autonomous robots (Basu et al., 2018).

In terms of promising applications, weed control and hoeing was a clear favourite with 88% of experts choosing it in Round 2. Given the increasing societal and environmental pressure on agriculture in Switzerland and around the world, it seems that experts see significant potential in technologies concerning weed control and hoeing. These technologies can help lower the input use. Similarly, increased data collection and monitoring can help adjust the crop farming practices in a way that input allocation is optimised. With that, it is not surprising that the second group of technology application which more than half of the expert panel selected was data collection and monitoring.

Next, we assessed experts' predictions for the four technologies (1) driver assistance systems, (2) electronic measurement systems for fertilisation, (3) electronic measurement systems for irrigation, and (4) hoeing. The prognoses for adoption were especially promising for irrigation and hoeing, possibly because these domains are under significant pressure from current issues such as climate change (e.g. droughts) and protection of the environment (e.g. through bans on pesticides). Experts in the current study expect the adoption rates in the domains of fertilisation, irrigation and hoeing to almost double in the next one or two years. In the next 10 years, they are expected to grow by four times and more as compared to the level of 2018 (Groher et al., 2020b). This expected increase will significantly affect the demand in technology supply and training and is therefore of interest to educators, researchers and technology marketers alike.

When asked about drivers of adoption, 88% of the experts in Round 2 chose resource saving as most important. Mentioned each by 50% of the experts are better compliance with the legal requirements, lower costs or higher revenues and the saving of time or labour. These results make it clear that economic aspects play a dominant role as drivers of adoption. Promising technologies such as hoeing robots may reduce the input use but the main drivers here seem to be of economic nature as well as societal and political pressure. In support of this interpretation, one of the experts commented: “from an environmental perspective, producers are forced to produce more sustainably”, which also highlights the pressure under which vegetable farms are currently operating.

In terms of possible barriers of technology adoption, it emerged that high costs and the level of technology development were the most important aspects mentioned across both Delphi rounds. It is well documented in the literature that technology costs are a major barrier to the adoption of new technologies (Lawson et al., 2011, Reichardt and Jürgens, 2008). The mention of the level of technology development indicates that for some of the users, it may seem too early to adopt. A study in Germany revealed that especially large farms were among the early adopters and that it required large amounts of time in the initial stage to make the technology work (Reichardt and Jürgens, 2008). This process could be accompanied and facilitated by advisory services (Lawson et al., 2011). In line with this, experts mentioned the lack of knowledge, expertise or training as the third important barrier. Not only does a farmer need a certain degree of knowledge in order to operate a technology, but also their seasonal workers need to be able to deal with these new challenges. Similarly, farmers need a certain degree of affinity for technology to operate digital technologies.

In conclusion, our study found that economic factors are crucial drivers and barriers of technology adoption. Furthermore, increasing the practical relevance emerged as a promising measure to assist technology adoption. With that, this research is in line with previous findings but adds important insights, which can help tailor policy and training measures aiming to increase the adoption of digital technologies. Specifically, experts identified a pronounced demand for financial support to overcome the cost barriers. Specific training accompanied by advisory support can help build more practical relevance and support farmers in technology adoption. The current level of adoption of digital technologies in vegetable farming has a lot of potential for growth and experts expect big increases within the next 10 years. Keeping this in mind can help improve efforts in training and policy measures to support technology adoption. Undoubtedly, changes in climate and the regulatory framework aiming to preserve natural resources will further increase the pressure on agriculture. Digital technologies can play a key role in mastering these future challenges.

Keywords

Smart farming, technologies, drivers, barriers, experts, agriculture

Presenter Profile

Jeanine Ammann studied food science at ETH Zurich and worked in various industries (bakery, laboratory). She then returned to ETH Zurich in 2016 to earn a doctoral degree in consumer behaviour, where she investigated food disgust sensitivity and raised her profile as social scientist. Following the doctorate, she worked as postdoctoral researcher and lecturer at ETH Zurich before starting a postdoctoral position at Agroscope in 2020, where she currently conducts research on smart farming, investigating the drivers and barriers of technology adoption.

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'Expensive things that haven't replaced a notebook': exploring the reality of 'agri-tech' down on the farm

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Abstract

The increasing use of 'agri-tech' is seen by many as a key solution to the sustainable intensification of agriculture globally, bringing benefits to people, production, and the planet. As the UK navigates towards new post-Brexit agricultural policies, government funding is being provided to assist farmers with the implementation of agricultural technology, support which is also being provided in other countries across the world. Yet, the scholarly and popular literature continues to struggle with defining what 'agri-tech' refers to. Whilst there have been attempts to define terms such as 'agriculture 4.0', 'precision agriculture', and 'digital agriculture', there remains a lack of understanding of what it means to farmers and what types of technologies are most valuable to them. This represents both a gap in the academic literature, but also a practical challenge for those policy-makers wishing to know what types of agricultural technologies to support. Drawing on work from Science and Technology Studies, sociology, and histories of science, particularly ideas centred on 'innovation delusion' and 'the shock of the old', we explore the reality of 'agri-tech' down on the farm, inviting farmers and innovation brokers to shed light on what it means for them, as well as envisioning its future use by the year 2030. We use a mixed methods approach, including 17 interviews of key innovation brokers in the UK agri-tech ecosystem, social media analysis, as well as a survey of UK farmers combined with follow-up interviews. The analysis of these methods will be completed before the conference presentation and results will be reported then.

Keywords

Adoption; Agriculture 4.0; Agri-tech; Innovation; Technology; Transitions.

Presenter Profiles

David is the Elizabeth Creak Associate Professor of Agricultural Innovation and Extension at the University of Reading. He received his Bachelors (first-class) in Geography from the University of Cambridge, followed by a Masters in Geographical Research and a PhD (Geography) from the same university. He was Director of Studies in Geography at Gonville and Caius College (2015-17). After short post-docs at Cambridge and UCL, he took a Lectureship position in Human Geography at the UEA. He joined Reading in October 2019. His academic interests centre around the social impacts of agriculture 4.0, including extension, behaviour change, user-centred design and the ethics of new technologies. He is also working on projects on farmer mental health and policy co-design. He is a Fellow of the Higher Education Academy and co-Director of the Centre for Effective Innovation in Agriculture. https://research.reading.ac.uk/change-in-agriculture/

Catherine is a sociologist who has worked with David on two projecs related to the use of agri-tech in the UK. She received a BSc (Hons) in Environmental Science and an MSc in Science

Communication and Environmental Decision Making from the Open University. She received her PhD in Sociology from the University of Warwick. She has held post-doctoral positions at the University of Warwick and the University of East Anglia. Her research interests include agricultural technology adoption, the social and ethical impacts of agricultural technologies, relationships between humans and the more-than-human world, and the environment.

Keynote Presentation: Precision agriculture - key ingredient for sustainable development

David Zilberman

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Abstract

Meeting the challenges of growing populations, food demand, and climate change will require increased production from existing resources with reduced negative side effects. Productivity of land, water, and climate has to increase across the board. Precision technologies that tend to enhance input use efficiency in various stages of production can play a crucial role in meeting these challenges. Agriculture operated under conditions of random weather and heterogeneous agro-climatic conditions, and precision technologies have the capacity to adjust the selection of inputs, as well as production practices to changing conditions. These technologies require monitoring and assessment of situations, design of appropriate responses and application. These technologies are knowledge-intensive and improve as scientific knowledge grows and technologies improve. The agro-food system is challenged to develop these technologies and develop mechanisms to distribute them so they will be adopted when appropriate. That may require continuous links between researchers and extension and the private sector, and ongoing education of farmers. Thus far, adoption of decision technologies has been limited to high-value sectors and the developed world. To reach their potential, precision technologies need to be adapted to and adopted in developing countries. We will present some examples of successful applications of precision technologies and suggest some of the promising directions and polices to implement them in the coming decades.

Presenter Profile

David Zilberman is a Professor, Extension specialist in the Department of Agricultural and Resource Economics, UC Berkeley. David was born in Israel and got his PhD at Berkeley. He has done fundamental research on the economics of bioeconomy, water, farming systems, environmental policy supply chain, risk and pest control. He is the recipient of the 2019 Wolf Prize in Agriculture and a member of US National Academy of Science and served as the 2018-19 President of Agricultural & Applied Economics Association (AAEA), and he's a Fellow of multiple scientific societies. He has served as a consultant to the USDA, CDFA, the World Bank and FAO. Has served as a consultant to Mars Corporation, BP, and California commodity groups.

Economic Implications of Field Size for Autonomous Arable Crop Equipment

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Abstract

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

Keywords

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

Presenter Profile

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

Introduction

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

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

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

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

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

Methods

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

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

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

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

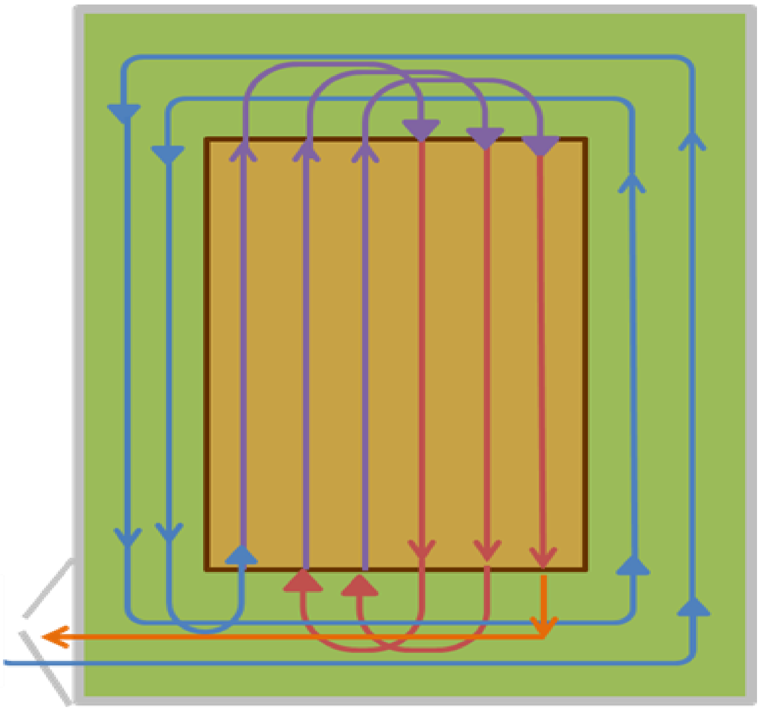

Figure 1: Typical field path considered in the algorithms based on the HFH demonstration project experience.

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

Modelling the economic implications of field sizes on equipment use

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

The objective function:

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

Subject to:

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

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

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

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

Case Study and Data Sources

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

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

Results

Effects field sizes on field efficiency and equipment times

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

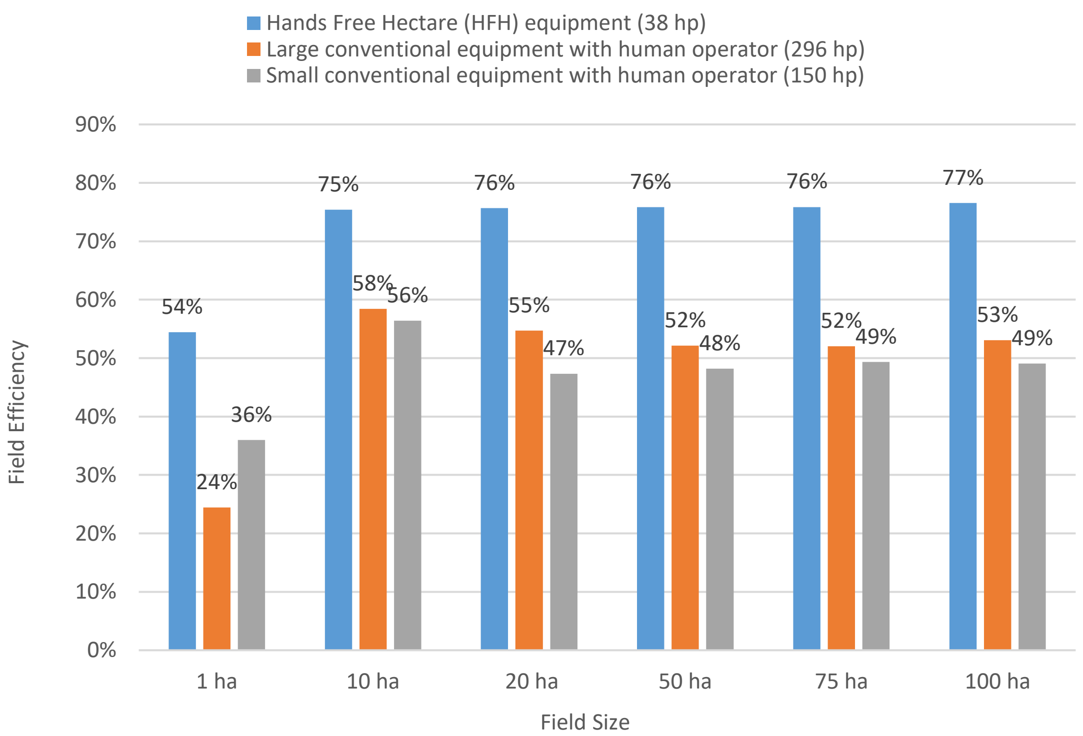

Figure 2: Estimated (weighted average) whole farm field efficiency of HFH equipment (assumed same for both HFH small conventional equipment with human operator and autonomous swarm robotics), large conventional machine, and small conventional technology in different sized rectangular fields.

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

Economic implications of field sizes on machinery use

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

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

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

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

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

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

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

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

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

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

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

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

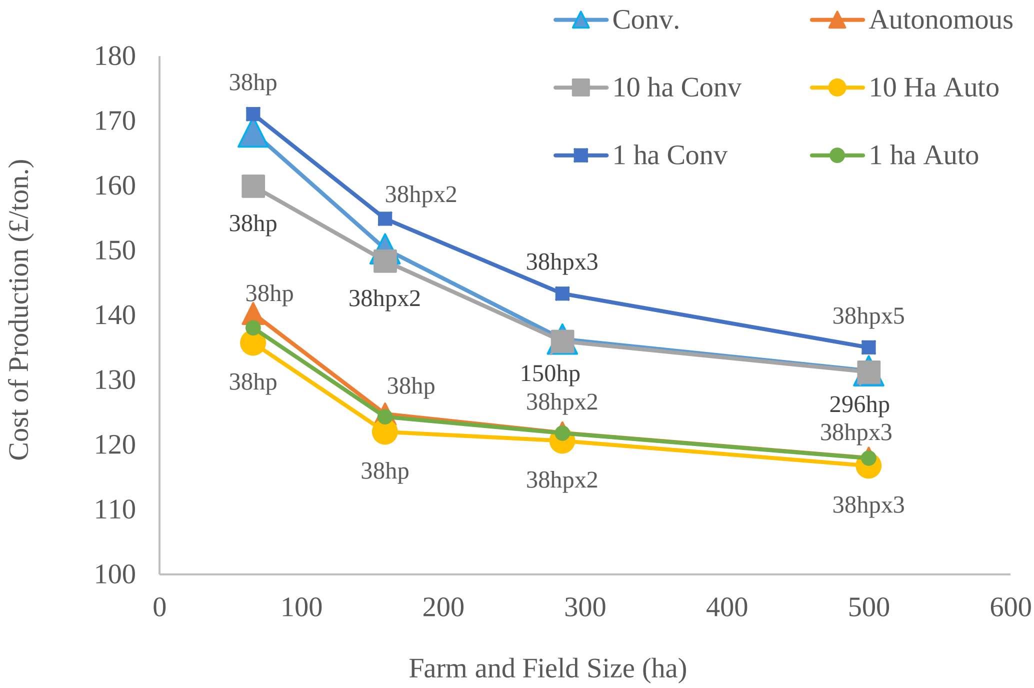

Figure 3: Wheat unit cost of production in pounds per ton with a reference to farm and field sizes. The labels on the data points are the size of the tractor used and the number of equipment sets.

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

Discussion

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

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

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

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

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

Conclusions

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

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Adoption of VRT in small-scaled farming: A choice experiment approach

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Abstract

Reducing negative environmental impacts (nitrogen losses, pesticide use, etc.) is one of the biggest challenges for agricultural production. Precision agriculture technologies are expected to help reduce these negative environmental impacts by providing timely, detailed and site-specific production information. However, the uptake of such technologies is still relatively low, especially in small-scale farming systems that are common in Switzerland. With our analysis, we aim to gain new insights into farmers' decision making regarding the adoption of more environmentally friendly technologies such as variable rate nitrogen (VRN) fertilization. We use a discrete choice experiment to elicit preferences and determine the willingness to accept as well as the willingness to pay for such technologies among Swiss arable farms. Based on a literature review and focus group discussion, we selected the following choice attributes for our analysis: 1) additional profit margins/additional costs, 2) ownership of the technology, 3) reduction in nitrogen use, 4) uncertainty about the actual impact of the technology on yields, and 5) technical support. The online survey was conducted in spring 2021 among 424 Swiss farmers in the cantons of Solothurn and Bern. The preliminary results show that the adoption rate of VRN is still below 10% among Swiss farmers. Furthermore, our results show that the potential of nitrogen reduction in particular has a big impact on both the willingness to adopt such technologies. Findings from our survey can help to better understand farmers' adoption decisions and factors that influence them and, based on that, support the design of effective policies to increase the adoption of such technologies that promote climate-smart agriculture.

Keywords

Variable rate technologies, adoption, choice experiment

Presenter Profile

Karin Späti holds a Bachelor's degree in Environmental Sciences from ETH Zurich with a focus on forests and landscapes, as well as a Master's degree in Environmental Sciences, focusing on evolution and ecology. Since June 2018, she is a PhD student in the Agricultural Economics and Politics Group at ETH Zurich. Her interdisciplinary PhD project focuses on digital innovations for more sustainable agricultural production techniques.

Introduction

Reducing the negative environmental impacts of agriculture has been and still is a major challenge for agricultural production. Precision farming technologies are expected to help reduce such negative environmental impacts (nitrogen losses, pesticide use, etc.) by providing timely, detailed and site-specific production information (Schimmelpfennig and Ebel, 2016, pp. 97-115). Precision farming is also seen as a potential starting point to reduce the climate footprint of agriculture and contribute to climate-smart agriculture (e.g., Roy, 2020, pp. 199-220). However, adoption rates of such technologies are still relatively low, especially in small-scale farming systems (Finger et al., 2019, pp. 313-335; Lowenberg-DeBoer and Erickson, 2019, pp. 7-20; Groher et al. 2020, 1327-1350). Adopting optimal site-specific nitrogen management is a complex decision for the farmer and several studies found that a variety of socioeconomic factors play a role in the adoption process (Aubert, Schroeder and Grimaudo., 2012, pp. 510-520; Barnes et al., 2019, pp. 66-74; Tey and Bindal, 2012, pp. 713-730). However, most studies examining adoption of these technologies have been conducted in large-scale farming systems, and there is little research on adoption of precision farming technologies in small-scale, family-based farming systems. In this work, we aim to help fill these gaps and improve understanding of farmer decision making regarding adoption of more environmentally friendly technologies such as variable rate nitrogen fertilization on small-scale farms. We intend to determine farmers' willingness to accept (WTA) as well as their willingness to pay (WTP) for such technologies, the factors determining it and how differently designed policies may influence adoption decisions.

Methods

To address this research gap, we use an online survey with a discrete choice experiment approach. This method provides an opportunity to assess the economic value of VRN use in different policy contexts. Using a discrete choice experiment approach allows us to measure both participants' willingness to accept as well as willingness to pay for such technologies. To explore farmers' willingness to accept (WTA), or willingness to pay (WTP), for VRN, we use a split sample design. Thereby, we vary the amount of additional profit margins obtained through higher yields, label premiums, or subsidies for one group (WTA) and the additional cost of the technology for the other (WTP). The other attributes identified in a literature review and focus group discussion are: 1) Ownership of the technology, i.e., the farmer invests in the technology himself, along with other farmers, or uses the services through a contractor. 2) Potential to increase nitrogen use efficiency and thus reduce loss of nitrogen to the environment (Walter et al. 2017, pp. 6148-6150; Wang et al. 2019, pp. 877-882). 3) Uncertainties regarding the actual impact of the technology on yields and recyclability also need to be considered, as this may influence farmers' decisions. 4) Support in case of technical difficulties, as this can also be important for the farmer. Furthermore, we used additional questions to elicit socioeconomic and behavioural characteristics of the participants such as risk preferences, self-efficacy, and environmental awareness to explain the underlying heterogeneity in willingness to accept or pay. The choice experiment was conducted online in spring 2021 with Swiss arable farmers in the cantons of Solothurn and Bern.

Results

We sent the survey to all (N=4850) crop farmers in the cantons of Bern and Solothurn in Switzerland. We received a total of 424 complete responses. More specifically, 216 completed questionnaires in the WTA group and 208 in the WTP group, which results in a response rate of 8.74%[1]. Preliminary results show that the application rate of VRN is still very low. Only 19 of the participants (4.48%) stated, that they use VRN on their farm. 24 (5.66%) of the farmers indicated, that they already tested VRN on their farm. and that farmers are rather sceptical about the economic viability of VRN. Furthermore, it is shown that especially the reduction potential of nitrogen use has a high positive influence on the farmers' willingness to accept and pay for such technologies. The availability and reliability of the technology are other important drivers for adoption. A reduction in uncertainty about the impact of the technology, i.e., an increase in the rate where the technology actually provides the expected positive benefit (reduction in nitrogen or increase in yields) increases the willingness to accept and pay for the technology. Farmers are also sceptical of additional subsidies and prefer to see direct economic benefits, either through reductions in nitrogen use or higher yields from using the technology.

Discussion

By conducting a discrete choice experiment, we contribute to a better understanding of adoption decisions of farmers in smallholder systems regarding greener technologies. Identifying the main drivers influencing the adoption decision can support the design of efficient policies to increase the adoption of such technologies. The reduction potential of nitrogen seems to play a significant role in the acceptance of VRN. Furthermore, behavioral aspects play an important role in the application decisions of farmers when it comes to sustainable production technologies (Dessart, Barreiro-Hurlé and van Bavel., 2019, pp. 417-471). Therefore, green nudges might be an approach to trigger farmers adoption of more sustainable technologies like VRN. Reliability and service provision is key to foster farmers VRT adoption and thus shall be clearly communicated. The high cost of VRN adoption is a major barrier for many farmers in small-scale systems. Therefore, it is important to take steps to reduce costs for individual farmers, for example, through the use of a contractor. In addition, it is important that the technology effectively increases production efficiency by increasing yields or reducing nitrogen inputs.

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Economics of reduced soil compaction with controlled traffic farming in spring barley – a feasibility study

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Extended abstract

Intensive soil tillage with heavy machinery may often create soil compaction followed by yield reductions. As opposed to conventional cultivation with Random Traffic Farming (RTF), a solution to reduce soil compaction could be the application of fixed tracks using RTK-GPS guidance systems (Real Time Kinematic Global Positioning System), also known as Controlled Traffic Farming (CTF). A study among European farmers shows that farmers are concerned about heavy machinery and the induced soil compaction on their fields. Several farmers indicate that an important motive to use CTF are to reduce soil structure damage and to improve profits on their farms. Nonetheless, a further adoption seems to be constrained by high costs of modifying existing machinery, cost of RTK systems as well as lack of compatibility between different systems from different manufacturers. In addition, some farmers indicate that lack of evidence on benefits are reasons for a low adoption (Thomsen et al., 2018). The objective of this study is to assess the changes in cost and benefits from using CTF compared with RTF in arable farming on two experimental fields with spring barley in Denmark. Findings shows that CTF is profitable under certain conditions compared with RTF. The use of large agricultural equipment seems to be critical, as it reduces the negative impact of compaction, while the size of the field only play a minor role in regard to the saving potential of CTF. Secondly, if the axle widths of the tractors and the harvester are not identical, it decreases the economic potential of CTF significantly.

Method

This study sets up two scenarios to compare the impact and changes in cost and benefits of implementing CTF systems with RTF as the reference system. In this way, we apply a partial budgeting approach that focuses only on the changes in cost and benefits when shifting from RTF to CTF systems. Changes in crop yields rely on data from three experimental spring barley fields in Denmark. The field experiments were designed with plots that were not compacted and other plots that were fully compacted from different wheel loads (track by track) (see Pedersen & Pedersen, 2013; Schjønning et al., 2016). In addition to this, we provide a number of technical and economic assumptions about axel and working width and wheel load that enable an analysis of the costs and benefits at the farm level. By setting up a number of elaborated assumptions and scenarios, it is possible to assess the cost and benefits of applying CTF compared to RTF when growing spring barley in Denmark. Based on these assumptions, two scenarios were hypothesized, one representing a farm with a small working width and the other farm with a larger working width of equipment. The two scenarios are denoted 6-24 and 9-36, which relates to the working width (meters) of each scenario.

Conclusion

This study shows that CTF could be profitable compared to RTF on large scale farms (400 ha) with spring barley in Denmark. The main benefits are related to reduced soil compaction. Less compaction leads to increased yields of between 3 and 6 % compared to RTF. Two properties of the farm scenarios delineate the significance of this result. The most important property is the existing working widths of machinery on the farm, where larger working width means less tracks and thereby decreasing the area affected by compaction. The second most important property of the farm is to what extent the axle widths of the existing machines are harmonized. If they are not, CTF is only profitable on farms with wide working widths (e.g. 9 and 36 meter). It was also demonstrated that field size and field shape has limited influence on the net benefits of CTF. In a scenario of which the farm size and equipment can be attributed to most large Danish farms, we find a net return of 24.2-27.2 € $ha^{-1}y^{-1}$. In summary, findings from this study shows that CTF is profitable under certain conditions compared to RTF. The use of wide agricultural equipment seems to be critical, as it reduces the compaction effects, while the size of the field only play a minor role in regard to the saving potential of CTF. Secondly, if the axle widths of the tractors and the harvester are not identical, it decreases the economic potential of CTF significantly.

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Keywords

Control traffic farming; smart-farming; yield; soil compaction; field efficiency; conservation agriculture

Presenter Profile

Søren Marcus Pedersen is associate professor at Department of Food and Resource Economics at University of Copenhagen. His research focus on adoption of new farm technology, agricultural economics and agribusiness innovations. Main topics has included smart farming systems such as precision farming in field crops, auto-steering and field robots. He is the author or co-author of more than 200 publications, including 50 international peer review papers and 8 book chapters. Currently he teaches in European Food and Farming systems and Business Economics at University of Copenhagen.

Economically Optimal Nitrogen Side-dressing Based on Vegetation Indices from Satellite Images Through On-farm Experiments

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Abstract

A methodology is introduced that combines data from on-farm precision experimentation (OFPE) with remotely sensed vegetative index (VI) data to derive site-specific economically optimal side-dressing N rates (EONRs). An OFPE was conducted on a central Illinois field in the 2019 corn growing season; the trial design targeted six side-dressing N rates ranging from 0 and 177 kg ha^{-1} on field plots, and yields were recorded at harvest using a standard GPS-linked yield monitor. NDRE values were calculated from Sentinel-2 satellite imagery during the V10 to V12 corn growth stages of the experiment's crop. After partitioning the field by NDRE quartile, economically N side-dressing rates were calculated after estimating each quartile's yield response function. Consistent with agronomic expectations, results showed that the parts of the field with lower NDRE values had higher yield; but the impact of increasing NDRE levels on the side-dressing rate's marginal product and EONR was not monotonic. Simulations predicted that compared to the side-dressing strategy the farmer would have implemented if not participating in the OFPE, net revenues could have been increased by \$54 ha^{-1} by using the methodology presented, suggesting high potential value of combining OFPE and VI data. A key advantage of the proposed methodology is that the data's inference space is the field to be managed. Further study is needed to improve the featured methodology.

Keywords

Side-dressing, NDRE, EONR, on-farm precision experimentation

Presenter Profiles

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 seven-year USDA-sponsored "Data-Intensive Farm Management" project, which uses precision agriculture technology to conduct large-scale, on farm agronomic experiments, to generate data that improves farmers' management of nitrogen fertilizer and other inputs. He received his Ph.D. from the Department of Economics at the University of Chicago in 1989.

Qianqian Du is a first-year Ph.D. student at the Department of Agricultural and Consumer Economics at the University of Illinois. Her academic interests focus on precision agriculture for sustainable, profitable, and high-productivity agricultural production.

Introduction

Mid-season nitrogen (N) side-dressing offers two potential informational benefits over management strategies that apply N earlier in the crop growth season: more flexibility in responding to post-planting weather variability and better synchronization of N supply with the crop's nutrient uptake capacities (Silva et al. 2005; Rutan and Steinke 2018). Also, since N is side-dressed after crop emergence, remote imagery of the crop canopy, such as can be summarized with vegetative indices (VIs) of reflectance, provides additional information about plant chemical content that may prove useful for subsequent N management (Raun et al. 2002; Inman et al. 2007; Tilling et al. 2007; Shanahan et al. 2008; Hunt Jr et al. 2011; Shaver et al. 2011; Montealegre et al. 2019). But important questions remain about how remote imagery can be used to improve side-dressing management. Numerous studies have found significant correlation between VIs and crop N status but have offered no concrete explanations of the management implications (Magney et al. 2017; K. Wang et al. 2019). Other studies have combined data generated in geographically and temporally in separate small-plot or strip trials to draw inferences about how VIs might be used to improve N management in other places and times (Lukina et al. 2001; P. Scharf et al. 2002, 2009; Tubaña et al. 2008; Holland and Schepers 2010). Because the relationships between VIs and economically optimal input management can change with growing conditions, drawing such inferences may be problematic. The many studies that combine data from small-plot experiments run in different locations have found relationships between VIs and economically optimal side-dressing strategies that may work well with their data set "on average," while working poorly in the experiments' individual locations, not to mention in other fields outside the experiments. Morris et al. (2018, p.19) recognized on-going research challenges when they stated, "*Reflectance sensing is a recent technology, … and there remains substantial disagreement about how to translate reflectance values to N rates. … More study comparing different interpretations is needed to determine which interpretations work best in which environments*."

The objective of the reported research is to answer Morris et al.'s call above by demonstrating how data from an on-farm precision experiments (OFPE) can be combined with VI data to inform mid-season site-specific N side-dressing management on the same field upon which the experiment was run. The methodology allows the geographic inference space of the experiment to be the very field to be managed site-specifically, and so may provide advantages over methods that expand the inference spaces of data from small-plot trials to other fields in other places. The OFPE provided 2019 side-dressing and yield data from a field in Effingham County, Illinois. Data used to calculate a map of the field's Normalized Difference Red Edge (NDRE) index values came from the Sentinel-2 satellite while the corn was in its V10 to V12 growth stages. The hierarchical generalized additive model (HGAM) approach was taken to estimate the yield response function. Results indicated that while increasing NDRE monotonically increased yield (total product), its impact on the marginal product of the N side-dressing rate, and therefore on the economically optimal nitrogen rate (EONR) was not monotonic.

Conceptual Framework

Equation (1) represents how yield at a site *i* responds to the *N* side-dressing rate and other factors:

$$y_i = f(N_i^{sd}, N_i^t, N_i^s, \mathrm{c}_i, \mathrm{z}^{post}). \qquad (1)$$

In (1), y_i denotes corn yield at site i, N_i^{sd} is the N side-dressing rate; c_i is a multi-element vector with site characteristics that vary spatially within a field but not much temporally, such as soil sand content and elevation and z^{post} is a multi-element vector of the weather events that occur after side-dressing, which vary temporally but not much spatially within the field. Yield also depends on N_i^t and N_i^s which are plant tissue N content and soil N content at a time right before side-dressing.

Assume that either (1) the decision maker has an estimate, $\hat{\tilde{f}}$, of the functional form of f and that the in-soil N content, plant tissue N content, characteristics and post-side-dress weather of f take on values of $\bar{N}_i^s$, $\hat{N}_i^c$, and $\bar{z}^{post}$, and therefore they can solve for an estimate of the reduced function form $\tilde{f}\left(N_i^{sd}, N_i^t\right) \equiv \hat{f}\left(N_i^{sd}, N_I^t, \bar{N}_i^s, \bar{c_\iota}, \bar{z_\iota}^{post}\right)$, or (2) that the producer simply has the estimated function $\tilde{f}(N_i^{sd}, N_i^t)$. Then (s)he could solve the profit maximization problem in (2):

$$\max_{N_i^{sd}} \; P_c \tilde{f}(N_i^{sd}, N_i^t) - P_N N_i^{sd}, \qquad (2)$$

where P_c and P_N are the prices of the crop and nitrogen fertilizer.

It is assumed that site i's vegetive index value VI_i provides information that can be used to estimate N_i^t, the N content of plant tissue at that site. Let $\hat{N}^t$ denote a function or algorithm used to make that estimation. With this estimate, the producer's profit maximization problem becomes

$$\max_{N_i^{sd}} \; P_c \tilde{f}(N_i^{sd}, \hat{N}_i^t(VI_i)) - P_N N_i^{sd}, \qquad (3)$$

The focus of the present report is on the value of having the estimates $\tilde{f}$ and a vegetative index map (i.e., a value of VI for each site i). Since the Sentinel-2 satellite images are free to the public, the cost of acquiring NDRE data is assumed to be zero. The first-order condition in (4) can be used to solve for an estimate the optimal side-dressing rate:

$$P_c \cdot \frac{\partial \tilde{f}(N_i^{sd}, \hat{N}_i^t(V_i))}{\partial N_i^{sd}} = P_N \qquad (4)$$

Figure 1 illustrates the concepts that estimated economically optimal N rates are different on site 1 and site 2 ($\hat{N}_1^{sd*} \neq \hat{N}_2^{sd*}$), both because the site's characteristics differ ($c_1 \neq c_2$), and because different vegetative index values lead to different estimates of crop N content: $\hat{N}^t(VI_1) \neq \hat{N}^t(VI_2)$.

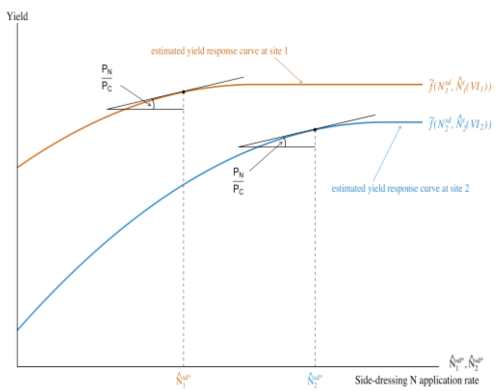

Figure 1: Estimated economically optimal side-dressing N rates, given estimates of the yield response function and of the vegetative index values

Methods

Data

In 2019, the Data Intensive Farm Management project (DIFM, (Bullock et al. 2019)) conducted an on-farm experiment on a 31.22 ha Effingham County, Illinois field, which generated data on corn yield response to nitrogen fertilizer application rates. The participating farmer planted corn on May 16th, 2019, and harvested on October 19th, 2019 using a CaseLH 8240 combine with a 12-row corn head. He applied an N base of 135 kg ha^{-1} uniformly across the field. Figure 2 shows that the experimental N side-dressing rates ranged of from 0 to 177kg ha^{-1}. Data from 9-meter buffer zone around the perimeter of the field was excluded from the experiment. The interior of the field was partitioned into twenty-two 8.8m-wide strips, each containing approximately 85 subplots, which were treated as units of observation. As a result, the trial was partitioned into 1867 subplots with an average size of 0.0167 ha. Urea ammonium nitrate (UAN, 32% N) was applied as the side-dressing N to the soil surface on July 16th, 2019 by DMI anhydrous applicators. The field's 2019 growing season's minimum and maximum temperatures of 14.9˚C and 26.6˚C were close to the 1999-2019 averages; its 855mm precipitation was higher than the 611mm 1999 to 2019 average. Figure 2 shows each subplot's mean as-applied side-dressing rate and yield.

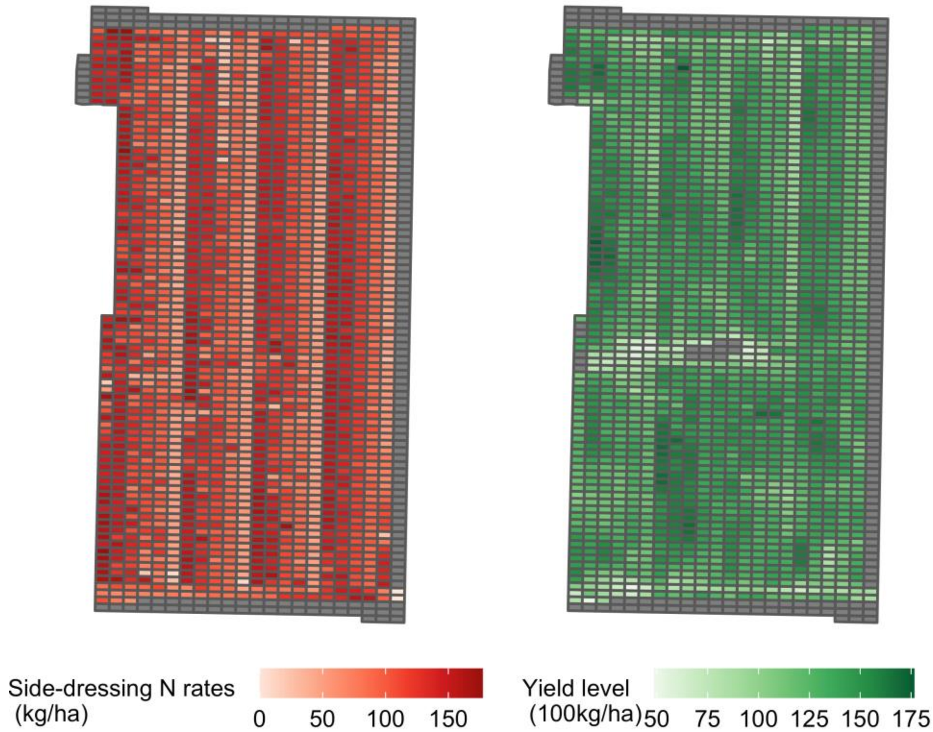

Figure 2: As-applied side-dressing N map (left) and yield level map (right).

The Normalized Difference Red Edge index (NDRE) (Barnes et al. 2000; Rodriguez et al. 2006) is a vegetation index related to the red edge reflectance obtained from multispectral image sensors. NDRE is calculated as:

$$NDRE = (R_{NIR} - R_{RED\ EDGE}) / (R_{NIR} + R_{RED\ EDGE}), \qquad (5)$$

where R_{NIR} and $R_{RED\ EDGE}$ refer to near-infrared bands (790 nm) and red-edge bands (720 nm), respectively. The R package, sen2r (Ranghetti et al. 2020), was used to acquire 10-m resolution NDRE images from the European Copernicus Program's Sentinel-2 satellite (Sentinel 2015). The participating farmer planted on May 17th. At the field's latitude, corn reaches the V10-V12 growth stages around eight hundred growing-degree days after planting (Lee and others 2011). The NDRE data mapped in Figure 3 were taken from June 30th, 2019 images, based availability from Sentinel-2. Growth stages were verified using the Midwestern Regional Climate Center's decision support tool (U2U@MRCC, n.d.). Table 1 presents summary statistics of the yield, NDRE, side-dressing (N), electro-conductivity (ECS), elevation (DEM), and slope levels.

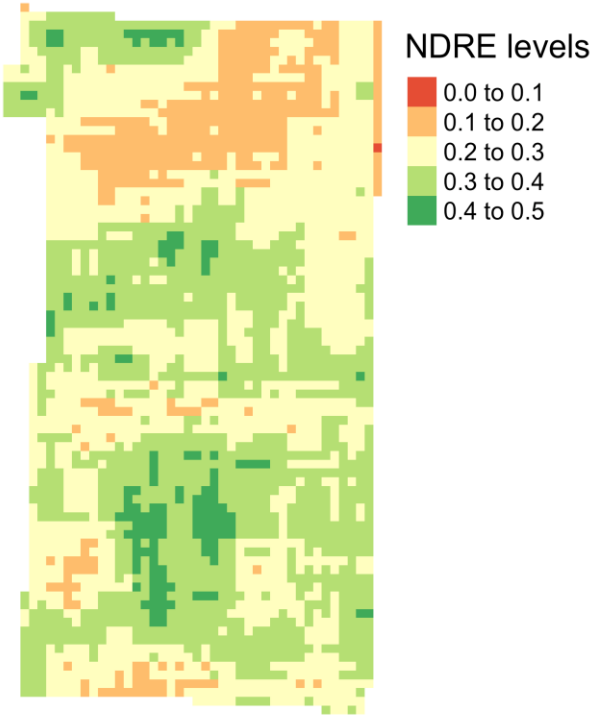

Figure 3: NDRE values observed on June 30th, 2019.

Table 1: Summary Statistics

	Yield	N[1]	NDRE[2]	ECS	DEM	Slope
mean	12967.03	104.94	0.29	29.55	625.73	0.04
SD	2001.09	36.88	0.06	5.47	2.76	0.01
Min	4877.22	0.00	0.14	16.09	620.91	0.03
Max	17650.45	177.21	0.47	53.65	631.94	0.10

[1]N is the side-dressing nitrogen rate (kg ha^{-1}) applied on July 16th, 2019

[2]NDRE was observed on June 30th, 2019

Methods

The hierarchical generalized additive model (HGAM) (Pedersen et al. 2019) was used to estimate the differential impact of side-dressing N rate on yield by the observed NDRE values. HGAM is a type of Generalized Additive Model (Wood et al. 2017), where the quantitative relationships of the dependent variable and independent variables can be estimated by group under the GAM framework. HGAM imposes no functional forms between the dependent variable and independent variables; rather, the method lets the data determine the nature of those relationships independent of assumptions about functional form. The entire sample was partitioned by NDRE quartile, and HGAM was applied to estimate yield response specific to each of the NDRE groups. The statistical model was,

$$y_i = f\left(N_i^{sd}\right) + f_z\left(N_i^{sd}\right) + \; g(ECS_i) + k(DEM_i) + h(Slope) + m(X_i * Y_i), \qquad (6)$$

where the dependent variable y_i is yield, and the covariates are site-specific nitrogen side-dressing rate (N_i^{sd}), shallow soil electrical conductivity (ECS_i), elevation (DEM_i), slope ($Slope_i$), and geographical controls for longitudinal and latitudinal spacial changes (X_i and Y_i). Among HGAM models introduced in Pedersen et al. (2019), the model used falls under the GI model category, where there is a single common smoother for the impact of N_i^{sd} on yield ($f(N_i^{sd})$) and group-level smoothers may have differing orders of wiggliness ($f_z(N_i^{sd})$). This model allows for flexible estimation of group-specific yield responses to N_i^{sd}. The impacts of other covariates were also estimated semi-parametrically without assuming particular functional forms, but were not differentiated by NDRE. Finally, including $m(X_i, Y_i)$ removed spatially correlated unobserved factors from the error term (Gardner et al. 2021). The model was estimated using the mgcv package (Meinshausen and Bühlmann 2010) in R (R Core Team 2020).

The EONR for each group was found as the solution to the problem of applying side-dressing at the rate maximizing net revenues:

$$\widehat{N}_i^* \equiv \max_{N_i^{sd}} \; P_c \tilde{f}(N_i^{sd}, N_i^t) - P_N N_i^{sd}, \qquad (7)$$

The inflation-adjusted average historical corn price in Illinois of P_c = 0.157 kg^{-1} and an N price of P_N = 0.88 kg^{-1} were assumed. Optimal side-dressing rates were bounded by the experiment's maximum and minimum targeted rates.

Results

As individual coefficients from non-parametric regressions are in themselves not meaningful. Figure 4 illustrates the results of the HGAM estimations of the by-NDRE-quartile yield response curves, and shows that increases in NDRE raise but do not necessarily flatten the yield response curves. In economics terms, marginal product is the amount of output gained by increasing one unit of input, which can be reflected on the slope of the yield response curve. Figure 4 shows that increasing NDRE raises the total product of N but does not affect the marginal product of N in a consistent direction. That raising the NDRE level raises the total product is consistent with agronomic expectations and not surprising; higher NDRE values reflect increased N content in plant tissue. However, (4) implies that if the objective of N application management is to maximize the field's profit, not yield, it is the NDRE's effect on the marginal product that determines optimal side-dressing rates. The estimated economically optimal side-dressing rates were $\widehat{N}_1^*$ = 142, $\widehat{N}_2^*$ = 133, $\widehat{N}_3^*$ = 146, $\widehat{N}_4^*$ = 125 kg ha^{-1}, as shown in Figure 5. Since the impact of raising NDRE does not consistently flatten or steepen the yield response curve, it does not change the EONR in a consistent direction; for example, the EONR in the first NDRE quantile is greater than in the second, but less than in the third, then again greater than in the fourth.

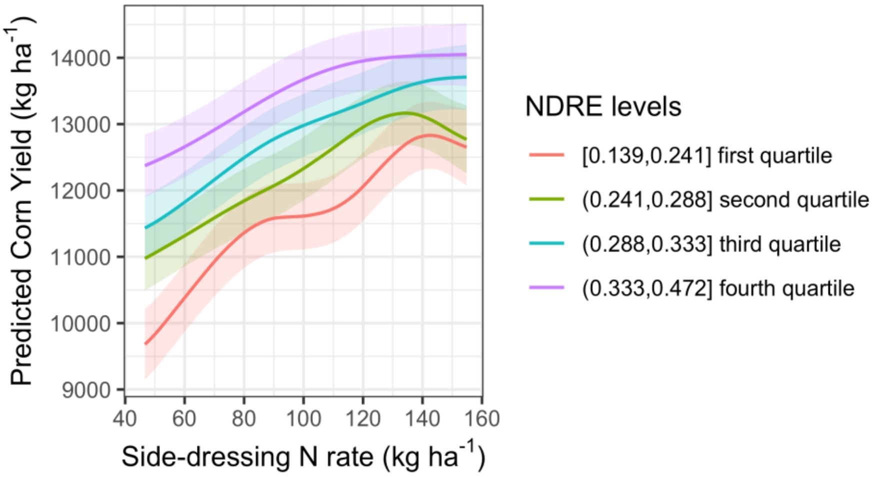

Figure 4: Predicted yield response functions by NDRE quartile, and 95% confidence intervals of their positions

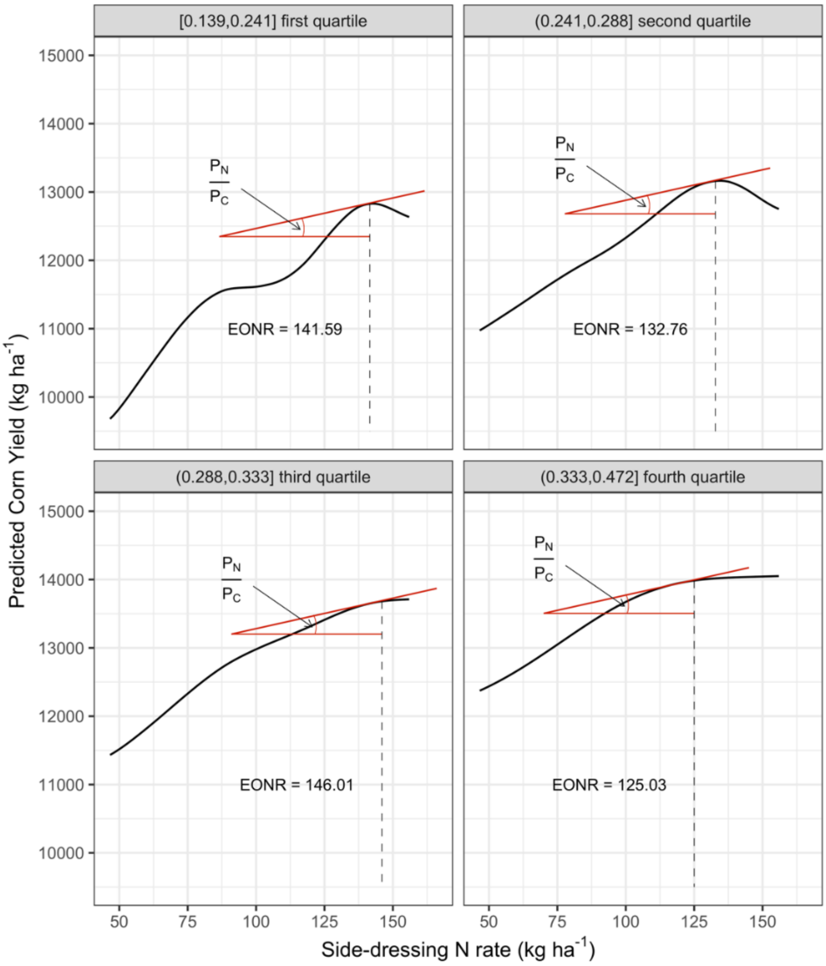

Figure 5: Predicted yield response functions and EONRs at each NDRE quartile

Figure 6 maps the experiment's site-specific estimated EONR levels, and shows that EONRs varied across the field, but not dramatically, from about 125 kg ha^{-1} to 146 kg ha^{-1}. This variance provided some opportunity to increase N-use efficiency using NDRE-based site-specific N side-dressing strategies. Table 2 reports an estimated economically optimal uniform side-dressing rate of 137.18 kg ha^{-1}, which implies a total of 4283 kg applied to the field, an estimated yield of 13390 kg ha^{-1} and estimated net revenues of \$1981.52 ha^{-1}. Table 2 also reports that under the economically optimal site-specific management plan shown in Figure 6, total side-dressing applied on the field would be 4256 kg (for an average of 136.35 kg ha^{-1}), and lead to a yield of 13414 kg ha^{-1} and net revenues of \$1986.05 ha^{-1}. Therefore, the model estimated that switching from the economically optimal uniform side-dressing plan to the economically optimal site-specific plan would have increased net revenues by \$4.53 ha^{-1} and \$141.43 over the entire field, and reduced the side-dressed N application by 0.83 kg ha^{-1}, for a total of 27 pounds on the entire field. These results are not dramatic, and reflect the relative spatial homogeneity of field characteristics on this “flat and black” central Illinois field. While the profit advantage of economically optimal site-specific side-dressing management over economically optimal uniform side-dressing management was relatively small, the value provided to the farmer by the information generated in the field trial and the NDRE readings was significant, with the economically optimal site-specific side-dress strategy generating net revenues of \$1986.05 ha^{-1}, which were \$54.85 ha^{-1} higher than the \$1931.20 ha^{-1} resulting from the farmer’s usual strategy of applying 115 kg ha^{-1} of side-dressed N uniformly on the field. This value comes from three sources: the VRT technology as compared to the URT technology, the information from the field trial, and the information from the NDRE data. Given the information from the field trial and NDRE data, the value of the VRT was \$4.53 ha^{-1}, which implies that the value of the information provided by the OFPE and the NDRE data was \$54.85 - \$4.53 = \$50.32 ha^{-1}.

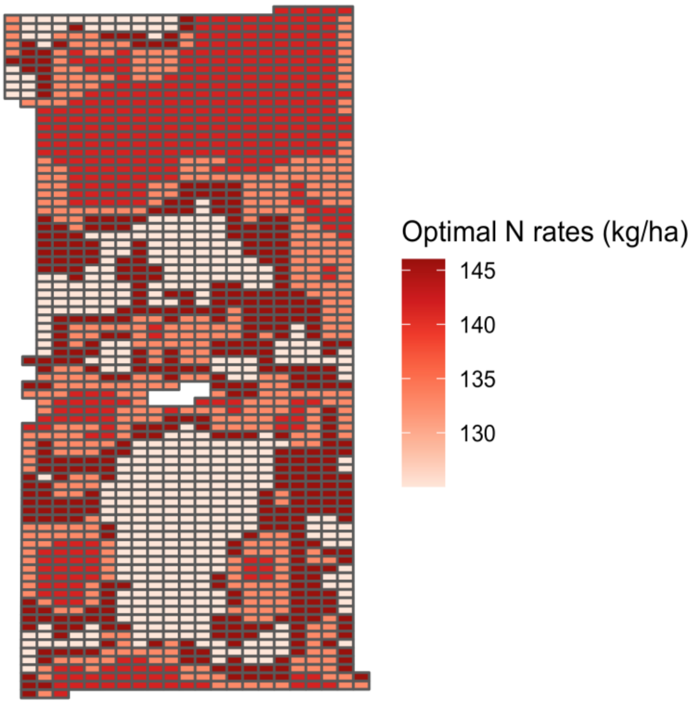

Figure 6: Optimal side-dressing N rate by subplots in the experiment in 2019

Table 2: Yield levels and net revenues under different N side-dressing strategies

N application method	N rate (kg ha^{-1})	Estimated revenue (kg ha^{-1})	Estimated yield (kg ha^{-1})
farmer chosen rate	114.75	1,931.20	12,944
site-specific N rate	136.35	1,986.05	13,414
uniform N rate	137.18	1,981.52	13,390

Discussion and Limitations

Much work remains to discover how sensor-based VIs can be used profitably to inform N side-dressing management. Many studies (e.g., Wang at al. (2019); Magney et al. (2017)) have simply confirmed correlation between VIs and crop N status but have not made the jump from there to develop VI-based site-specific side-dressing recommendations. Other studies (e.g., P. Scharf et al. (2002); P. C. Scharf and Lory (2009)) have generated data from small-plot N fertilizer field trials in multiple locations, then estimated a yield-response function and an economically optimal uniform side-dressing rate for each experiment. They then paired each experiment's EONR thus derived with an average VI measurement for the experiment, and examined whether the (VI, EONR) pairs from the experiments showed a general relationship between VI and EONR. The results of these studies are interesting, but not necessarily informative for the purpose of within-field site-specific side-dressing recommendations. This research took a step further to develop site-specific side-dressing recommendations for that same field.

The participating farmer applied a base N rate of 134 kg ha^{-1} uniformly on the experiment's field. Different application rates of base fertilizer would have changed NDRE readings, and possibly changed them differently in different parts of the field, which would have changed the NDRE quartiles, and so the results of this study. The experiment was conducted under 2019 weather conditions only. Other crop growing conditions would have affected corn yield response to N, and so the results reported here. During the 2019 corn growing season, precipitation was slightly higher than the twenty-year average and temperatures were very close to average. Differences in weed and pest presences and soil content could also affect our results; for example, increased weed presence might have increased the NDRE values and so reduced the recommended optimal N side-dressing rates. Optimal N side-dressing rates could also be influenced by field management practices such as planting date and choice of hybrid. Conducting similar experiments over multiple years would allow weather variables to be brought into the modelling framework presented.

Previous studies have provided evidence of the potential of using corn colours from the V6 to V9 growth stages for in-season N recommendations (P. Scharf et al. 2002; P. C. Scharf and Lory 2009; X. Wang et al. 2021). P. Scharf et al. (2002) pointed out that V6 is the earliest stage that crop N needs can be reflected by plant colours. Unfortunately, in the research just reported crop colours observed at a 10m satellite image resolution were insufficiently varied until V10 to V12 to be of use for side-dress management (Figure 7). For real-world side-dressing management, having to wait until V10-V12 to observe VIs and make N application decisions might require very time-intensive analysis right while the corn is growing too tall for conventional side-dressing equipment, possibly requiring the increased expense of equipment that could negotiate side-dressing the taller plants.

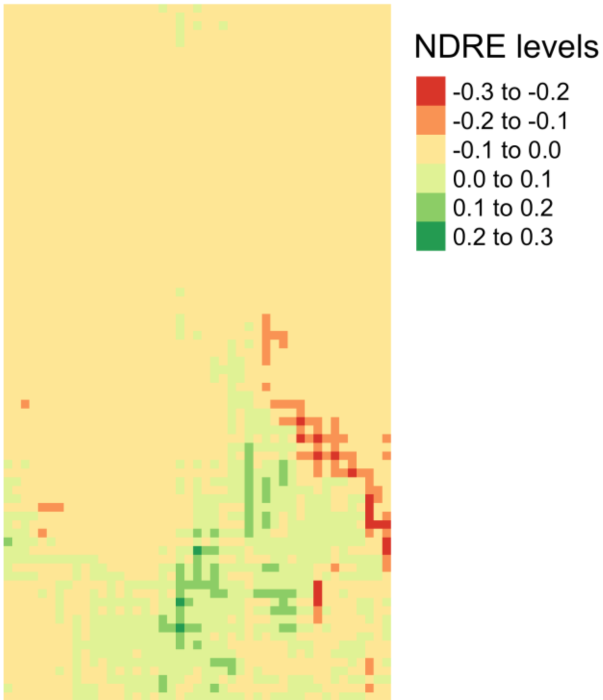

Figure 7: NDRE values observed on June 20th, 2019

Conclusion

Much work has discussed improving the in-season N management. The research reported here built on the previous work and took the methodology a step further, combining a field's VI data with data from a whole-field on-farm precision experiment to develop site-specific side-dressing recommendations for that same field. The combination of the VI and OFPE data is novel, and provides information not obtainable from small plot trials but necessary for improved site-specific side-dressing management of an individual field.

As future studies, it would be fruitful to explore the economics of alternative approaches to obtain VI information for side-dressing (e.g., unmanned aerial vehicles). Such studies should not just focus on how accurate the VI information is, but also need to consider its cost and examine the trade-off between the cost of information and the value of information.

Acknowledgment

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Keynote Presentation: Digital agriculture as a disruption and transformation in food systems: Who gets value from it?

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Abstract

The promise of economic, social and environmental gain from digital transformation remains unrealised. Slow uptake of digital technologies and limited embrace of digital transformation at firm and industry level is attributed to incentive structures. These are in turn influenced by investors' capacities to generate and retain value from digital technologies. A framework of 4 food industry domains is used to analyse specific innovations in the Australian farm and food industry. Innovations' impact, often thought of as disruptive, appear to be primarily cumulative. Where the analysis can identify value created and value accumulated, there is evidence of strong retention of value by incumbent economic actors. This is true for private, public and multiple-stakeholder entities in the food industry. Discussion centres on mechanisms by which value is accumulated, and the extent to which these can be offset by policy, the form of innovation, or knowledge management mechanisms.

Keywords

Digital transformation; digital agriculture; Australian food industry; innovation

Presenter Profiles

* Derek Baker is a research program manager with some 30 years' experience in agribusiness and agricultural development, at all stages of the supply chain. He is currently Professor of Agribusiness and Value Chains at the University of New England in Armidale, NSW, Australia, and Director of UNE's Centre for Agribusiness. He was formerly Program Manager for Value Chains and Trade at the CGIAR's International Livestock Research Institute, and Program Manager in Food Chain Innovation at The Food, Resource and Agricultural Research Institute in Denmark. Originally a farmer and farm consultant in New Zealand during the pro-market reforms of the 1980s, Derek has worked in over 30 countries.

Simon Cook is a scientist with over 30 years' international experience in research for agricultural development and natural resource management, specializing in the multiple roles for digital technologies. Trained in the UK, he strongly believes in the value of multi-disciplinary insight to help solve complex global problems. He has worked on projects globally for CSIRO Australia, the International Center for Tropical Agriculture and other CGIAR Centers and has experience of research in four continents. In 2012 he was the inaugural director of the CGIAR Program on Water, Land and Ecosystems and in 2016 he returned to Australia to take up the Western Australia Premiers Fellowship in agriculture. He lives in Australia and Colombia.

Elizabeth Jackson has an industry and educational background in agribusiness and food supply chain systems. Elizabeth has held positions related to the teaching and research of agri-food supply chain systems at Newcastle University (UK) and the Royal Veterinary College. Elizabeth is now a Senior Lecturer within Curtin Business School where her teaching relates to supply chain management, procurement and distribution and she continues to research food and agribusiness systems. She is on the board of Sheep Producers Australia, is a member of Western Australian Farmers' Federation Livestock Council and is a visiting scholar at the Royal Veterinary College (UK).

Dean Diepeveen is a researcher in the Genetic Improvement program at Western Australia’s Department of Primary Industries and Regional Development, focusing on frost, nitrogen-use and feed grain quality in cereals. He co-leads the Digital Agricultural Collaboration (DAC) involving several research organisations to improve the agricultural industry with new digital technologies. He has more than 25 years research experience in the analyses of grain crop research at Western Australian’s DPIRD with a further 10 years of medical research analyses. Dean is an adjunct Professor at Murdoch University and a visiting Associate Professor at Curtin University, in Western Australia.

Introduction

Substantial gains from digital agriculture have been widely anticipated. The World Bank (2021) estimates the value of food systems (US$8Tn in revenue plus US$6Tn in natural capital consumption). This means that even a 10% improvement in adoption through value-adding and efficiency gains would represent over US$1Tn each year. This value can be created at multiple locations within food systems. The Australian food and agricultural industry was addressed in similar terms by Perrett et al. (2017), with gains specifically associated with information exchange along supply chains.

Adoption however remains slow (Trendov et al., 2019): relative to other industry; at farm level relative to other supply chain stages; and in absolute terms across farm sectors. Digital transformation, as a broader process, is also slow in arriving in the agricultural industries. Commentary on this slow, and evidently disappointing, pace of change centres on the lack of a value proposition: farmers and others in the supply chain do not foresee a return on the necessary investment (Rojo-Gimeno et al., 2019) or lack the decision tools required for digitally-empowered business models (Leonard et al., 2017).

The extent of value generated, and its allocation amongst stakeholders, constitute investment incentives familiar to analysts of food system innovation. We argue that a specific understanding of these incentives in the context of food industry digital transformation is required by both the investor and the interested analyst and policy advocate. Referring to value acquisition, Schumpeter distinguished between disruptive and cumulative models. Much commentary on digital transformation focuses on gain associated with disruption, but we argue that in the food supply chain and the food industry more broadly, accumulation seems likely to be prevailing process. Notwithstanding projected changes in service and support industries, food industry investment in digital technology tends toward enhancing aspects of productivity and efficiency, and satisfying demand (Klerkx et al., 2019). New products and new processes play a rather smaller innovation role than do marketing and organization and the mobilization of various forms of network (Janssen et al., 2017). In such an industry, incumbency then proffers advantages when value is to be acquired from technological change.

Australia's case is of global interest due to its exposure to global value chains (Greenville, 2019), vertical orientation (Lammers et al., 2018), and stakeholder communication across the public-private divide (Janssen et al., 2017). Using specific examples, we explain how these changes occur and what they mean for broader transformations within the Australian food system.

Methods

We rationalise this argument by addressing two processes: value creation as a consequence of digital transformation; and value accumulation at various points in the supply chain. A recent contribution by Cook et al. (2021) identifies four domains of the food industry within which digital technology can create value. These are:

- production
- market
- capitals
- governance

In a series of examples of agricultural digital transformations, this framework is used to identify the value generated and its allocation along the supply chain. We examine specific digital innovations, and these are either generated by incumbents or incorporated into their business model. We identify value creation and accumulation for these cases and discuss its influence throughout the supply chain and in accordance with industry structure (Pavitt, 1984).

Results

Results suggest that incumbents do accumulate value, in many cases regardless of the identity of the value creator and the nature of value creation (Table 1). Innovations tend to focus on existing products and processes, handled along existing supply chains which are dominated by incumbents. There is interaction with the food industry domains [not shown in this abstract], to the extent that many incumbents are strongly vertically co-ordinated and so control value allocation: this reflects Australian conditions but conforms with Pavitt (1984).

Table 1: Examples of Value creation and Value accumulation.

Example	Value creation	Value accumulation
Chemical Suppliers Australia (CSBP), a commercial input supplier	Technology lowers production costs	Efficiency gains across existing product lines
CBH, a very large grain co-operative in Western Australia	Targeting demand niches by using technology to enhance logistics	Effective control of value creation.
John Deere, a global machinery supplier	A technology-enabled product	Protected IP and compatibility within platforms
Syngenta, a global input and service provider	A technology-enabled product	Protected IP and facilitated delivery of a premium product
Grain Research Development Corporation (GRDC), an industry-owned Australian research organisation partially supported by taxpayer funds	Research output delivered as a public good, specifically on the actual and potential uses of technologies	Continued industry and taxpayer funding
Public and private Australian meat industry partners using Dual Energy X-Ray Absorptiometry (DEXA) in carcass cutting	Technology optimizes carcass cuts' value	Processors reduce costs due to livestock volumes, as supply increases due to enhanced quality incentives. Branded product

Discussion

Australian industrial structures in the food sector facilitate value capture for various reasons, and this influences the environment for the adoption of digital technologies and overall digital transformation. Rather than disruption and change, accumulation and incumbency dominate. We discuss long term effects on high level policy and development goals.

Disruption is seen to play a role where incumbents fail to move rapidly enough to exploit the potential gain. To date, this has not occurred to any great extent and seems unlikely to occur if value cannot be identified or captured. The incentive structure extends to public-private partnerships and industry bodies. We discuss implications for start-ups and for technology policy.

Digital transformation of the system occurs when digital technology enables major changes, often through several changes connected within the system. Vertically co-ordinated systems across several of the identified domains ensure that incumbents retain the gains from such change. We discuss these incentives for several forms of digital innovation.

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A bio-economic analysis of harvesting fresh apples by platform harvesting systems

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Abstract

The apple industry is one of the major drivers of the New Zealand horticulture economy. Shortages of skilled labour, particularly for harvesting are a challenge for the continued growth of the industry. This has required the industry to consider the use of available alternatives namely platform harvesting system to deal with labour shortages. This study analyses the investment decision in utilising a platform harvesting system for harvesting fresh market apples under various varietal, orchard type, and size scenarios. The model is focused on revenues and costs of inputs including platforms and manual labour, to estimate the net present value and internal rate of return for a hypothetical two-dimensional orchard. Results suggest that fruit value and yield are the key drivers for utilising platform harvesting systems. Platforms are less profitable in single-varietal orchards compared to bi-varietal orchards planted with relatively low value and yielding varieties. Utilising platforms reduced manual labour required by an average of 7% across varieties and orchard sizes compared to manual harvesting.

Keywords

Platforms, labour, bio-economic model, net present value (NPV), internal rate of return (IRR), New Zealand, apple orchard.

Presenter Profile

Morteza Ghahremani has recently completed his doctoral degree in Farm Business Management at the School of Agriculture and Environment, Massey University in New Zealand. His dissertation was on the economic feasibility analysis of robot harvesting fresh apples in New Zealand. He has presented his research in several conferences and is currently finalising a journal article for publication. His research interest is in the analysis of innovations at the crossroads of agriculture, business, engineering, and socio-economic sciences with a focus on real-world research, such as improving farming systems through technology adoption that will enhance farm sustainability and profitability.

Introduction

The New Zealand apple industry relies mainly on manual labour, particularly for pruning and harvesting. However, the availability of labour at the time of harvesting is a potential constraint to the industry and its growth. With a short harvesting period, apples must be harvested quickly, and any unharvested apples are wasted. As a consequence, the inability to harvest within the harvest period could jeopardise the profitability and competitiveness of the industry. Temporary immigration labour programs, such as the Recognised Seasonal Employer program have been used by New Zealand apple growers; however, dealing with labour shortage remains a challenge for the industry. As a result, labour shortages have led the industry participants to consider alternatives. Several robotic technologies more suited to producing apples for the fresh market, have been developed and trialled around the world but are not yet commercially available. This has led apple growers to consider platform harvesting systems as available alternative to reduce the dependency on harvesting labour.

Methods

A bio-economic model was developed to assess the investment decision to utilise a platform harvesting system for single-varietal and multi-varietal orchards of various orchard sizes, taking into account varietal characteristics including fruit yield, value, harvesting window, purchasing and operating costs for platforms, and the cost for establishing an orchard with a tree structure suitable for platform harvesting. In the model, harvesting costs consisted of using either platforms or manual harvesting, taking into account the harvest speed and efficiency of platform systems (picking team). Given the harvesting window, not all areas could be harvested by platform and thus, the use of manual harvesting for areas unharvested by platforms was also considered.

Results

Manually harvesting 10 ha of single-varietal orchard planted with varieties Envy, Jazz and Royal Gala, produced NPVs of $8.0, $1.5 and $1.7 million, respectively over a 20-year period. To harvest 10 ha of single-varietal orchard by platforms, taking into account fruit yield, size, harvesting speed and efficiency of pickers on platforms, required five platforms for Envy, and four for each of Jazz and Royal Gala, and produced NPVs of $7.4 million, $846,794, and $1.0 million, respectively. Harvesting 10 ha of a multi-varietal orchard planted with Envy, Jazz, and Royal Gala with equal orchard size proportions, required two platforms and returned an NPV of $3.5 million.

Discussion

This research aimed to evaluate returns from an investment in platform harvesting systems based on single-varietal and multi-varietal orchard models compared to manual harvesting. Results from the single-varietal orchard model indicate that number of platforms vary across varieties given varietal characteristics and fruit density per tree. Varietal value and yield determine which variety harvested by platforms generates the highest profit. For relatively lower value and lower yield varieties, platforms are less profitable in a single-varietal orchard. In a multi-varietal orchard, a relatively high value and high yield variety such as Envy, is crucial to compensate the costs incurred from harvesting other varieties by platforms. Thus, growers producing relatively high value and high yield varieties are more likely to use platform harvesting systems. Otherwise, investing in platform harvesting systems could be more suitable for larger growers who are financially stable but have trouble supplying their required labour.

Given robotic apple harvesters are still in the commercial trial stage, potential adopters can opt for platform harvesting system given it fits within the same orchard architecture as robots and can reduce the current reliance on manual labour, not only for harvest, but also pre-harvest tasks. In addition, it can create a different demographic of labour as less fit or new workers are able to harvest more apples, while it may improve the efficiency of workers and make it physically less demanding, considering health and safety measures, and still generate a net return comparable to the case of using a manual harvesting system. It should be noted that platforms can either be a final or an interim step depending on various factors such as the final cost, labour availability and grower's decision. As an interim solution, it will allow potential adopters to gradually adapt new production strategies suitable for platform harvesting such as tree maintenance practices (e.g. pruning), which will also be applicable to robot harvesting. Therefore, when robotic harvest technology becomes commercially available, growers can have an easier and smoother transition to complete automation.

Evidence-based online courses: An educational model to increase agri-tech adoption?

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Abstract

There has been a huge increase in the number of innovative technologies available to support agricultural practices and over past few years, from satellite monitoring of crop growth to the precision application of pesticides and precision irrigation. There is evidence that adoption of agri-tech can lead to improved production and more environmentally friendly farming approaches, however, uptake has been low in some sectors. An evidence-based online course was developed that aimed to bring together evidence from published literature, agri-tech companies and farmers to present ideas on how arable farmers could integrate agri-tech into their own farming context. We describe the learners' engagement with the course and discuss how this approach could lead to increased adoption of agri-tech solutions, which ultimately can lead to enhanced environmental sustainability of farming systems.

Keywords

Precision farming, arable, education, online learning, agri-tech, adoption

Presenter Profile

Dr Alice Mauchline is a Senior Research Fellow at the University of Reading. Her research focuses on developing novel, sustainable, environmental approaches that can support crop production and biodiversity within our agricultural landscapes. In addition to ecological management, her research includes participatory elements such as the co-design of land management interventions with farmers, developing educational materials to support the uptake and adoption of these approaches and co-production of agri-tech decision support tools.

Introduction

Sustainable intensification of arable farming systems can be supported through the adoption of smart, innovative, precision technologies to enhance food production that have reduced environmental impacts (Balafoutis et al., 2017). Arable farmers can choose to adopt a wide range of innovations including precision instruments in agricultural machinery, sensors, monitors, integration of earth observation data and mobile decision support apps. Integrated use of these technologies has the potential to enhance both the efficiency and effectiveness of agricultural systems and food production across the EU and help farmers to develop more sustainable systems (Walter et al., 2017). However, uptake of these technologies by arable farmers has been limited, therefore we developed a Massive Open Online Course (MOOC) on the FutureLearn platform to provide farmers with evidence-based information that outlines the benefits and challenges of adopting new technologies and allows them to evaluate their use within EU arable farming systems.

Methods

The course was developed, with funding from EIT Food, by a consortium of partners from two Universities in collaboration with a large and two small-scale (start-up) industry partners. The course is illustrated with case studies in different contexts and explores practical mechanisms and frameworks that farmers can utilise to future-scan for new technologies, explore ways to overcome any challenges to adoption, evaluate the potential of agri-tech to enhance production within their own farming context while meeting environmental and social responsibilities. The course is delivered in a social learning environment which provides a forum for discussion, supported by academic mentors, and allows learners to consider ways to educate and inform consumers about the sustainable farming practices used to produce their food.

The course is structured around a conceptual ecosystem for data-driven agricultural applications (Paraforos et al., 2016). Learners explore the concepts of innovation and sustainability and are introduced to precision techniques and how these can contribute to the sustainability of food production by balancing economic, social and environmental aspects.

In order to explore the impact of this course, we analysed the comments and discussion points made by learners. We performed a thematic analysis of the topics discussed by learners and, in particular, examined their thoughts on the potential use of these technologies to enhance environmental sustainability of farming systems. We also consulted the start-up industry partners involved to investigate whether engagement in educational projects had any impact on the uptake of their technologies with farmers.

Results and Discussion

The MOOC opened for registration in late 2020 and has had over 1,000 learners in the first 12 months. The comments left on the course helped us identify that approximately one third of the learners were farmers; mainly smallholder farmers or those just starting out in farming. Comments from various farmers on the course from around the world have illustrated that agri-tech adoption is increasing. The use of an action plan within the course proved to be a useful tool to get farmers to think about what agri-tech they could use, and the course provided time and space to explore some options. For example, one farmer who owns a small arable farm stated, *"This has certainly made me think and has given me plenty of discussion topics for meetings with my farmer contacts".* Farmers do not have access or the time to delve into the scientific literature therefore setting up course in “chunks” and summarising the literature provided them with concise, evidence-based insights.

The impact on the industry partners of developing this educational course has been beneficial and they reported that adoption rates are increasing. It is difficult to attribute an effect of this course on adoption as there are many parallel activities, but the industry partners all reported benefiting from the knowledge exchange and business development opportunities that grew from the collaboration.

Acknowledgements

The MOOC was developed with funding from EIT Food, the innovation community on Food of the European Institute of Innovation and Technology (EIT), a body of the EU, under the Horizon 2020, the EU Framework Programme for Research and Innovation. Dani Whitington was funded by the School of Agriculture, Policy and Development on an Undergraduate Research Opportunities placement. We thank Thomas Engel (John Deere), Dimitrios Paraforos (University of Hohenheim), Camilla Bizzari & Federica Ferroni (Agricolus), Przemysław Żelazowski & Stefan Jozefowicz (SatAgro) and the OOC team at the University of Reading for their collaboration in the development of the MOOC.

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Analysis of the Determinants of Adoption of Bio-Herbicide Technology for Sustainable Food Production in the North-Eastern Region of Nigeria

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Abstract

There is a growing concern in many developing countries of sub-Saharan Africa on the harmful effects of synthetic herbicide usage on the agro-ecology as well as food crop production. Therefore, this study focused on analysing the factors that influence the adoption of Bio-herbicide Technology as an alternative to the chemical herbicides used by rural farmers in the North-Eastern region of Nigeria. Multi-stage random sampling technique was used to select 330 small-holder farmers in the study area using structured questionnaires. The data obtained were analysed using Probit Regression Model. The results of Probit Regression identified the farmers age, educational status, farm-size, access to extension services, farming experience and membership in cooperative society as the factors which influenced adoption of the Bio-herbicide Technology by farmers in the study area. It was recommended that awareness campaign on the new Bio-herbicide Technology among farmers in the area should be intensified. The farmers access to education and extension services should be improved to enhance adoption of Bio-herbicides technology which will impact significantly on the food production in the area. Also, farmers should be encouraged to be part of cooperative societies as a way to improving the adoption of Bio-herbicides for increased productivity.

Keywords

Adoption, Bio-herbicides, Sustainable, Food, Probit Model.

Presenter Profile

Dr. Adewuyi, A.K. is a senior Researcher with the Federal Polytechnic, Mubi, Nigeria. He lives and works in Nigeria, West Africa. He has published journal papers in both international and local peer review Journals. He has attended several conferences in various Agricultural Economics related events. He is a member of Research-promoting Associations which include; Agricultural Society of Nigeria (ASN); Nigerian Association of Agricultural Economist (NAAE); Agricultural and Applied Economics Association (AAEA); International Association of Agricultural Sustainability (IAAS).

Introduction

The need for sustainable food production and elimination of perennial hunger occasioned by the insurgency in the North-eastern states of Nigeria top the priority of Government programmes and policies. However, if activities that have the tendency of causing land degradation and environmental hazards are not properly addressed; many laudable efforts of the Government would not yield the expected results. Adebayo (2014) opined that the agricultural sector of the Nigerian economy, which provides about 70% of rural employment, cannot be treated with levity. Wrong use of synthetic herbicides is one of the major activities that have a potential threat on the environment and agricultural land. The multiplier effects of increasing use of chemical herbicides, which include land degradation, depletion of essential soil-microbes, loss of nutrients, erosion and deposition of toxic elements in the soil etc., pose great danger to the efforts at improving food sufficiency in Nigeria, especially the North-Eastern States that have been severally ravaged by insurgent activities and communal crisis.

Many researchers have raised concern on the damaging impacts of chemical herbicides on the environment and human life (Govinda, 2014; James *et al.,* 2017; Sanzidur and Chidiebere, 2017). According to Govinda (2014) pesticide residues cause nutrient imbalance and reduction in the quality of agricultural products. World Bank (2006) reported that an estimated 1–5 million farm workers suffer from pesticide poisoning every year, and at least 20,000 die annually from exposure, mostly in developing countries. The potential of chemical herbicide released into the environment causing harm is measured largely in terms of its toxicity and persistence. Majekodunmi (2014) reported that environmental pollution affects farmlands and water supply, and erodes the people's sources of livelihood, which in turn makes them susceptible to violence resulting from disputes on farmlands. This violence is manifested in form of insurgency leading to low farm productivity and subsequently contributing to food insecurity especially in the North-Eastern parts of Nigeria. Haggblade *et al*. (2007) observed that agricultural production which is critical to poverty reduction, has been stifled due to impacts of soil degradation with resultant negative influence on the livelihood of rural communities. Mercy and Anthony (2017) further stressed that environmental degradation factors such as climate change effects e.g. shrinking of Lake Chad, erosion, flooding, desert encroachment etc. are increasingly aiding the fast deterioration of the agriculture production resources.

James *et al* (2017) stressed that weed management is essential for agricultural production and management of landscapes. They further observed that proper weed management will play an important role in determining whether we meet future food production requirements. Hence, awareness on bio-herbicides as alternative to chemical herbicides become inevitable to ensure good weed management and preservation of the environment. Ojo (2016) stated that there has been alarming rate of low level of information and awareness on the dangers associated with the use of pesticides among Nigerian farmers. Mass-production of microbes applied as bio-herbicides to suppress weeds is a promising method of weed control (James *et al.,* 2017). Bio-Herbicide technology provides excellent alternative to the current adverse effects inherent in the application of chemical herbicides with a bid to enhancing environment-friendly agro-ecology and sustainable food production in the North eastern Nigeria. The already negative pressure on the region due to several insurgent activities coupled with increasing effects of land degradation such as desert encroachment, erosion, flood etc. necessitates a research to creating awareness and adoption of technology that provides ways of addressing these critical challenges that affect food productivity in the North-Easter region of Nigeria.

Improvement in agricultural technologies through researches and the capacities of end users to adopt and utilise these technologies are critical in boosting agricultural productivity in developing countries (Mapila, 2011). The adoption of modern agricultural technologies has been shown to be influenced by some factors. Mamudu *et al.* (2012) identified age as an important factor that influences the probability of adoption of new technologies because it is said to be a primary latent characteristic in adoption decisions. Furthermore, farm size significantly affects the adoption of different agricultural innovations and technologies by rural farmers in developing countries (Daku, 2001; Doss and Morris, 2001). A study by Gabre-Madhin and Haggblade (2001) showed that large commercial farmers adopted new high-yielding maize varieties more rapidly than smallholders. Furthermore, Caswell (2001) identified education as an important factor that create a favourable mental attitude for the adoption of new agricultural technologies. The influence of farmer's education on the adoption of new technologies was corroborated by Mamudu *et al.* (2012) in their study of Adoption of Modern Agricultural Production Technologies by Farm Households in Ghana. The harmful effects of synthetic herbicide usage on the agro-ecology as well as food crop production cannot be over-emphasized. This has necessitated the increased researches on finding alternative methods of weed management towards sustainable agricultural production. Therefore, this study is focused on analysing the factors that influence the adoption of Bio-herbicides by farmers for sustainable food production in the North-east, Nigeria.

Methodology

The Study Area

The study will be carried out in Adamawa State, Borno State and Yobe State which are all located within the North East, Nigeria. These three States have suffered from insurgent activities recently especially by Boko-Haram and Fulani-herders-men/Farmers clashes. Adamawa State is located at the northern part of Nigeria. It shares with Taraba State in the south and west with Gombe State in North-West and Borno Statee to the North. The State has an international boundary with Cameroun Republic along its eastern side. It lies between latitude 7^0 and 11^0 north, and longitude 11^0 and 14^0 East Adamawa State has a land area of about 38,714 km^2 and a population of 2,974,114. The people of Adamawa State are predominately peasant farmers, though few are cattle herdsmen. The capital of Adamawa State is located in Yola. Adamawa State, like other Northern State of Nigeria, has ever recorded a high incidence of poverty and land degradation. The state is notably agrarian environment with farmers growing cereal crops such as maize, guinea corn, cowpea, groundnuts, millet etc. animal husbandry is also predominant in Adamawa State mostly among the Fulani dwellers. The Northern States, which are substantially rural and having less exposure to education, experiences more poverty than other parts of the country. A third of Nigeria's poor are concentrated in the Northern States (Federal Office of Statistics, 1996).

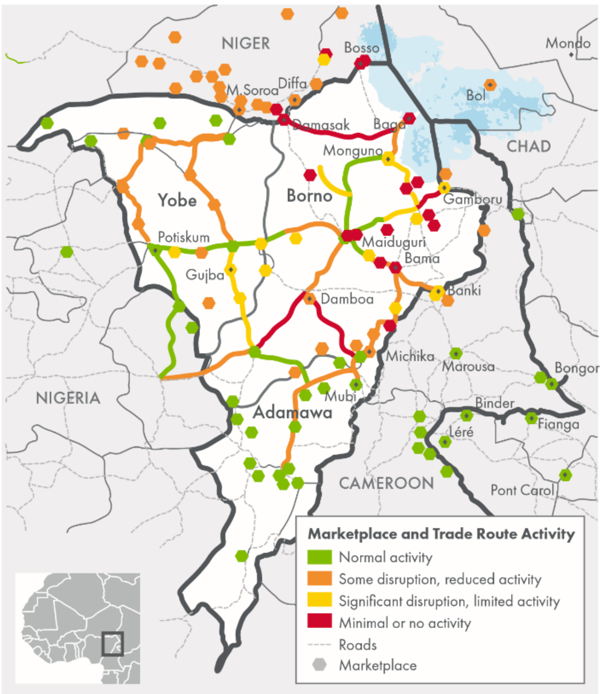

Figure 1: Map showing the Study Area.

Sampling Technique

Primary data for this study were collected through the use of structured questionnaires. The questionnaires were distributed by enumerators using multi-stage sampling survey for the study. The first stage involved random sampling of three Local Government Areas each from Adamawa State, Borno State and Yobe State within the North-Eastern region of Nigeria. Second stage involved the random sampling of four wards from each of the 9 Local Government Areas sampled in the three selected States. Thus, a sum of 36 Wards were randomly sampled and ten (10) farmers were selected from each of the Wards to give a total sample size of three hundred and sixty (360). At the end of the survey, three hundred and thirty (330) properly filled questionnaires were returned and used for the analysis.

Analytical Framework

Probit Regression Model was used to evaluate the determinants of adoption of the Bio-herbicide technology among farmers in the area. Probit Regression model has been widely employed by many researchers to evaluate the functional association among the probability of adoption and its determining variables (Daku, 2001; Caswell, 2001; Mamudu *et al.,* 2012).

The probit model assumes variable Yi as binary with only two possible outcomes (1 for adoption and 0 for non-adoption). It also considers a vector of explanatory variables *xi* which explains Yi.

The empirical specification of the probit model for the study is given as follows:

$Yi = \beta_0 + \sum^{0}_{n=1} \beta_n X_{ni} + u_i$

where *Xi* represents a vector of explanatory variables, u_i is a random disturbance term, *n* is the total sample size, and *β* is a vector of unknown parameters to be estimated by the method of maximum likelihood.

Hence, Yi = Adoption of Bio-Herbicides = (1 if rice farmer adopted, 0 otherwise); *X1* =Age; *X2* = Marital status; (1 if farmer is married, 0 otherwise); Gender (1 for Male farmer, 0 otherwise); *X3* = Household Size; *X4* = Education; *X5* = Farm Size; *X6* = Farming Experience; *X7*= Access to Extension Services (1 for Access to Extension Services, 0 otherwise); *X8* = Access to credit; (1 if farmer had access to credit, 0 otherwise); *X9* = Membership of Cooperative Society (1 if farmer belong to Cooperative Society, 0 otherwise).

Results and Discussion

Determinants of Adoption of Bio-herbicide Technology by Farmers in the Area

The results of the probit regression analysis revealed that the factors which influenced the adoption of Bio-herbicide technology among the farmers in the North-Eastern Region of Nigeria include the age of the farmers, educational status, farm size, their access to Extension Services, farming experience and their membership in Cooperative Societies. The findings showed that age of the farmers, educational status, farm size and their access to Extension Services were identified as having statistically significant influence on the adoption of the Bio-herbicide Technology by the farmers in the study area at 1% level of significance. In addition, at 5% significant level, farming experience and their membership in one Cooperative Society or the other also influence the farmers' decision in adopting the new technology.

Age of the farmers was identified from the result of the study as an important determinant of adoption of the Bio-herbicide technology in the area. This result supports the similar report by Mamudu *et al.* (2012) that age of farmers is an important factor that influences the probability of adoption of new technologies because it is said to be a primary latent characteristic in adoption decisions. The study further showed that the level of farmer's education plays major role in determining the attitude of the farmers towards adopting the Bio-herbicide technology. The result indicates a statistically significant relationship between the farmers' education and the adoption of Bio-herbicide technology. This report corroborates the findings of Caswell (2001) who identified education as an important factor that create a favourable mental attitude for the adoption of new agricultural technologies. Moreover, the size of the farmland used by the farmers was also shown to have a positive and significant influence on the adoption of the new technology. This implies that farmers with larger farm sizes were ready to adopt the technology more than those with smaller plots. Generally, commercial farmers have greater capacity to take risks than peasant and subsistent farmers. The result agrees with the report of Gabre-Madhin and Haggblade (2001) who showed that large commercial farmers adopted new high-yielding maize varieties more rapidly than smallholders. Another factor identified in the study as influencing the adoption of Bio-herbicide technology in the area is the access to extension services by the farmers. The result revealed that there is a positive and significant relationship between the access to Extension Services by the farmers and the adoption of the Bio-herbicide technology. It implies that the more access the farmers have to Extension Services, the better the attitude towards adopting the Bio-herbicide technology in the study area. Moreover, the study revealed farming experience as another important factor that determined the adoption of Bio-herbicide Technology by the farmers in the area. The result showed that the more the years of their experience in farming, the higher the probability of adoption the new technology. Also, their membership of cooperative societies was identified as a significant factor which influence the decision of the farmers towards adopting the Bio-herbicide Technology. Consequently, the formation of cooperative societies provides an added advantage to the farmers in taking corporate decision on issues that would improve their productivity.

Table 1: Determinants of the Adoption of Bio-Herbicides by Farmers in the Study Area

Variable	Coefficient	Standard Error	Z-Statistic	P-Value
Age	-0.201857	0.042283	-4.773945	0.0000 *
Marital Status	-0.166895	0.109739	-1.520831	0.1283
Household Size	-0.007683	0.083502	-0.092008	0.9267
Education Level	2.366165	0.840941	2.813712	0.0049 *
Farm Size	2.998871	0.960444	3.122379	0.0018 *
Farming Experience	0.760099	0.358506	2.120184	0.0340 **
Extension Service	2.858395	0.607396	4.705984	0.0000 *
Access to Credit	0.131725	0.243569	0.540812	0.5886
Membership of Cooperatives	1.376817	0.633800	2.172322	0.0298 **
McFadden R-squared	0.743352			
Sum squared residue	16.59865			
Log likelihood	-57.47980			

Source: Field Survey, 2021. * Significant at 1%; ** Significant at 5%;

Conclusion and Recommendation

The study had shown the various factors that have significant effects on the readiness of the farmers in the study area to adopt the Bio-herbicide technology as alternative method for weed control instead of using the mostly harmful synthetic chemical herbicides. The determinants of the farmers' adoption of the new technology according to the results of the study include age of the farmers, educational status, farm size, their access to Extension Services, farming experience and their membership in Cooperative Societies.

Therefore, it is recommended that awareness campaign on the new Bio-herbicide Technology among farmers in the area should be intensified. Furthermore, the farmers' access to formal education should be improved, especially through adult literacy programme as this will positively influence their adoption of new technology thereby enhancing their productivity. Moreover, the need to raise the farmers' access to Extension Services should also be stressed as it has been shown as a critical factor which influences the rate of the adoption of new technology by the farmers. Also, the need for the farmers to be part of cooperative societies in their farming communities should be emphasized. This will encourage useful all-inclusive decision with concerted efforts towards increased food production in the area.

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Factors affecting consumers' willingness to buy produce grown in indoor farming environment

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Abstract

Background: Indoor farming systems in this context refers to soilless crop in controlled environment in greenhouses using sunlight or sunlight supplemented by artificial light or other indoor facilities using artificial lighting only (including containers). Three common growing systems are hydroponic, aeroponic and aquaponic. Crops grown in indoor vertical farming systems typically include microgreens, herbs and leafy greens. The global indoor farming technology market is estimated at $14.5 billion in 2020 and is projected to grow at a compound annual growth rate of 9.4%, to reach $24.8 billion by 2026 (Research and Markets.com). However, in addition to the widely recognised challenges of high costs of production, consumers' perception and acceptance of produce grown in such an unconventional way has been seen as a pre-condition for the success of indoor farming commercialisation.

Methods: This study aims to explore key factors affecting consumers' willingness to buy produce grown in indoor farming system based on 202 responses obtained in April/May 2021 via an online questionnaire survey. Structural equation modelling with AMOS was used to establish the influencing factors. It should be noted that this is a convenience sample and may not be representative of the total UK consumer profile.

Results: The study found that previous knowledge, positive attitudes towards indoor farming systems, consumers' perceived characteristics of produce grown this way significantly influence consumers' willingness and likelihood to buy indoor farmed produce. Pricing at similar level as conventionally grown produce was the most important predictor of consumers' intention to buy. The findings highlight the importance of raising awareness of indoor farming technologies amongst general consumers, communicating the key attributes and sustainable benefits of produce grown indoor and reducing production costs in commercialisation of the system.

Keywords

Indoor farming, controlled environment agriculture, consumer behaviour, willingness to buy, structural equation modelling

Presenter Profiles

Elizabeth Cook graduated from Harper Adams University in 2021 with a First-Class Honours Bachelor of Sciences Degree in Agri-Food Marketing with Business. During her degree study, she developed a strong interest in indoor farming technologies and consumers' perception of food produced in indoor environment and its implications in food consumer behaviour. She is currently working with world leading farm machinery manufacturer, John Deere ltd as the Sales Support Representative for UK and Ireland.

Dr Iona Yuelu Huang is a senior lecturer at Harper Adams University. She has been a member of several research teams, including AgroCycle (a Horizon 2020 funded project on valorisation of agri-food waste) and the Newton Fund Institutional Links project "Sustainable Agribusiness Model for Poverty Reduction among Thai Small-scale Rubber Farmers". Her research interests fall into the broad categories of food waste management, governance of supply chain, agribusiness decision making and economic impact of agri-tech and innovation adoption.

Estimation of the weather-yield nexus with Artificial Neural Networks

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Abstract

Weather is a pivotal factor for crop production as it is highly volatile and can hardly be controlled by farm management practices. Since there is a tendency towards increased weather extremes in the future, understanding the weather-related yield factors becomes increasingly important not only for yield prediction, but also for the design of insurance products that mitigate financial losses for farmers, but suffer from considerable basis risk. In this study, an artificial neural network is set up and calibrated to a rich set of farm-level yield data in Germany covering the period from 2003 to 2018. A nonlinear regression model, which uses rainfall, temperature, and soil moisture as explanatory variables for yield deviations, serves as a benchmark. The empirical application reveals that the gain in forecasting precision by using machine learning techniques compared with traditional estimation approaches is substantial and that the use of regionalized models and disaggregated high-resolution weather data improve the performance of artificial neural networks.

Keywords

Yield Prediction, Machine Learning, Weather Risk, Index Insurance, Basis Risk.

Presenter Profile

Lorenz Schmidt holds a master's degree in Agricultural Economics from Humboldt-Universität zu Berlin. Since August 2021, he has been a research assistant at the Department of Agricultural Economics at Humboldt-Universität zu Berlin, Germany. His research focus lies in the field of applied econometrics and machine learning.

Introduction

Understanding yield variability is essential for agricultural risk management at the sectoral as well as farm level. Crop yields depend on a variety of factors including soil and weather conditions, fertilizer, and pest control. Among these factors, weather is pivotal because, in contrast to other production factors, it is highly volatile and can hardly be controlled by farm management practices. Extreme weather events lead to harvest failures and thus threaten food security all over the world (Wheeler and Braun, 2013). Since there is a tendency towards increased weather extremes in the future, understanding the weather-related yield factors will become increasingly important not only for yield prediction, but also for the design of insurance products that mitigate financial losses for farmers. Indeed, weather-based insurance products, such as index insurance and weather derivatives, have been propagated as a promising alternative to classical crop insurance (Barnett and Mahul, 2007). Elabed *et al.* (2013) and Jensen, Mude and Barrett (2018) find that the uptake of weather index insurance products depends to a great extent on the inherent basis risk, i.e., the discrepancy between the insurant's losses and the indemnity payment which is derived from the weather index (Elabed *et al.*, 2013; Woodard and Garcia, 2008). This discrepancy can evolve from weather differences between the insurant's location and the reference station of the weather index (geographical basis risk, see for example Ritter, Mußhoff and Odening (2014)) or an imperfect correlation between crop yields and the weather index (production basis risk or design risk). The relationship between weather and crop yield, however, is complex and brings challenges to the design of appropriate weather indices for various reasons. Firstly, several weather variables must be considered simultaneously, particularly precipitation and temperature. Secondly, these variables interact in a highly nonlinear way (Schlenker and Roberts, 2009). Finally, not only the aggregated level but also the temporal distribution of weather variables affects crop yields (Musshoff, Odening and Xu, 2011).

Two general approaches have been used for modelling the weather-yield nexus. The first is crop growth models that rest on biological and physical relations and simulate the dynamics of water, nitrogen, carbon, and other yield determinants in a specific soil context considering phenological stages and plant requirements (e.g. Asseng, 2004). The second approach consists of statistical methods, particularly regressions models, which have been employed to estimate crop yields as a function of weather variables (see Section 2 for a detailed literature review). These methods are mainly data driven and do not strive for an identification of causal relations. In this paper, we focus on statistical approaches, as they are most common in the context of weather insurance. Musshoff, Odening and Xu (2011) show that a trade-off exists between the regression model's simplicity and the yield variation that cannot be explained by weather variables, i.e. basis risk. Several directions have been suggested to improve the fit of statistical yield models, including nonlinear regression or quantile regression (Conradt, Finger and Bokusheva, 2015). More recently, machine learning techniques have been applied to yield modelling (e.g. Khaki and Wang, 2019). The strength of this approach compared with traditional statistical methods arises from its flexibility in capturing complex functional relations and its capability of handling large data sets. This is particularly useful because it allows the consideration of weather variables with high temporal resolution, such as daily precipitation and temperature.

Against this backdrop, the objective of our paper is to explore the potential of machine learning for estimating the relationship between crop yield and weather conditions on a farm level and to use it as a tool for reducing basis risk in index insurance applications. More specifically, we want to investigate three hypotheses: First, we conjecture that machine learning allows a better fit to yield data compared with traditional regression models due to its flexibility. Second, we hypothesize that disaggregated weather data contain more information compared with aggregated weather variables, which allow for improving the estimation of crop yields. Third, we expect that the definition of small and homogeneous production regions eases the design of tailored weather indices and thus reduces the level of basis risk. We test these hypotheses for a large set of farm-level yields. Our data set contains 68,944 observations for winter wheat and 14,624 observations for rapeseed and in total covers many production regions in Germany over an observation period of 16 years. The use of individual farm yields avoids the underestimation of yield volatility that arises from the use of aggregated data, such as county yields (Popp, Rudstrom and Manning, 2005). To answer the aforementioned research questions, we specify an Artificial Neural Networks (ANN) and measure its performance relative to a nonlinear regression model (Hypothesis 1). Firstly, we focus on Germany as a whole and investigate the model performance for different aggregation levels of weather data, namely using monthly and daily weather data (Hypothesis 2). Subsequently, we repeat the analysis for selected homogeneous soil-climate regions within Germany (Hypothesis 3). We trace estimation errors back to particular time periods and regions. Moreover, we distinguish the viewpoint of insurers and the insured when analysing deviations between actual and predicted farm yields.

The remainder of this paper is structured as follows: Section 2 provides a literature review of standard statistical as well as machine learning approaches to estimate the weather-yield relationship; Section 3 presents details on the neural network applied in this study and introduces a regression model that is used as a benchmark; Section 4 contains the empirical application to German farm-level data; and Section 5 concludes with implications for the design of weather index insurance.

Literature Review

The estimation of the weather-yield relation by means of statistical approaches has a long tradition. Teigen and Thomas (1995) studied the relationships for US state-level yield for the period 1950–1994 and find that weather can explain 90 % of yield variation in most cases. This high percentage, however, can mostly be traced back to the time trend and not to the weather variables themselves (Vedenov and Barnett, 2004). For the application of weather derivatives to agriculture, Turvey (2001) estimates the linear dependency of county yields of corn, soybean, and hay on cumulative rainfall and cumulated degree days in Oxford County, Ontario, for the period 1935–1996, with a best fit $R^2$of 0.33. Also, in the context of weather derivatives, Vedenov and Barnett (2004) apply more complex non-linear models to estimate the relation between U.S. district-level yields in 1972–2001 and temperature and precipitation. With data-driven combinations of the weather variables and derived indices, they achieve an R^2 between 35 % and 87 %. Vroege *et al.* (2021) assess the potential of drought risk management with soil moisture data from satellites and weather stations for 89 farms in Eastern Germany. They applied quantile regression and found that the risk exposure of farmers could be reduced significantly with new insurance products based on soil moisture. Besides weather risk management, another purpose of the statistical modelling of the yield-weather relationship is the prediction of climate change impacts. Seminal papers in this context are Schlenker and Roberts (2006, 2009), who combine a county-level data set for U.S. maize yield with daily temperature observations and observe non-linear weather effects on yields; and Schlenker and Lobell (2010), who apply different specifications of the weather variables (linear, quadratic, and piece-wise linear) and find robust negative effects of climate change on agriculture in Africa. At the country-level, Lobell, Schlenker and Costa-Roberts (2011) regress yield outcomes on linear and squared monthly temperature and precipitation. It turns out that the largest share of the explained variation comes from the country-specific intercepts and the quadratic time trend rather than the weather variables. To detect spatiotemporal patterns in the yield-weather relation, Trnka *et al.* (2016) used data for ten countries and two regions in Europe over the period 1901–2012 for wheat and barley. In addition to the classical weather variables, they applied drought indicators, frost days, potential evapotranspiration, and water vapor pressure deficit, and achieved adjusted R^2 for wheat of between 0.00 and 0.71, and a normalized RMSE between 65 % and 130 % also when looking at subperiods. Nevertheless, they found an increasing influence of climatic variables in the more recent years. Bucheli, Dalhaus and Finger (2021) apply different weather indexes on a farm level yield data set in Eastern Germany and show that a tailored farm-specific drought index leads to the greatest reduction of basis risk and that no single universally best underlying drought index exists.

All of these studies show how difficult it is to explain the yield-weather relation using classical statistical approaches. Hence, a lot of hope is put in the use of machine learning and the increased computational power, which allows a more sophisticated analysis of the relationships. Van Klompenburg, Kassahun and Catal (2020) conducted a systematic literature review and identified 50 studies since 2008 that used machine learning for crop yield modelling. Explanatory variables are mostly related to weather, but also other features such as field management or nutrients. For example, Matsumara *et al.* (2015) predicted the maize yield in Chilin province, China, based on weather variables and fertilizer usage, using a multi-layer perceptron with one hidden layer and compared the results with those of a linear regression model. The artificial neural network clearly outperformed the linear regression model, and the predictive performance could mainly be traced back to fertiliser use and not to weather variables. Jeong *et al.* (2016) applied random forests to global wheat yield grid data from 2000, U.S. county-level maize grain yield 1984–2013, and potato tuber and maize silage yield data from over 1,000 points in the Northeastern U.S. in selected years. They achieved an RMSE between 6 % and 14 %, which clearly outperformed a multiple regression model (RMSE between 14 % and 49 %). Also, with random forests, Everingham *et al.* (2016) aimed to predict regional sugarcane yields at Tully, Australia, at different time points up to a year before harvest to optimise fertiliser usage. The shorter the forecast horizon, the more important variables such as rainfall and temperature range became, and up to 79 % of the variability can be explained. Using a semiparametric version of a deep neural network, Crane-Droesch (2018) model county-level yield in the U.S. Midwest from 1979 to 2016 using daily weather variables such as precipitation, temperature, humidity, wind speed, and radiation. It turns out that while the semiparametric model performs the best (with the largest effect being a time variable), the fully nonparametric neural network performed much worse than OLS regression. In a crop modelling challenge, Khaki and Wang (2019), as one of the winning teams, achieved an RMSE of 12 % with a deep neural network when predicting the yield performance of maize hybrids at over 2,000 locations in the U.S. They find considerable effects of solar radiation, temperature, and precipitation. Some studies also use remote sensing data and derived indices such as the Normalized Difference Vegetation Index (NDVI) or Enhanced Vegetation Index (EVI) (Fernandes, Ebecken and Esquerdo, 2017; Johnson *et al.*, 2016; e.g. Pantazi *et al.*, 2016; Sun *et al.*, 2019; Wolanin *et al.*, 2020).

Applications of machine learning methods for the estimation of the yield-weather relation in Germany, however, are rare. Paudel *et al.* (2021) designed a workflow for large-scale crop yield forecasting at different steps between planting and harvesting and applied it to the Netherlands, Germany, and France. For all of Germany, they achieved a normalized RMSE of between 7 % and 17 % at the end of season, which is much larger than the corresponding values from predictions by the European Commission's MARS Crop Yield Forecasting System (MCYFS). At the county-level, Webber *et al.* (2020) combine support vector machines and process-based modelling using data on weather, soil, and crop phenology to explain yield failures. Their model, however, was not able to capture the losses in 2018, an exceptionally dry year in Central Europe (Toreti *et al.*, 2019).

It can be concluded that the use of machine learning in crop yield forecasting has continuously gained more attention in recent years and that it has the potential to reduce basis risk. However, until now, it is still not clear what kind of data and what geographical aggregation form of the region is beneficial for the use of machine learning.

Methods

This study aims to explore the weather-yield relationship with different models. Even though weather is only one of the factors explaining yield deviations, the application of weather data for estimating yield variation is advantageous in comparison to other farm related information, especially when it comes to developing risk management tools such as index-based insurances. First, weather data are available at a high-resolution and independent from farmers' specific participation in the data collection process. Therefore, with weather data in general, it is possible to provide a continuous data stream. Another major advantage is the fast availability of weather data. This is especially important if it comes to an ad-hoc projection of the current expected yield. Other data such as fertiliser use, genomic information, used capital and labour as considered in Albers, Gornott and Hüttel (2017) or Khaki and Wang (2019), cannot be used for this purpose due to its lagged availability. Finally, weather data are reported by independent weather services and cannot be influenced by the insurance holder or provider. To reduce the influence of non-weather-related factors in our yield data, we do not consider in this study the yield itself, but rather the deviation of the yield from the farm yield average. By subtracting the farm-specific mean, constant location, or farmer-specific factors influencing the yield are removed to reduce the risk of omitted variable.

For a realistic insurance application, an out-of-sample evaluation is essential. Therefore, we split the data into three subsets: training data, validation data, and test data. The training data set is used to adjust the weights and to train the models. The validation set is used to evaluate the different settings of the models and to choose the optimal hyperparameters. In the end, the out-of-sample performance of the model is evaluated based on the test set. For a more realistic scenario, the split is not done randomly but by complete years. Even if this split is not necessary for the regression model, we apply this process to ensure comparability across the models. To guarantee the independence of the data sets, the aforementioned farm yield averages are calculated based only on the training data.

Different measures are applied in this study to assess the performance of the models and their potential to reduce the basis risk of an index insurance. The main tool is the root mean squared error (RMSE), which can be used to assess the average deviation between predicted and observed values. This measure, however, is an absolute value. Thus, a comparison across different regions and crop types is only possible to a limited extent due to the different yield levels. Because of this, we use the normalized root mean squared error (nRMSE) as a second measure. This puts the RMSE in relation to the respective average yield level in the region. A drawback of both indicators is that overestimates as well as underestimates are weighted equally, although they have different implications for both the insurance holder and insurance provider. Hence, the level of basis risk is not reflected properly. From the perspective of an insurance holder such as a farmer, basis risk is defined as the probability of having a loss but not receiving compensation: $P(\text{no indemnity} \mid \text{loss})$ (Elabed *et al.*, 2013). This is the case when a negative value is observed, but a positive value is predicted. From the perspective of an insurance provider, however, the opposite is considered as basis risk: an indemnity payment despite no actual loss, $P(\text{indemnity} \mid \text{no loss})$. This is the case if a negative value is predicted, but a positive value is observed. Please note that this definition of basis risk only focuses on the presence, but not on the severity. Complementing the RMSE and the nRMSE, we use both categories of basis risk (of the insurance holder and the insurance provider) as additional metrics in the model comparison and evaluate the shares of misclassified observations as realizations of the related basis risk. By studying different ways of exploiting and aggregating the weather data, we focus on production basis risk or design risk.

Regression Model

Our regression model, which serves as a benchmark for the neural network model, is a multiple regression model. As the dependent variable for both the regression model and the ANN, we use the previously described deviation of the yield from the farm yield average in the training data measured in dt/ha. Following Vedenov and Barnett (2004) and Vroege *et al.* (2021), we use the average temperature, total precipitation, and average soil moisture as independent variables. All weather variables are calculated as monthly values for April, May, and June, which represent the growing period for winter wheat and rapeseed. As in Vedenov and Barnett (2004), we additionally apply squares and same-month interactions of these variables to allow for a non-linear relation. The regression model can be defined as follows:

$$\boldsymbol{\Delta y_{it}} = \boldsymbol{\beta_0} + \sum_{k=\text{April, May, June}} \beta_{1k}T_{kit} + \beta_{2k}P_{kit} + \beta_{3k}M_{kit} + \beta_{4k}T_{kit}^2 + \beta_{5k}P_{kit}^2 + \beta_{6k}M_{kit}^2 \\ + \boldsymbol{\beta_{7k}T_{kit}P_{kit}} + \boldsymbol{\beta_{8k}T_{kit}M_{kit}} + \boldsymbol{\beta_{9k}P_{kit}M_{kit}} + \boldsymbol{\beta_{10k}T_{kit}P_{kit}M_{kit}} + \boldsymbol{\epsilon_{it}} \quad (1)$$

where Δy_{it} denotes the yield deviation for farm i in year t and T_{kit}, P_{kit}, and M_{kit} the values of the weather variables temperature, precipitation, and soil moisture, respectively, at farm i in month k (April, May, June) of year t. The βs denote the coefficients to be estimated and ϵ_{it} the error term. To estimate the model parameters, we use the ordinary least square (OLS) method.

Artificial Neural Network

Second, we apply an artificial neural network (ANN) to estimate the weather-yield relationship based on the same dependent variable as in the regression model ANNs with at least two hidden layers are able to recreate any form of mathematical model, which is in line with the non-linear relationship between weather and crop yields (Sharma, Sharma and Athaiya, 2020). In this study, we use an ANN with one input layer, two hidden layers, and one output layer. Since we are facing a regression problem, we have one neuron in the output layer. The used layers are all fully connected layers, which means that all neurons in the previous layer are connected to all neurons in the latter one. While setting up and training an ANN, hyperparameter tuning is essential. In our study, we develop an ANN of two hidden layers and perform grid search on a search space (Table A1) with Tune as platform (Liaw *et al.*, 2018) for hyperparameter tuning. The application of grid search, as opposed to other methods such as random search, allows us to use a reproducible approach of hyperparameter tuning. This is important since we apply different machine learning models with a separate grid search for each model. To decide for the best setting of hyperparameters, the lowest RMSE on the validation set is used. This is also known as cross validation. The search space for the grid search included learning rate, batch size, and the number of neurons per hidden layer as hyperparameters. For training the model, we use stochastic gradient descent and the Adam optimizer (Kingma and Ba, 2014). To account for the non-linear relationship between weather and crop yields, we opt in line with Sharma, Sharma and Athaiya (2020) for a non-linear activation function and use the ReLU function (rectifier linear unit) $g(x) = \max(0, x)$. The activation function is used for all neurons in the layers except for the output layer. The ANN was implemented in Python using the PyTorch library and trained on a Linux engine (Paszke *et al.*, 2019). Before training the ANN, the input variables were normalized. With this it was tried to counteract overfitting and to enhance the performance of the model (Ioffe and Szegedy, 2015). This also accounts for the different dimension in the input variables.

Empirical Application

Study Region and Data

In the empirical application, we use annual yield data for winter wheat and rapeseed of German farms. Germany is a convenient study region for the effects of drought on yield since only 2.7 % of the agricultural area in Germany is irrigated (Schimmelpfennig, Anter and Heidecke, 2018). Moreover, the conditions of farmland vary largely across Germany, which allow us to study the effect of different spatial aggregation levels (Hypothesis 3). Germany is subdivided into 50 regions with comparable soil and weather conditions, so-called soil-climate-regions (SCRs), by the chambers of agriculture of the federal states and the Federal Biological Research Centre for Agriculture and Forestry. A clustering procedure was used to combine municipalities with similar characteristics in terms of soil quality, temperature, and precipitation into larger areas, which have relatively homogeneous conditions for agricultural production (Roßberg *et al.*, 2007). In addition to Germany as a whole, we will later estimate regionalized models for five selected SCRs.

Our data set consists of annual winter wheat yields from 4,309 farms and annual rapeseed yields from 914 farms in 2003–2018, measured in deciton/hectare (dt/ha). In total, the data set consists of 68,944 observations for winter wheat yields and 14,624 observations for rapeseed yield. The data were provided by a financial accounting firm and an insurance company who collected the data via a farm survey about planting areas and harvest quantity for various crops. The farms are spread across Germany with a higher density in Southern Germany. Their exact locations have been deleted for confidentiality reasons, but the municipalities in which they are located are available in the data set. To correct for outliers from inaccuracies in the data collecting process, we identify farms within the 1st percentile and the 99th percentile of yearly yield per hectare in the years from 2003–2018 and delete those farms from the data set. This is done for Germany and the SCRs individually. For both crops, the complete data sets are split by years into training data (2003–2012), validation data (2013–2015), and testing data (2016–2018).

In line with our research aim and Hypothesis 3, we first use the entire data set (Germany) and then turn to regionalized models for the three SCRs with the largest number of farms in our data set (SCR South 1, SCR South 2, and SCR South 3) as well as one SCR in north-western Germany (SCR Northwest) and one in eastern Germany (SCR East). Figure 1 shows the location of these SCRs. The descriptive statistics for the cleaned yield dataset for all of Germany and the selected SCRs are depicted in Table 1.

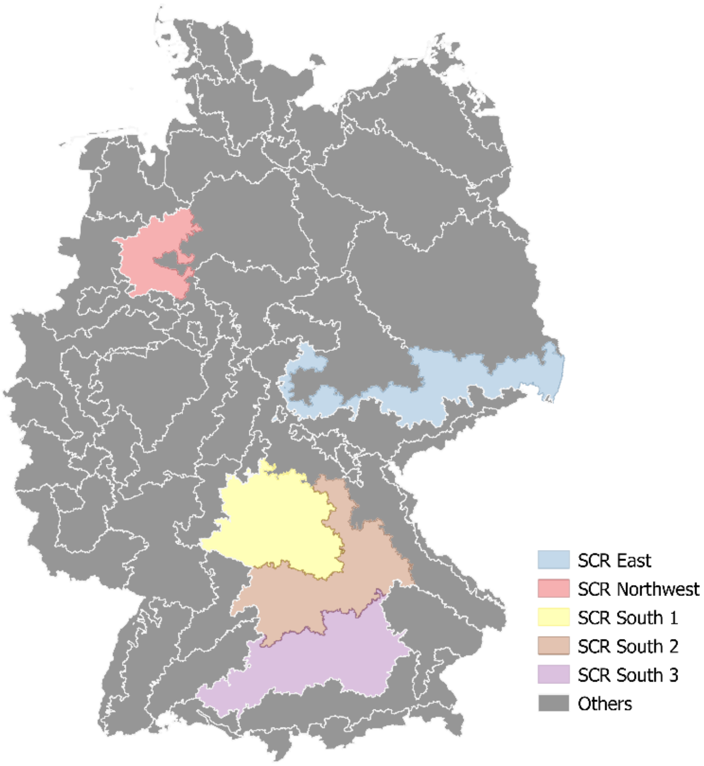

Figure 1: Soil-climate-regions (SCR) considered in this study

Table 1: Descriptive statistics of the yield data (dt/ha) for whole Germany and the considered soil-climate-regions (SCRs)

	# farms	# obs.	Mean	St. Dev.	Min.	25 %	50 %	75 %	Max.
Winter wheat									
Germany	3,344	53,504	74.20	13.57	26.59	65.86	75.09	83.02	113.58
SCR South 1	373	5,968	67.57	14.27	21.54	59.48	69.65	78.21	101.69
SCR South 2	482	7,712	73.96	12.17	32.21	66.84	74.99	81.21	114.25
SCR South 3	394	6,304	77.64	12.06	31,26	71.11	78.84	85.00	113.44
SCR Northwest	97	1,552	80.11	12.83	37.65	72.63	80.28	89.01	136.16
SCR East	7	112	79.33	13.50	51.48	70.19	79.91	89.84	106.81
Rapeseed									
Germany	698	11,168	37.79	8.71	10.44	32.72	38.47	43.49	63.59
SCR South 1	72	1,152	35.95	9.58	10.66	30.91	37.35	42.27	63.27
SCR South 2	104	1,664	37.67	8.77	10.67	32.48	38.44	43.72	63.30
SCR South 3	64	1,024	40.82	8.36	10.48	36.15	41.48	46.21	62.50
SCR Northwest	26	416	40.56	6.96	12.79	36.57	40.60	45.02	62.00
SCR East	6	96	40.90	10.95	11.17	34.45	42.55	49.98	62.47

Note: Due to the separate outlier removals in all data sets, minima/maxima of the SCRs can be smaller/larger than the ones for Germany.

The five considered SCRs comprise about 40 % of all farms in the dataset, but the number of farms per SCR varies largely with a minimum of less than ten farms for SCR East, which was included to obtain a larger regional variation. The average winter wheat yield is 74.20 dt/ha for all farms and varies between 67.57 dt/ha (SCR South 1) and 80.11 dt/ha (SCR Northwest) for the selected SCRs. Naturally, the average yield of rapeseed is 37.79 dt/ha lower than the average yield for winter wheat and there is a smaller range among the SCRs.

Weather data are provided by the Climate Data Center of *Deutscher Wetterdienst* (DWD) and contain information on daily precipitation, daily temperature, and daily soil moisture spanning the same period as the yield data (2003–2018). This detailed information allows us to feed the ANN with daily or monthly data and hence to study the effect of different temporal aggregation levels according to Hypothesis 2. Daily temperature is an average of 24-hourly values and is measured in Celsius two meters above the surface. The amount of precipitation is measured in mm. Soil moisture data are estimated by the water balanced model AMBAV (agrometeorological model to calculate the current evaporation) (Löpmeier, 1994). Since we do not know the exact locations of the farms, we connect the yield data with the weather data via the respective municipality. The DWD interpolates temperature and precipitation data coming from around 300 weather stations to a 1 km x 1 km grid based on the interpolation method by Frei (2014). Descriptive statistics for the monthly aggregated weather variables (April–June) for Germany and the selected SCRs are depicted in Figure 2. It can be observed for Germany that the conditions in 2018 were more extreme compared to 2016 and 2017. While the temperature was generally higher in 2018, median soil moisture and precipitation were lower. This development is also reflected in the selected SCRs.

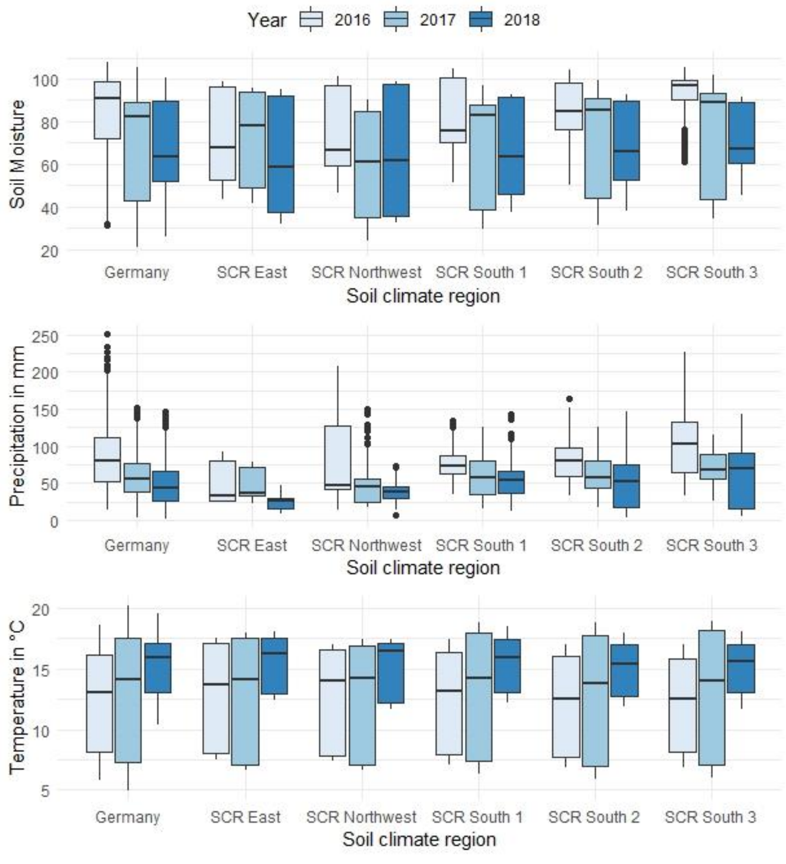

Figure 2: Monthly weather values for all farm locations (Germany) as well as for selected soil-climate-regions (SCRs)

Results

First, we consider the models for all of Germany before moving to the regionalized models. A separate grid search was performed for each model. While in some models only marginal improvements could be achieved, performance could be increased by about 40 % in other models through grid search. The best performing hyperparameter configurations are shown in Table A2. All ANNs in this study are trained with 100 iterations each and during the training process no overfitting occurred.

Addressing our first hypothesis, we first examine errors for the regression models and the ANN models for Germany as a whole and then examine the basis risk of these models. Table 2 depicts the RMSE and nRMSE for models using all farms in the data set (Germany) for the two different crop types. For winter wheat, the regression model achieves an RMSE for the testing data of 13.06 dt/ha. Compared to an average yield of 74.20 dt/ha during the entire study period, this error appears quite substantial (17.6 %). Even for the training data, the RMSE of the regression model is substantial (10.23 dt/ha or 13.8 %), which demonstrates that the regression model cannot explain a large share of the yield deviations. This finding is also reflected by an R^2 of 0.172. The daily and monthly ANN models perform better in-sample with an RMSE of 7.99 dt/ha (10.8 %) and 8.37 dt/ha (11.3 %) on the training set, respectively. However, this superiority does not hold for the test data, as the neural network with monthly data has a higher RMSE (14.44 dt/ha) than the benchmark model. The use of daily weather variables, however, reduces the RMSE to 12.38 dt/ha (16.7 %), so that it seems beneficial not to aggregate the data. Evaluating the performance of the models for the five SCRs separately reveals that the ANN with monthly data performs the worst in all southern SCRs whereas it outperforms the regression model in SCR East and SCR Northwest (Table 2). The ANN with daily data constantly performs the best, even though only with small differences in some cases. Comparing these results with other applications of machine learning models, e.g., Khaki and Wang (2019), a similar level of the RMSE (14.96 dt/ha) in the out-of-sample data can be observed.

For rapeseed, the regression model performs worse than the machine learning models. The RMSE of the test set reduces from 9.02 dt/ha for the regression model to 7.89 dt/ha for the ANN with daily data. Compared to the average yield of 37.79 dt/ha, these errors remain substantial (23.86% and 20.9% for the regression model and ANN with daily data, respectively) and are even larger compared to the nRMSE for winter wheat. Evaluating the performance of the models for the selected SCRs shows a similar picture: Except for SCR South 1 and SCR South 2 – where the RMSE remains more or less constant across models – the use of the ANN with daily data improves the results.

These first results support Hypothesis 1 that the ANN is in general better performing in comparison to the regression model. The results also support Hypothesis 2 that the use of non-aggregated data is in general beneficial.

Table 2: RMSE and nRMSE for regression and ANN models based on all farms, evaluated for whole Germany and the five selected SCRs

		Winter Wheat						Rapeseed					
	Data set	Regression Model		ANN Monthly Data		ANN Daily Data		Regression Model		ANN Monthly Data		ANN Daily Data	
Germany	Training	10.23	*13.8 %*	7.99	*10.8 %*	8.37	*11.3 %*	6.98	*18.47%*	8.57	*16.2 %*	6.07	*16.1 %*
	Validation	12.21	*16.5 %*	12.77	*17.2 %*	12.18	*16.4 %*	9.13	*24.15%*	8.94	*21.5 %*	9.62	*25.5 %*
	Testing	13.06	*17.6 %*	14.44	*19.5 %*	12.38	*16.7 %*	9.02	*23.86%*	8.62	*22.2 %*	7.89	*20.9 %*
SCR East	Testing	16.00	*20.2 %*	14.96	*18.9 %*	14.72	*18.6 %*	9.68	*23.7 %*	7.84	*19.1 %*	7.62	*18.6 %*
SCR Northwest	Testing	13.95	*17.4 %*	12.75	*15.9 %*	12.40	*15.5 %*	9.05	*22.3 %*	8.28	*20.4 %*	7.45	*18.4 %*
SCR South 1	Testing	13.35	*19.8 %*	14.24	*21.1 %*	12.44	*18.4 %*	9.01	*25.0 %*	8.86	*24.6 %*	9.00	*25.0 %*
SCR South 2	Testing	13.15	*17.8 %*	15.58	*21.1 %*	12.59	*17.0 %*	7.83	*20.7 %*	7.67	*20.3 %*	7.80	*20.7 %*
SCR South 3	Testing	12.43	*16.0 %*	14.98	*19.3 %*	12.42	*16.0 %*	8.13	*19.9 %*	8.39	*20.5 %*	7.53	*18.4 %*

To further explore the spatial variation of the forecasting power of the ANN, the RMSE of the daily model is depicted at the municipality level for both crops in Figure 3. The maps reflect the unequal distribution of the farms over Germany, their concentration in the south and northwest of Germany, and the lower number of farms with rapeseed. The RMSE shows a large range from 0.3 dt/ha to 37.2 dt/ha for winter wheat and from 1.1 dt/ha to 21.1 dt/ha for rapeseed. It seems that there are clusters with a lower RMSE and isolated municipalities with a very high RMSE. This spread of the results underlines the conclusion that the model is not performing equally across the regions. It shows large heterogeneity in model performance, which could be due to the unequal representation of the regions in the model. This finding supports our research aim to investigate whether more homogeneous regions can improve the model and thus reduce risk and improve the performance of the model.

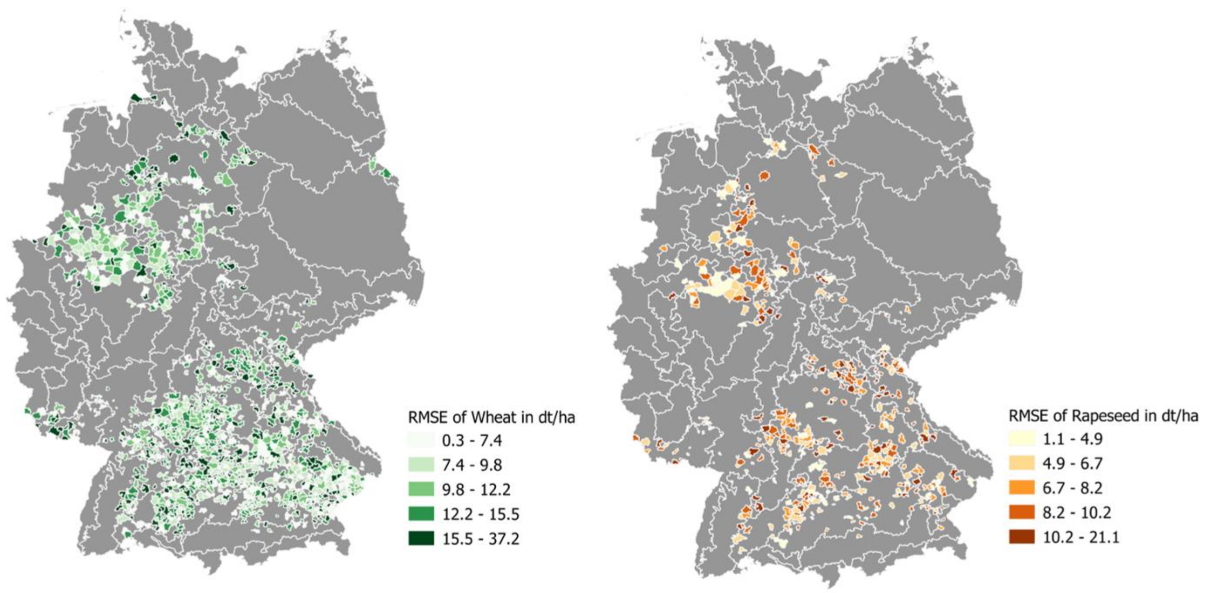

Figure 3: RMSE for test years per municipality for ANN based on daily data

To further investigate these errors, we take a closer look at the residual plots of the models for Germany (Figure 4). The variance of the predicted values is lower for the ANN, especially for the ANN with daily data, compared to the regression models. Table 3 depicts the share of observations with positive predicted but negative observed yield deviations (a disadvantage for the insurance holder) and the share of observations with negative predicted but positive observed yield deviations (a disadvantage for the insurance provider). These observations can be interpreted as realizations of the basis risk for the insurance holder and the insurance provider, respectively. The minimal share of misclassifications for the insurance holder is achieved by the ANN with monthly data for winter wheat (19.4 %) and the ANN with daily data for rapeseed (18.1 %). This supports our first hypothesis that using ANNs can improve the estimation of the weather-yield nexus.

Performance differences between years can be seen in both Figure 4 and Table 3. For the regression models, Figure 4 shows a clear separation of the years into layers. This is also confirmed by the results in Table 3, where most incorrect classifications disadvantageous to the insurance holder can be traced back to observations from 2018. In 2017, there is a small share of observations with no payout despite an observed loss that can be identified across the models and crop types (between 0 % and 12.6 %). Thus, for this year the share of misclassifications disadvantageous to the insurance holder is lowest. However, at the same time the insurance provider faces the largest share of misclassifications in 2017 (between 37.8 % and 71.1 % across models and crop types). These results demonstrate the expected asymmetric distribution of the basis risk between the insurance holder and insurance provider, which could not be seen from the (n)RMSE.

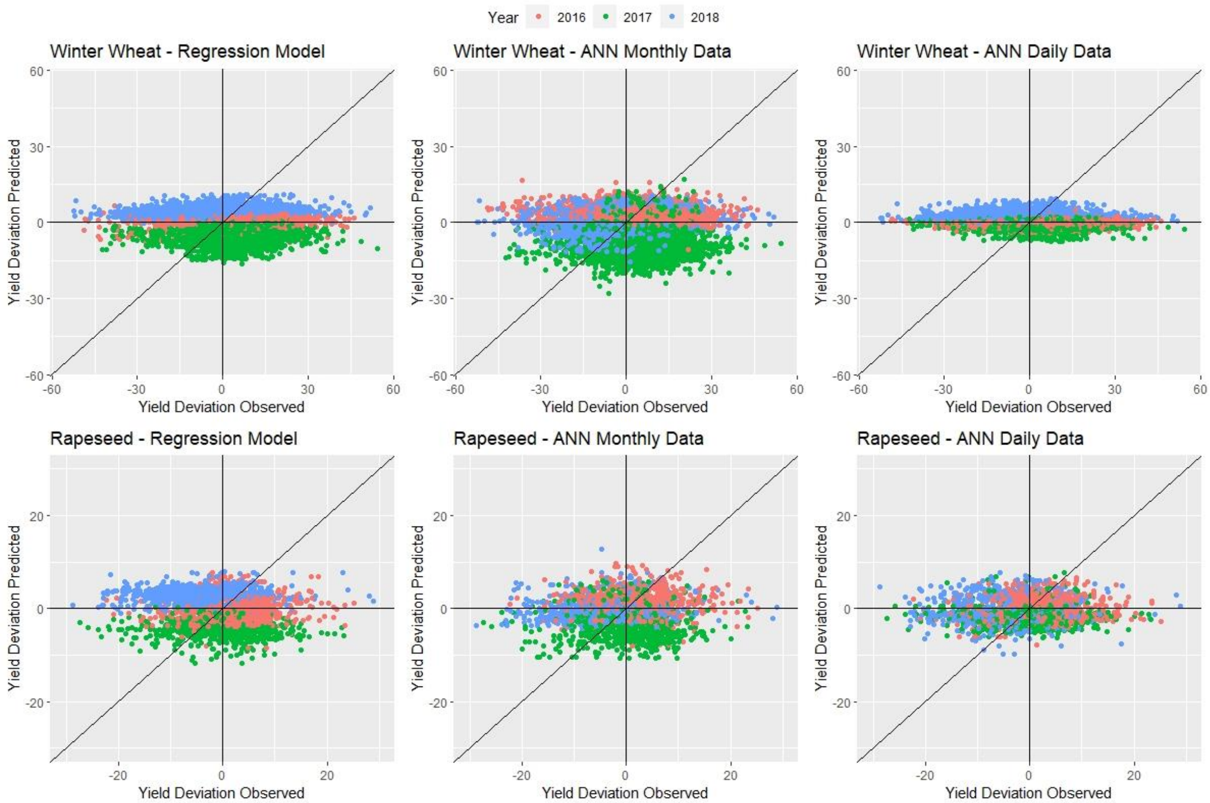

Figure 4: Residual plots for winter wheat and rapeseed for Germany

Table 3: Share of observations with (no indemnity | loss) disadvantaging the insurance holder (H) and (indemnity | no loss) disadvantaging the insurance provider (P) for winter wheat and rapeseed for Germany

	Winter Wheat						Rapeseed					
Year	Regression Model		ANN Monthly Data		ANN Daily Data		Regression Model		ANN Monthly Data		ANN Daily Data	
	H	P	H	P	H	P	H	P	H	P	H	P
2016	21.9%	22.8%	31.5%	6.6%	22.2%	28.2%	13.5%	28.2%	25.8%	19.8%	14.1%	37.8%
2017	0.0%	71.1%	1.2%	68.4%	12.6%	37.8%	0.0%	51.9%	7.5%	46.5%	7.2%	44.7%
2018	42.0%	0.6%	25.8%	19.5%	42.0%	0.9%	68.4%	0.9%	30.0%	13.8%	32.7%	14.1%
Overall	21.3%	31.6%	19.4%	31.6%	25.6%	22.3%	27.3%	27.0%	21.1%	26.7%	18.1%	32.3%

To investigate Hypothesis 3 that more homogenous regions can improve the performance of the models, we will split the data into subsets using the aforementioned SCRs and estimate separate models for each SCR. Moreover, we examine the temporal differences in the performance of the regionalized models. Due to the greater availability of yield data, we focus on winter wheat.

The results for the SCR-specific models in Table 4 strongly differ between the three southern SCRs and the other two SCRs. Regarding the regression model, the southern SCRs have an nRMSE for the test data between 15.8 % and 19.3 %. This is close to the results of the model that has been specified for the entire data set (cf. Table 2). The ANN with monthly data does not change the performance substantially, but the ANN with daily data is able to reduce the nRMSE up to 14.5 %. The latter outperforms the model based on all farms with an nRMSE between 16.0 % and 18.4 %.

On the other hand, the results for SCR East and SCR Northwest show a different picture. The nRMSE for the regression model increases to 35.4 % (SCR Northwest) and 49 % (SCR East) and for the ANN with monthly data it increases to 20.8 % and 22.3 %, respectively. These errors are much larger compared to those based on one model for all farms (between +1.9 and +28.80 percentage points). Only the ANN with daily data shows comparable results, with a clear decrease in the nRMSE for SCR East (–3.6 pp.) and a slight increase for SCR Northwest (+1.0 pp.). It turns out that estimating SCR-specific models can substantially worsen the results whereas only the NN with daily data seems to have a robust performance. By using daily weather data, the ANN has far more parameters that can be trained compared to the ANN with monthly data. Thus, the ANN with daily data can better capture certain weather events. A substantial difference between the southern SCRs and the other two is the number of farms and hence the number of observations in the data set. The southern SCRs include between 373 and 482 farms whereas the other two consist only of 97 (SCR Northwest) or even 7 farms (SCR East). Given the size of the data sets, the results may lead to the conclusion that the ANN can reduce the error by using individual models for homogeneous sub-regions (supporting Hypothesis 3), but that these regions must contain enough observations to benefit from these similarities.

Table 4: nRMSE of Winter Wheat for five SCR-specific regression and ANN models

	Data set	Regression Model	ANN Monthly Data	ANN Daily Data
SCR East	Training	16.3 %	9.5 %	10.2 %
	Validation	47.7 %	13.5 %	16.7 %
	Testing	49.0 %	22.3 %	15.3 %
SCR Northwest	Training	12.9 %	10.2 %	11.2 %
	Validation	21.8 %	18.5 %	13.8 %
	Testing	35.4 %	20.8 %	16.5 %
SCR South 1	Training	18.9 %	11.6 %	11.2 %
	Validation	21.2 %	14.3 %	14.9 %
	Testing	19.3 %	19.1 %	15.9 %
SCR South 2	Training	14.1 %	10.5 %	10.3 %
	Validation	16.2 %	15.5 %	14.6 %
	Testing	16.8 %	17.6 %	16.2 %
SCR South 3	Training	12.6 %	10.1 %	9.8 %
	Validation	16.6 %	16.1 %	13.2 %
	Testing	15.8 %	15.7 %	14.5 %

To examine the model performance over time and the influence of the drought year 2018, we compare the nRMSE for each year separately for one model for all farms (Germany) and the five SCR-specific regionalized models (Figure 5). The nRMSE for the regression model is particularly high in SCR East and SCR Northwest in 2018. From the monthly weather values in Figure 2, however, it cannot be concluded that 2018 was an exceptional year only in these regions, so that the exact reason for the high nRMSE remains unclear. The performance of the ANN based on monthly data also differs between the three years although with a smaller range. The ANN with daily data does not only lead to the smallest nRMSE, but its performance also varies little between the three years, demonstrating its robustness.

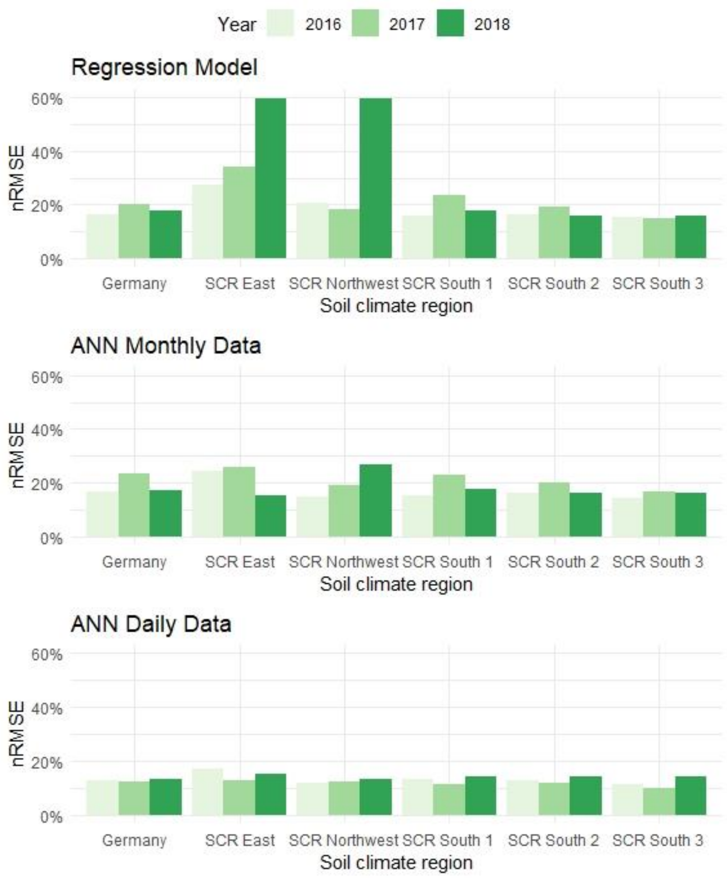

Figure 5: nRMSE by year for winter wheat of the testing set for one model for all farms (Germany) and SCR-specific regionalized models

Figure 6 depicts the share of misclassifications disadvantageous to the insurance holder and insurance provider for the regionalized models. There are two main observations. First, the total share of misclassifications is lowest for the ANN with daily data, which again seems to be more robust compared to the other models. Second, the share of misclassifications is rarely fairly distributed between the insurance holder and insurance provider – in many cases, just one side is affected. Which side is affected depends not only on the year, but also on the selected model. Compared to the results from one model for all of Germany (Table 3), it can be seen that the very high level of misclassifications disadvantageous to the insurance provider in 2017 could be reduced by using the regionalized ANN with daily data.

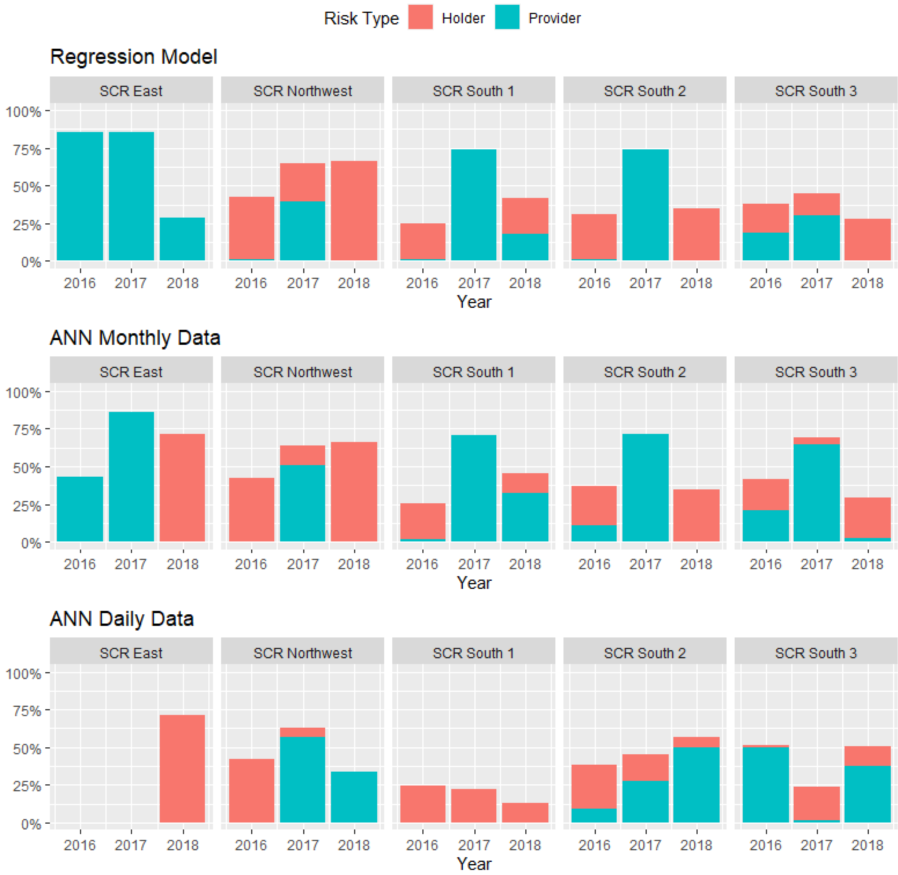

Figure 6: Share of misclassified observations with (no indemnity | loss) and (indemnity | no loss) for winter wheat for SCR-specific models

Conclusions

In this paper, we explore the potential of using machine learning techniques for improving the estimation of weather-induced yield losses. We specify an ANN and calibrate it to a rich set of farm-level yield data in Germany covering the period from 2003 to 2018. A nonlinear regression model, which uses rainfall, temperature, and soil moisture as explanatory variables for yield deviations, serves as a benchmark. Our empirical application reveals that the gain in estimation precision by using machine learning techniques compared with traditional estimation approaches is quite substantial. This improvement of model fit can be traced back to two sources: the flexibility inherent to ANN and the use of daily weather data instead of monthly weather data. In contrast to the common expectation that yield models can be better fitted to smaller, homogeneous regions, we find that the use of regionalized models is only beneficial if a sufficient sample size is available. From an insurance perspective, however, it is noteworthy that even for the best fitting ANN, the level of the nRMSE amounts to 14.5%. This shows that a considerable part of yield variability at the farm level cannot be captured by statistical methods which solely use “big weather data.”

Our findings have important implications for the design of weather-index based insurance because they document that a rather high level of basis risk remains if insurance products are based on an estimation of the weather-yield relationship. This suggests the use of other indices, such as area yields, as an underlying index for index-based insurance. Our results, however, should be considered as a first attempt to tap the full potential of machine learning in this context. Future research should use models with flexible model structures, e.g., convolutional neural networks or locally connected layers, to better estimate the meteorological factors affecting yields. Moreover, considering basis risk explicitly in the objective function of the ANN could further improve the design of weather indices for yield insurance. Finally, we propose the application of neural networks with high-resolution data to other crops and regions to generalize the findings of our study.

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Overview of Farm Mechanization and Potential for Adoption of Central Pivot Irrigation System in Malawi

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Abstract

Malawi's agricultural economy comprises of the smallholder subsector on communal land, and the leasehold and freehold estate subsectors. Large farms and estates use modern inputs more frequently, than the smallholder farmers. Jayne, (2016) reported the ratio of cultivated land area to total land holding size declines as farm size increases. This paper highlights an overview of farm mechanization and the potential role for robots in Malawi. We focus on the Central Pivot System which was introduced to Malawi a couple of years ago. Farm mechanization often follows various stages, starting from the use of mechanical power for power-intensive operations that require little control to increased use of mechanically powered technologies, and finally to automation of production. Past state-led mechanization in Africa often failed due to insufficient understanding of the nature of demand for mechanization technologies among farmers and insufficient knowledge of private-sector functions. Irrigation development in Malawi is guided by the Irrigation policy and the Irrigation Act. We review literature and present case studies (Illovo Sugar and Thandwe Irrigation), performance and cost benefit analysis of central pivot irrigation system in Malawi. This is done in order to demonstrate its the potential for adoption among various categories of farmers. Three inventors with ties to agriculture were inducted into the National Inventors Hall of Fame. Frank Zybach, the inventor of center-pivot irrigation system, and Sylvia Blankenship and Edward Sisler, who co-invented 1-MCP for fruit, vegetable and flower freshness, were all honoured for their pioneering achievements in the agriculture industry. Zybach began developing a self-propelled irrigation system after observing another farmer irrigate crops by using a tractor to systematically tow a long pipe, outfitted with sprinklers, across the field. By 1947, Zybach's system featured two sections of pipes on skids, suspended by cables from two towers. By 1949, the device included five towers with pipes running on wheels and could irrigate 40 acres. Zybach then added water valves for siphoning pressurized water from the main pipe to drive the wheels and maintain tower alignment. Later in 1952, Zybach was granted a patent on a larger irrigation system with a 600-foot boom that could water a 135-acre circle (all but the corners of a standard 160-acre section of land). In 1954, Valley Manufacturing, a small manufacturer of farm equipment, acquired the patent rights from Zybach, and its engineers improved the machine's efficiency and dependability. Today, the Omaha-based company, since renamed Valmont Industries Inc., is a global leader for center-pivot systems and other agricultural products. We focus on various aspects of the central pivot system and application in Malawi. We conclude and make recommendations on policy environment, regulatory framework, characteristics of the technology, and other attributes that can assist in wider adoption.

Presenter Profile

Mr. Kumwenda is a seasoned economist with vast experience in programme/project development, evaluation of projects and programmes and undertaking business studies. Mr. Kumwenda has extensive experience in policy formulation and policy analysis, general micro economic using various programs such as excel, SPSS and STATA. He holds a Master of Science Degree in Agricultural Economics from the University of Aberdeen in UK, Bachelor of Science Degree in Agriculture from Bunda College of Agriculture, University of Malawi. He also has certificates in Agricultural Policy Analysis and Cooperative Development. He has recently undertaken Monitoring and Evaluation of Agriculture Input Programme (AIP) funded by the EU, Fertilizer Market funded by AFAP, Capacity Assessment for PRIDE project and Developed the Youth and Women for the ministry of Agriculture funded by AGRA. He has published over 20 publications in form of papers and reports. He has attended a number of short courses, workshops and seminars at national and international fora. He is a member of the International Association of Agricultural Economists and a Member of the Economic Association of Malawi (ECAMA).

Is it really a win win situation: Henna (*Lawsonia inermis* L.) farming for rural sustainability and economic security in arid zone

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Abstract

Henna (Lawsonia inermis L.), is a perennial shrub dominating the agro-ecosystem of Pali district of Rajasthan, India, which is priced for its leaves which have natural dying properties. From ancient times, Henna has been employed as a cosmetic dye for hair, skin and nails and it has acquired a particular significance in Islamic culture. It is dryland shrub which can tolerate extreme dry and high temperature conditions and survives well on problematic soils with high pH and saline water where other crops cannot be grown. The development of Henna cultivation and processing in Pali, Rajasthan, is a blend of indigenous knowledge and people's innovations. Presently Henna cultivation in the region is under 40,000 hectares which is the largest area under this crop at single location and it is purely rainfed with no use of fertilizers or pesticides. In this crop generally, no fertilizers and plant protection measures are used and a single leaf cutting is taken every year under the rainfed conditions and two cuttings where water is available. Under rainfed conditions for a dense planting the dried leaf yield in the first year is about 250 kg ha^{-1} while over the second, third and fourth years the yield normally ranges from 500 to 2,500 kg ha^{-1}. The crop starts generating returns from its second year onwards, which continues for 20 years while incurring only maintenance costs in the form of hoeing, weeding and harvesting. By following these measures, on average they produce 15-20 quintal dry Henna leaves ha^{-1} from their barren fields. The financial analysis indicated that Henna farming due to its high quality at Pali is a profitable and attractive option for farmers livelihoods. Sustainable income from Henna benefits the farmers of the district as it can tolerate high salinity, drought and incidences of pest and diseases.

Keywords

Henna (*Lawsonia inermis* L.), arid zone, labour, socio-economic parameters, economic viability, rural livelihoods

Presenter Profile

Dr. Dheeraj Singh is working as Programme Coordinator (P.C.), at Krishi Vigyan Kendra, Central Arid Zone Research Institute (CAZRI), Pali, Rajasthan, India. Prior to this, he had served as academician in different Agricultural Universities. His main area of interest includes farmers and farming scenario in arid zone. He had visited several countries for scientific deliberations of his research work and experiences in agriculture and forestry sector of arid and semi arid zones. To his credit are two books, 17 conference papers, 67 research papers, 78 popular articles, 25 bulletins and leaflets along with number of other publications.

Introduction

Henna (*Lawsonia inermis* L.), is a plantation crop native to tropical and subtropical regions of Africa, Asia, and Australia and is found in arid and semi-arid zones. From its leaves a red-orange dye agent is extracted which has an affinity for bonding with proteins, and thus is used to dye human body parts (skin, hair, fingernails), as well as leather, silk and wool. Its leaves contain the reddish orange dye named lawsone that has been used since biblical times as a cosmetic dye. It also served as a textile dye until the advent of fast synthetic dyes. Further, many Ayurvedic and Unani medicines are based on the curative properties of Henna leaves and other plant parts. Preferring hot climates for growth, it is indigenous to the area between the Islamic Republic of Iran and northern India (Green, 1995), North Africa, the Arabian Peninsula, the Middle East and South Asia (Cartwright-Jones, 2006). Rao et al. (2005) reported that Henna grows best in tropical savannah and tropical arid zones, in latitudes between 150 and 250 N and S, and produces the highest dye content in temperatures between 350 and 450°C. It does not thrive where minimum temperatures are below 11°C and temperatures below 5°C will kill the Henna plant (Khandelwal, 2002). It can also occupy frost-free Mediterranean scrub zones, although it does not develop maximum dye content without high summer heat. The optimal soil temperatures range for germination is 25–30°C. It likes saline soils and the maximum lawsone content develops under dry and harsh conditions of the arid zone (Rao et al., 2005). Henna is a very delicate and perishable commodity. Henna leaf loses its freshness after 1 day, so it needs some extra care to store for long periods. Due to the lack of storage facilities, farmers sometimes face problems with unsold leaves (Ahmed et al., 2008). Rajasthan, India leads the world in Henna production with 40,000 hectares cultivated and its production largely confined to Sojat (95%) in the Pali district. Statistical data indicates that in 1955, India produced 2800 tonnes of Henna with Rajasthan contributing only 5 per cent share in the total production, but in 2018-19 Rajasthan dominated with 90% share. Presently the Pali district of Rajasthan is the most heavily cultivated Henna production area in India, with over 250 Henna processors operating in Sojat City alone. Henna is commercially cultivated in Western India, Pakistan, Morocco, Yemen, Iran, Sudan and Libya.

Methods

The field work for this research was undertaken by ICAR-CAZRI, Krishi Vigyan Kendra, Pali located at 24.75° to 26.48° N and 72.78° to 74.30° E in state of Rajasthan during *rabi* season from 2016-17 to 2019-20 (4 years) in the farmers' fields of ten adopted villages of Pali district in the Arid Zone of Rajasthan. For the study two blocks, Sojat and Marwar junction, were selected as these are the main areas where Henna is grown on a commercial scale. In the initial phase a primary survey was carried out in these blocks to ascertain the important socio-economic parameters of the study area and to select the respondents for detailed study. The selected villages (five each) from two blocks were visited frequently and interviews were conducted using a structured questionnaire; group discussions were held with key informants in the villages, including local leaders and public representatives. After this preliminary survey, socio-economic parameters of potential value for the study were chosen and checked by further discussion with the key informants. From a total of 400 farmers cultivating Henna 100 were selected randomly for the study following a sampling intensity of 25%. A semi-structured questionnaire was developed for face-to-face interviewing of the farmers and it was further supplemented by direct observation of the Henna farms. Questions were included to assess the land allocated for cultivation of Henna, propagation materials, silvicultural techniques, contribution to the household economy, and problems faced in Henna farming. Data were collected from the study was further subjected to statistical analysis and utilized to generate information on different aspects of Henna farming.

Results

Analysis of data indicated that Henna farmers have major portion of their land (73%) under Henna cultivation besides this 15% farmers left their land fallow and take only kharif season legumes under rainfed conditions (Table 1). Only 12% of farmers who have assured irrigation facilities with good quality water take cereals during winter season with a part of land covered under vegetable cultivation. In addition to Henna, cropping pattern includes cereals (wheat, pearl millet, sorghum, etc.), oilseeds (sesame and rape-mustard), and cash crops (cucurbitaceous vegetables, fennel, etc.).

Table 1: Basic socio-demographic features of the respondents

Parameter	Component/Range	Frequency
Age group	21-30	9
	31-40-	25
	41-50	45
	>50	21
Literacy	Illiterate	24
	primary	18
	Middle	23
	Metric and above	35
Size of land holdings	Marginal(< 1 Ha)	35
	Small(1-2 ha)	44
	Medium(2-10 Ha)	12
	Large (>10 Ha)	9
Farming situation	Rainfed	91
	Irrigated	9
Land utilization pattern	Rainfed Henna as sole crop	73
	Rainfed arid legumes	15
	Rainfed legumes with irrigated cereals and vegetables	12
Farming experience	1-10 year	16
	11-25 years	31
	25 and above	53
Major occupation	Farming	62
	labour	32
	Job/Business	6
Annual Income	>INR 60,000	62
	INR 60,000-1,000,00	22
	>INR 1,00,000	16

The results of present study conducted revealed that the majority, 45.0% of Henna plant growers belonged to age group of 41-50 years, 25.0% of growers belonged to age group of 31-40 years, 9.0% of growers belonged to age group of 21-30 years and above, while 21.0% of growers belonged to age group of 50 years and above. Literacy status and the educational level of selected growers were analysed and found that 24.0% of Henna plant growers were illiterate, 18.0% having a primary level of education, 23.0% Henna plant growers were middle education and 35.0% having metric and above level of education in the study area. The farming experience of selected farmers were analysed and found that 31.0% Henna plant growers have 11-25 years farming experience followed by 16.0% having 1 to 10 years' experience, and the remaining 53.0% of Henna plant growers having 21 or more years of Henna farming experience. In this study 62.0% of Henna plant growers were engaged in farming, 32.0% were engaged in labour, 6.0% were engaged in a job/business such as shop keeping, government or private employment in the study area. 91% of Henna plant growers depend on rains for their Henna crop and only 9% used open well water for supplementary irrigation. Almost all the members of respondents' families (82%) were involved in Henna production. Collection of planting materials, nursery raising and preparation of planting sites and sale of Henna leaves are carried out by males only, while other cultural operations such as weeding, hoeing, harvesting and most of post-harvest operations are mainly performed by females and children. The farmers hire labourers for harvesting of Henna leaves which is a time-specific job and it is one of the major expenses in Henna cultivation. Management of established Henna plantation thus involves operations like one or two hoeing and weeding, harvesting, drying, threshing and filling of bags on the threshing floor. However, these are linked with rainfall and carried out by all the cultivators at the same time. Consequently, there is a shortfall of skilled labourers and the competition for hiring labourers among the cultivators raises labour charges to a great extent. At the time of harvesting the labour charges go up to Rs. 1500-2000 per labour unit per day as compared to normal rate of Rs 400-600. In this situation large farmers (having more capital to invest) are able to carry out operations in time, but the medium farmers are constrained and consequently operations are delayed causing losses in the form of low overall production and productivity. Small farmers generally do not hire labour and only family labour is used.

The present study also assessed the factors responsible for profitability, economic viability and dominance of Henna cultivation in Pali district (Table 2). Henna cultivation has been found to be a financially viable based on net present value, internal rate of return and benefit cost ratio for farmers. Profitability of mehndi farmers assessed based on the intensity of inputs used. In this study 42% farmers have low input; 35% farmers have medium input and 23% of farmers have high or use recommended inputs in Henna cultivation.

Table 2. Establishment cost of Henna in Pali district of Rajasthan

Cost components	**Low input farmer Rs ha^{-1}**	**Medium input farmer Rs ha^{-1}**	**High input farmer Rs ha^{-1}**
1. Field preparation	3900	4440	5100
2. Labour cost	11400	11700	13400
3. Cost of materials and inputs	4704	11120	15848
4. Interest on working capital, Risk margin and managerial cost	2496	4620	6532
A. Total variable cost (1-4)	22500	31,880	40,880
B. Total fixed cost	2000	2000	2000
Total establishment cost (A+B)	24,500	33,880	42,880
Subsequent years maintenance cost (After 3 years) 4th Year	8,000	12,000	22,000

Productivity and profitability of the farm depends on the intensity of inputs used by Henna farmers. The initial establishment cost of cultivation of Henna varied from Rs. 24500 ha^{-1} with low input farmers to Rs. 42880 ha^{-1} with high input farmers and Rs. 33880 ha^{-1} with medium input farmers. In the subsequent year maintenance and inputs cost is varied due to the intensity of inputs used by farmers and varied from Rs 11930 to 18530 ha^{-1}. Similar to the cost of cultivation, gross returns, net returns and benefit cost ratio (BCR) also varied for Henna farmers. High input farmers achieved average gross returns of Rs. 90000 ha^{-1} followed by medium input farmers at Rs. 67500 ha^{-1} and low input farmers at Rs. 46800 ha^{-1} after 3 or 4 years and onwards. High input farmers achieved average net returns of Rs. 71470 ha^{-1} followed by medium inputs farmers at Rs. 52570 ha^{-1} and low input farmers at Rs. 34870 ha^{-1} after the deduction of total cultivation costs after 3 years. This trend follows the same pattern after the 3rd year and net returns show a positive trend (Figure 2). Similar to the aforesaid economic parameters the BCR of Henna farmers varies with the highest BCR of 4.86 for high input farmers, 4.52 for medium input farmers and 3.92 for low input farmers.

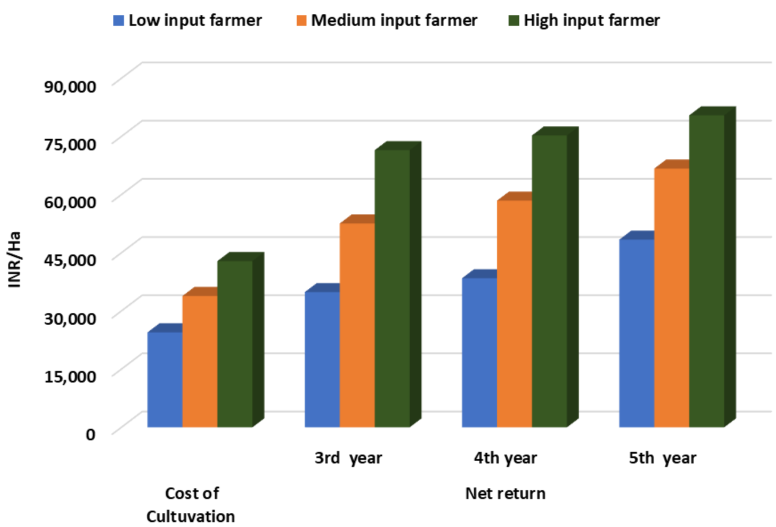

Figure 2: Cost of cultivation and returns from 3rd year onwards

Discussion

The financial analysis indicated that Henna farming, due to its high quality at Pali, is a profitable and attractive option for supporting rural livelihoods. Even for small and medium farmers, the net return from Henna leaf sales is satisfactory at the individual grower level and contributes a large share to annual household income. Pulse crops is not cultivated over a significant area in either season (rabi/kharif) due to high salinity and poor soils with very low organic carbon content. Secondly the major pulse crops in the area (moong bean and moth bean) cultivated in kharif season is now dominated by Henna farming (Chand et al., 2002). The results of present study concluded that most of the Henna farmers are mature farmers of more than 40 years of age due to migration of the younger generation towards cities in search of jobs and other opportunities. Similarly, the majority of the farmers have low levels of education as the educated youth are not interested in agriculture due to its lower income compared to other avenues. The study area within the arid zone where water quality is very poor and soils are saline. Due to this reason most of the Henna cultivation in the area is rainfed with minimal irrigated Henna. In this study most farmers used low input or medium input systems and very few farmers used high or recommended inputs for Henna cultivation. This is supported by the fact that the majority of the area under Henna cultivation is on degraded land and it is not very suitable for growing other crops. Under these conditions' farmers are happy with what they are getting without any or minimum investment. Only resource rich farmers use the recommended inputs for Henna cultivation. The main promoting factor in growth of its area is that it requires only one-time planting and during later years only two operations are required (Kavia and Verma, 2001). This corresponds with the suggestion of Cartwright Jones (2006), who advocated the harvesting of Henna within a month of new growth or when the leaves begin to turn yellow. In another study in Bangladesh, the farmers were found to harvest Henna leaves twice in the first year and four times in successive years (Chowdhury et al., 2009).

There is no major threat or damage to the crop from grazing animals and thus no fencing and after care is needed. It looks like `planting once and harvesting for whole life', only with cost of intercultural and harvesting operations. The initial establishment cost of cultivation of Henna varied from Rs. 24500 ha^{-1} to Rs. 42880 ha^{-1} due mainly to the high cost of labour and use of manure, compost, insecticides and weedicides to maintain soil fertility and control termites and weeds. This is in accordance with the results of Chand et al. (2002) who stated the cost of cultivation of Henna varied from Rs.15707 (small farmers) to Rs.16532 ha^{-1} in Pali district of Rajasthan.

With regard to returns there is an increasing trend in net returns from the 4th year as the fixed costs cease and only maintenance cost are involved. Also, Henna grower farmers achieved higher BCR's compared to other arable crops grown farmers in the study area during kharif season as described by Singh and Gupta (1998). The high BCR is mainly due to near zero cost of maintenance after establishment and getting good crop yields if rains are sufficient. Secondly, due to increasing interest towards Henna art, use of Henna in herbal products and tattoos, the demand in national and international markets is very high. The results are also in conformity to the study of Noonari (2015) who found that Henna growers in Pakistan on average earned Rs.54406 per acre net income, with Rs.121600.00 of gross income and Rs.67194.00 of total expenditure in the Tharoshah district of Naushahero Feroze Sindh. The financial analysis made by Chowdhury et al 2009 also indicated that Henna farming is a profitable and attractive option for rural livelihoods. Existing cultivation, processing and trade practices in Sojat, India are a unique blend of the farmers' innovations, development of marketing procedures and refinement of processing methods. Today more than 250 industrial units engaged in Henna processing are located in and around Sojat, providing employment to rural masses during lean periods and becoming an important revenue earning enterprise (Sukla et al., 2012). These factors also indicate a positive trend towards Henna as the land dynamics is diverting from other enterprises towards Henna cultivation.

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How did you become a pluriactive farmer?

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Abstract

Long criticized, pluriactivity is now perceived as an alternative agricultural strategy and it is becoming a subject of support policies in certain territories. But having an off-farm professional activity can generate significant work overload and organisational problems that might be complicated to manage in the long term. This study focuses on pluriactivity as a dynamic strategy that evolves over time due to family circumstances and job opportunities. We differentiate the initial project of pluriactivity and the strategies farmers use in order to manage overwork. We use an original qualitative approach and 28 interviews of pluriactive farmers in "Nord Pas de Calais" (NPdC), region located in northern France. We find that even if the main motivations of pluriactivity are patrimonial and economic, the initial projects of pluriactivity vary a lot, for some farmers pluriactivity is a patrimonial investment or passion for farming project but for others pluriactivity is intended to be a short-run strategy until the farms gets bigger and more profitable. Then farmers develop different strategies that lead to develop the farm or they reduce farm activities because they cannot give more time to the farm.

Keywords

Pluriactivity, agriculture, organisation, strategy

Presenter Profiles

Amar Djouak, data analysis researcher and head of the interpreneurship team and Clarisse Ceriani, economics researcher, are both members of the agricultural economy laboratory (GRECAT) of "JUNIA", which is a multidisciplinary engineering school located in Lille, France. They have both been interested for several years in issues related to the agricultural diversification and particularly to the concept of pluriactivity applied to the agriculture field.

Introduction

The agricultural sector has experienced several crises in recent years that challenge the conventional production model and encourage farmers to develop new strategies. One of them is to work outside the farm. In fact, pluriactivity is an old agricultural strategy but little appreciated by the agricultural world and by the research community which for a long time-thought that working outside the farm was a marginal-short-run strategy. Nevertheless, pluriactivity presents a set of advantages at the territorial and individual levels. In some respects, this strategy responds to the new requirements of multifunctionality of agriculture, including land use and social networking. Often synonymous with part-time salaried employment, pluriactivity can support local development by favouring the reception of new urban populations with specific needs (sport, cultural activities ...) and thus meet the new objectives of the agricultural policies that aim to boost rural space by creating jobs. Some territories have integrated the economic and social cohesion benefits of pluriactivity and set up new policies to support this strategy (Tallon and Tonneau, 2012). For farmers, pluriactivity can compensate for low farm incomes and financial uncertainty of farmers' families due to farm income volatility and can even play a structural role by facilitating investments on the farm (Glauden and al., 2006, Butault and al. 1999). Finally, it can therefore provide an interesting economic answer to new farmers who are more sensitive to "comfort of life" and for whom farm's income volatility is an impediment to installation (Simon, 2013)

On the other hand, having an off-farm job might be hard to handle and can generate significant work overload and organisational constraints which are difficult to maintain over the long term (Coy and Filson, 1996, Keating, 1987). Therefore, can pluriactivity be a long run strategy or is it just a step in the life trajectories of farmers? According to us, these questions have been studied very little, whereas they are important for evaluating this strategy and its ability to constitute a sustainable alternative to the dominant agricultural model. Indeed, many studies have worked on pluriactivity and found that most of the time pluriactivity is a permanent path (Bertlett, 1986) but it does not mean that most of pluriactive farmers wanted to be and stay pluriactive when they set up in agriculture. In a recent study, we found that for most of the pluriactivity farmers, pluriactivity was a second choice since they would have been full time farmers if the farm had been big enough and profitable. How did a farmer become a permanent pluriactive farmer? Is the farm organisation specific? Does the off-farm job require to be flexible?

In this work, we are interesting on pluriactivity as a dynamic strategy. We define a dynamic typology that consider both farmer's initial motivations and current organisation of pluriactivity in order to study farmer's strategies that lead to a permanent pluriactivity. We use an original qualitative survey with 28 semi-structured interviews of pluriactive farmers in NPdC region that allows exploring farmers life trajectories and expectations about pluriactivity. After presenting our survey and our methodology, we present our results about initial projects of pluriactivity and type of pluriactivity and trajectories to permanent pluriactivity. To conclude we discuss our results.

Methods

The "Nord Pas de Calais-(NPdC)" region which is the target of this study, is a French region (called "Hauts de France" since 2014) located in the extreme north, bordering Belgium. Agriculture is important and occupies two-thirds of the territory: in 2010, the utilised agricultural area (UAA) represents more than 66% of the area of the region. Agriculture remains highly diversified: field crops, livestock (Avesnois and Boulonnais dairy), vegetable culture (in particular near cities) (Agreste, 2015). Pluriactivity is an old phenomenon that tends to develop, but so far, there is still a lack of empirical data and studies on pluriactive farmers in NPdC. In this paper, our interest is particularly concerned with duration of pluriactivity, we analyse pluriactivity as a dynamic and responsive strategy whose motivations and expectations can change over time. We study farmers' pluriactivity because we want to focus on pluriactivity as a (new) professional strategy and a famer is considered pluriactive if he has a job outside the farm[1].

Many studies have worked on the durability of the agricultural pluriactivity and found that most of the time pluriactivity is a permanent path (Bertlett, 1986) but it does not mean that farmers wanted to be part time at first. Recently (Ceriani & Djouak, 2018), we have studied more than 60 pluriactive farmers' interviews (It was a pilot study which will serve as a preliminary step for a larger study and which will include more than 300 pluriactive farmers) and have found that most of them wanted to be only a farmer when the set up but the farm was not profitable enough. Therefore, for some farmers pluriactivity was intended to be transitory and in support of a gradual installation but life constraints or job opportunities have impacted their motivations and expectations. Some studied before us, also noticed that the "intend" of the operator is an important factor that should be used to discriminate the "potential continuing part-time farmers" to the "potential full-time farmers" (Mage, 1976). To introduce the dynamic process of pluriactivity, we define a typology that differentiate initial motivations and expectations of part time farming and the strategies that have been developed by farmers and that can lead to a permanent pluriactivity.

First, we define four initial pluriactivity projects that depend on farmer's motivations and professional situation at the time they set up in agriculture. Like Bartlett (1986) and Mage (1976) before, we consider short-run projects since farmers can use the off-farm job to invest in the farm and become a full-time farmer or to survive and maintain the farm when it has financial issues. On the other hand, some pluriactive projects are intended to last either because farmers clearly have strong patrimonial motivations and never really intended to become a full-time farmer or to indulge an agricultural passion. Table 1 displays more details about our typology for the initial pluriactivity project.

Regardless of the initial motivations and projects of pluriactivity, combining two activities generates an additional workload even when the other job is a source of well-being and personal fulfilment. According to Wilkening (1981), the same number of hours spent in an off-farm job will be more stressful for the farmer since it will represent "wasted hours" for his real job as a farmer. The same observation is made by Keating (1987) who highlights a feeling of competition between the off-farm employment and agricultural activity. Mc Coy and Filson (1996) go further by highlighting the fact that pluriactivity impacts the quality of the time spent by the pluriactive farmer with his family but also his own free time.

To last, pluriactive farmers have to develop strategies in order to reduce time constraints and organisational issues. More specifically, we believe that pluriactivity might become a permanent stage or not by different path that should be analysed. We will pay a particular attention to organisational strategies since exercising an off-farm professional activity can

[1] This definition does not include activities of diversification which, being an extension of agricultural activity, does not open up to another status.

generate significant work overload and organisational constraints. These difficulties of pluriactivity are variable, directly related to the farm characteristics and the type of off-farm job but they can be a source of stress and dissatisfaction (Coy and Filson, 1996, Keating, 1987) and can reduce the durability of this strategy. Indeed, some farmers will develop strategies to maintain the pluriactivity and to make it more comfortable and others will try to leave this situation.

Table 1: Initial pluriactivity project

Setting up ad farmer: Farmers already have a job when setting up. They keep the off-farm job in order to finance investments in the farm such as acquire new lands or create new productions, in order to increase farm's revenue. Pluriactivity motivation is essentially economic and it **is intended to be transitory because i**n the long term, farmers want to be 100% on his farm (what Mage (1976) calls the "aspiring type").
Survival: This situation is a necessity, **farm is the main activity** and farmers have to take another job because **farm has financial issues** and cannot meet the needs of the farmer and his family. Those farmers do not want to be pluriactive but it is the only way to continue and save the farm. ("transitional part time farmer" for Barlett (1986)).
Patrimonial investment: Farmers already have a full-time job outside the farm, they want to keep it because it is important to them economically but also socially and have no intention to leave it. The main motivation for pluriactivity is the maintenance of the family heritage. Pluriactivity is supposed to last. ("Investors" for Barlett (1986)).
Passion: the main motivation is passion for land and farm activities. Farmers already have a full-time job that is important, for revenue but also for open mindness. F**armers would have been only on the farm when they set up but farm revenues are not sufficient**. They set up in agriculture to live their dream and keep the family farm and maybe one day they will quit the off-farm job in order to be full time farmers. ("Hobby farmers" for Mage,1976)

We assume that farmer's strategies can be analysed regarding two factors: (i) **farm investments and prospects** (ii) **pluriactivity organisation and farm workforce**. In particular, we will pay attention to farm projects (the will to develop new productions or to find new lands...) and we will differentiate farmers who still invest on the farm to increase profitability and farmers whose farm engagement tend to decrease. For the organisation of pluriactivity, we analyse organisational constraints related to pluriactivity according to the regular needs of the farm in labour force and the resources available in labour (employee, volunteer ...). However, since agricultural activities have to deal with exceptional constraints such as bad weather, livestock surveillance, we also investigate the way off-farm job flexibility might be important for farmer satisfaction and farm sustainability. Table 2 gives a description of the different strategies.

Table 2: Pluriactivity strategies

Development strategy: Farmers works on the farm regularly and farm activities tend to become more important for farmers. Farmers have been working to develop farm activities and they continue to invest in the farm and farm revenues tend to increase. **The off-farm job is secondary** and the farm has not been arranged or adapted to the off-farm job. Pluriactivity is not well organised and tend to be tough for farmers.
Farm disengagement strategy: Farmers **works on the farm regularly and does most of the duties themselves. The off-farm job is not flexible so farmers** cannot develop the farm. They do not invest anymore in the farm and farm activities tend to become less important for farmers when the off-farm job gets more important. *Farm has financial issues and. Farmers accept their situation to save the family farm. They intend to keep the off-farm job because it is the only way to maintain the farm and because it provides a constant revenue.*
Responsive strategy: Farmers **works on the farm regularly and does most of the duties themselves but pluriactivity has been organised in a way to avoid time constraints** and organizational issues. The farm uses salaried labour force when needed to do one part of the duties or the off-farm job is compatible with the work farm obligations. Farmers still **develop and invest in the farm**. *Moreover, pluriactivity is meaningful and has social and economic advantages.*
Managerial strategy: Pluriactivity is well organized and **most of farm duties are done by salaries**. Pluriactive farmers do not feel pluriactivity is restrictive since they do not have to be on the farm every day. Farm revenues are sufficient to pay bills at least.

The semi-directive aspect of the interviews gives the collected data a strong qualitative identity. Indeed, we used open questions in order to give more voice to farmers and to obtain a deeper understanding of farmers' initial motivations, the way they perceived their current situation and their future expectations. On particular, semi-directive interviews allow a dynamic perspective since farmers can contextualize their motivations and plans with the family farm history and their professional career. Finally, we have selected 28 pluriactive farmers who have a wide variety of personal and professional situations so even if field crop farms are common in the region, we also selected farmers with farms in livestock or mixed farming. To analyse pluriactivity trajectories we need pluriactivive farmers with experienced that is why we have primarily surveyed farmers who have been pluriactive for a long time but we also interviewed some recent pluriactive farmers. Table 3 gives a summary description of these 28 farmers.

Interviews lasted from 1h to 1h30m were recorded. They started with some questions concerning farmers (age when setting up in agriculture, education level, family situation ...) and farms (UAA, legal status, production ...). Secondly, we asked farmers to tell us about their installation in agriculture and their personal/professional trajectory. Then, we asked the farmers to explain in more detail their pluriactivity, the initial and current motivations as well as the advantages and disadvantages of this double life, the way they considered the future and how their pluriactivity is perceived by agricultural sector. At the end of the interview, some questions relating to the financial situation of the farm and the work force were asked. The richness of the collected answers is a precious material which, according to us, makes it possible to study qualitatively the satisfaction of the pluriactive farmers and the factors which influence it.

Table 3: Description of interviewed pluriactive farmers

Farmer	Description
A1 Female	Farmer in PLFC[2] and farm management advisor, field crop farm of 68 ha, 38 years old, installed for 12 years, married with 3 young children
A2 Male	Farmer in PLFC and sales executive, field crop farm of 62 ha, 37 years old, installed for 5 years, married with 2 young children
A3 Male	Individual farmer and mechanical workshop manager, crop-livestock farm of 41 ha, 40 years old, installed for 5 years, married without children
A4 Male	Individual farmer and employee in a battery factory, field crop farm of 42 ha, 52 years old, installed for 18 years, married with 2 children over 20.
A5 Male	Individual farmer and trader in cattle cooperative, cattle breeding on 35 ha, 36 years old, installed for 8 years, married with 2 young children
A6 Male	Individual farmer and gardens-parks manager, crop-livestock farm of 20 ha, 45 years old, installed for 15 years, single, 3 children from 5 to 18 years old.
A7 Female	Individual farmer and an agricultural advisor, field crop farm of 80 ha, 40 years old, installed for 1 year, married with 2 children of 12 and 18 years old.
A8 Male	Individual farmer and hospital employee, field crop farm of 24 ha, 48 years old, installed for 17 years, married with 2 children of 13 and 16 years old.
A9 Male	Individual farmer and agricultural union director, field crop farm of 57 ha, 41 years old, installed for 14 years, married with 2 children of 13 and 16 years old.
A10 Female	Individual farmer and specialized educator, horse breeding on 10 ha, 34 years old, installed for 6 years, married with 1 children of 5 years old.
A11 Male	Individual farmer and manager of a transport company, field crop farm of 50 ha, 52 years old, installed for 22 years, married with 2 children over 20
A12 Male	Individual farmer and works in the construction industry, crop-livestock farm of 52 ha, 60 years old, installed for 21 years, married with 2 children over 20
A13 Male	Individual farmer and machine operator, field crop farm of 31 ha, 35 years old, installed for 8 years, married with 2 children of 5 and 8 years old.
A14 Male	Individual farmer and employee in a battery factory, field crop farm of 42 ha, 52 years old, installed for 18 years, married with 2 children over 20.
A15 Male	Individual farmer and electromecanician, field crop farm of 98 ha, 35 years old, installed for 5 years, single with 2 young children
A16 Male	Individual farmer and gardens-parks manager, field crop farm of 25 ha, 40 years old, installed for 16 years, single, no child.
A17 Male	Individual farmer and teacher, field crop farm of 67 ha, 54 years old, installed for 20 years, married with 3 children between 16 and 26 years old.
A18 Female	Individual farmer and worker in industry, cattle farming of 18 cows, farm of 10 ha, 38 years old, installed for 16 years, married with 3 children of 9 and 13 years old.
A19 Male	Individual farmer and worker in a medical institute, field crop farm of 36 ha, 60 years old, installed for 35 years, single with 3 children between 1è and 31 years old.
A20 Male	Individual farmer and CUMA manager, field crop farm of 75 ha, 34 years old, installed for 6 years, married with 2 children of 2 and 4 years old.
A21 Male	Individual farmer and computer scientist, field crop farm of 65 ha, 44 years old, installed for18 years, married with 2 children over 20
A22 Male	Individual farmer and teacher, field crop farm of 140 ha, 36 years old, installed for 8 years, married with 2 children between 3 and 6
A23 Male	Individual farmer and farmer employees, field crop farm of 57 ha, 42 years old, installed for 22 years, married with 2 children of 14 and 10 years old.
A24 Male	Individual farmer and industrial contract manager, field crop farm of 36 ha, 36 years old, installed for 4 years, married without children
A25 Male	Individual farmer and teacher, crop-livestock farm of 140 ha, 40years old, installed for 18 years, married without 5 children between 13 and 17
A26 Male	Individual farmer and teacher, crop-livestock farm of 20 ha, 33 years old, installed for 13 years, single without 3
A27 Male	Individual farmer and manager in Chamber of Agricultural, field crop farm of 40 ha, 45 years old, installed for 12 year, married with 2 children of 14 and 17 years old.
A28 Male	Individual farmer and executive manager, field crop farm of 15 ha, 48 years old, installed for 18 years, married with 3 children of 18 and 22 years old.

[2] Private limited farming company

Finally, a thematic approach was used to analyse the collected data because it allows to focuses on examining themes within data. Moreover, thematic analysis is useful because it allows to go beyond simply counting words or phrases in the text, as in “content analysis” approach, and to explore explicit and implicit meanings within the data. It is finally important to specify that a certain redundancy of the transcribed speeches was observed when approaching 30 farmers questioned, which can be interpreted by the effect of a form of a data saturation relating to the various encountered situations.

Results

First, we dipslay the results about the initial motivations and projects of pluriactivity and then we analyse farmer’s strategies**.**

Initial projects

We asked farmers about the reasons for which they decided to become pluriactive at first (Figure 1) and if they wanted to be pluriactive when they settled up. Like Barlett (1986), we find that the main motivation is economic, but we have to differentiate farmers who use the off-farm job to increase the household revenue or to reduce the risk and those who use it to invest on the farm or to pay debts. Almost all the farmers we interviewed took over the family farm, which implies patrimonial motivations even if its weight differs among farmers.

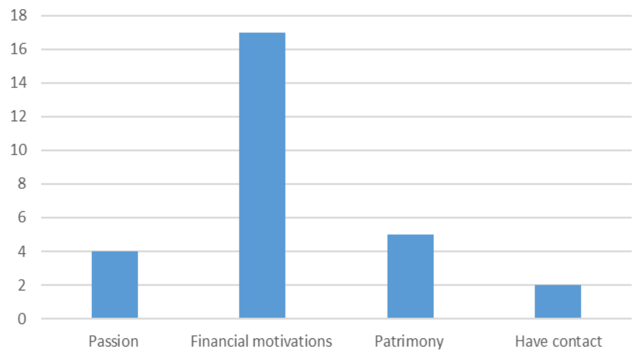

Figure 1: Pluriactivity initial motivation

Over 28 farmers, 21 clearly admit that they would have been 100% on the farm when they settled up in agriculture if farm’s revenue would have been sufficient (Figure 2). So, 75% of the pluriactive farmers we interviewed did not want to be or did not want to stay pluriactive at first but it doesn’t mean that all tried to develop the farm and make it more profitable. In any event, it is an important result because it means that for many pluriactive farmers pluriactivity was not the optimal choice. It is not contradictory to previous studies that found that pluriactivity was a permanent way since pluriactivity motivations and aims might change over time.

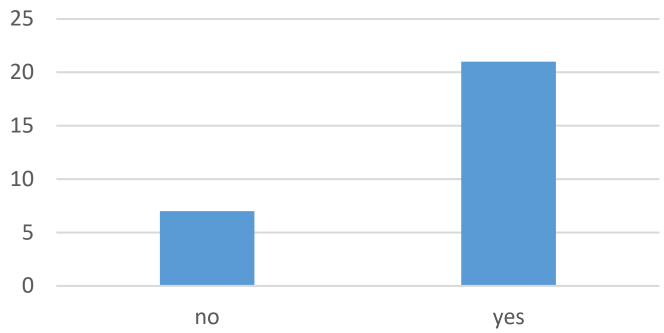

Figure 2: Willing to be only a farmer when set up

Eventually, when we apply our initial typology to the 28 interviewed farmers using motivations and projects at the time they set up in agriculture, we get the distribution described in table 4. We observe that among the 28 farmers 16 knew if they wanted to stay pluriactive or not, for the others pluriactivity duration was more uncertain. Indeed, 6 farmers had a patrimonial project and never intended to become a full-time farmer. Those farmers have strong patrimonial motivations and if most of them wanted to become a farmer, work in the family farm, they never intended to be 100% on the farm. They consider agriculture as a secondary or complementary activity while the off-farm job plays an important role, financially but also for personal identity *" (speaking of agriculture) it is secondary because my off- farm job is really important in my professional life*" (individual A7). For these farmers, pluriactivity has indeed imposed itself, the only way to preserve the family farm, perpetuate a family tradition, a work undertaken long time ago by parents, grandparents... but also the only possibility to leave their passion for agriculture."*. It is only in a family project ... [...] it is the result of the work of generations before us but it is true that if there had not been children behind we did not necessarily need it ... we would not necessarily have taken the step* "(individual A7)

Table 4: Initial project typology

Survival (7) A11, A12, A16, A19, A21, A25, A26	**Setting up (8)** A3, A5, A6, A10, A14, A15; A17, A22
Patrimonial (6) A1, A7, A8, A9, A13, A27	**Passion (7)** A2, A4, A18, A20, A23, A24, A28

Among the 28 farmers, only 8 wanted to use pluriactivity as a transitory project in order to develop the farm and make it more profitable. 7 farmers did not really know if their pluriactivity was going to last, they were passionate by agriculture and they wanted to become a farmer at least a part time one. These farmers all grew up in an agricultural environment, mostly settling in a family setting and as a multi-worker. According to them the financial situation of their farm was not bad when they set up but the farm was not big enough to leave the off-farm job and be only a farmer. Moreover, the other job was important for them, economically and socially, that is why they decided to combine two activities. Pluriactivity was a positive choice : "*Yes, it was a desire to be pluriactive, in fact I did not see myself a full-time farmer ... I had a real love and interest in farming, but at the same time I had the desire to have a salaried activity, physically to be on the move, to be able to travel a little bit .... so farming seemed a little too sedentary to me actually* "replied - as an example - one of the farmers multi-active respondents belonging to this category when we asked the question about their desire to be multi-active at installation.

A dynamic strategy

Pluriactivity motivations and expectations tend to change over time depending of family context and job opportunities. The use of semi-structured interviews allows to contextualize farmers' motivations and plans by integrating them into farmers' family and professional history. First, we display some results regarding the way farmers consider their pluriactivity in the following years. Then, we analyse the organization of pluriactivity, including work on the farm, the advantages and disadvantages of pluriactivity felt by the farmer as well as farm investments and prospects in order to classify the different strategies farmers have been using.

When we ask farmers about their future and if they want to stay pluriactive (Figure 4), 12 farmers seem to be quite confident and say they want to stay pluriactive. They put forward their off-farm job and will never drop it, for them stopping pluriactivity means giving up the farm and with-it part of their passion and family history. On the contrary, 8 farmers do not want to stay pluriactive and think about leaving the off-farm job and 2 farmers want to stop agriculture.

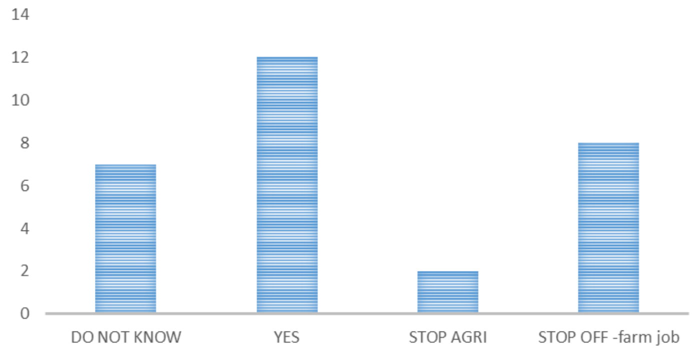

Figure 4: Keep on pluriactivity?

7 farmers do not really know and for 6 of them the future of their pluriactivity will depend on the farm profitability and farm opportunities. Those farmers seem to be willing to leave their off-farm job one day to become "just a farmer" because the work overload will be too hard so that they will have to make a choice, which often means stop the off-farm job, if the farm is profitable. *"I like it. Satisfied, yes. After that, I'm not saying it's easy every day. Some days when you have to run, you have to run. That's why I put it into perspective. Today, I'm young, it's okay. Maybe in ten years from now, I will not be willing to run like this anymore. There is, I think, an evolution over time, with age, that will make priorities elsewhere. Pluriactivity works great for a while, but not forever I don't see myself multiactive until I'm 65." (individual A22)*

Development strategy

Some farmers are in a proactive strategy, they are using pluriactivity to develop the farm in order to be able to quit the other job one day soon. For them, farming is the most important activity and the other job is a good way to develop the farm or a specific activity on the farm such. They would leave the other job and live entirely from farm income if it was possible but for the moment farm's income is not sufficient. For them, the profitability of the farm is not a current issue but one day the farm will have to be profitable and they all intend to leave their jobs to devote themselves to agriculture. Those farmers are more likely to use the other job to invest in the farm in order to create new agricultural activities or to improve the farm. This is the case for individual A4 who was leaving the other job at the time of the interview. This farmer was really satisfied of his pluriactivity because he was convinced that the other job provided lots of things to his agricultural activity and personal life but time constraints and organisational problems make his pluriactivity impossible to continue. Some of them have already totally transformed the family farm and made their own organisation such as individual A24 who says that thanks to the other job she is able to develop the agricultural activity, take some risks without pressure or such as individual A25 who stopped producing milk in order to take an off-farm job and develop a direct selling activity until it is profitable. *"Anyway, we are much more confident in what we do. There are choices.... I knew I wanted to do organic vegetables, but it was really unknown, I had no idea how to do it, I even complicated things by working with the old varieties of wheat, by working in short circuit, etc. …With respect to the agricultural profession, the other profession allows me to take more risks in my agricultural activity if necessary"* (individual A24). Farmers who belong to this type of pluriactivty are quite satisfied with their plutriactivity because it allowed them to settle up in agriculture in better conditions, with less risk and in particular the other job and the financial security give them the opportunity to develop the farm.

Farm disengagement strategy

For some farmers we observe that pluriactivity has not been organised at first and the off-farm job is a full time and does not benefit from flexibility. The farm financial situation is not good enough to employ extra work, so the only way to maintain de farm unless farmer's absenteeism due to the other job is to use reduce farm activities and devote more time to the off-farm job. In this category, we can differentiate two types of farmers (i) the happy one who want to keep on being pluriactive. Those farmers seem quite satisfied of their pluriactivity because eventually they have found a solution to reduce time constraints and maintain the family farm. The other job enables to increase revenues and it reduces the risk but they finally find that it enables social contacts and open-mindedness. But for other farmers who have a lot of work on the farm, pluriactivity is still complicated to manage and the other job leads to overwork and stress. These farmers put forward tight schedule, weeks that sometimes exceed 60 hours of work and leave little time for leisure, family and for rest. Like other studies, we note that there is some frustration among these farmers when they are not present on the farm so that the off-farm job that is not complementary happens to be in competition with their farm activity (Keating, 1987). For some farmers, time spent outside the farm may even be perceived as lost time for the "real" job of farming (Wilkening, 1981). "*What is difficult for me is to accept the day when it's nice to be locked up or to accept because an animal is not good or maybe I'll find her dead at night is this difficulty to say: all in all, I would be there, I would manage to cure it or I would be at home I would be able to cut wheat because it is nice* "(individual A3). Indeed, some farmers are quite unsatisfied of their pluriactivity and they might quit agriculture one day because the farm's financial situation is bad but for most of them and others so difficult that he feels he isn't good enough and doesn't belong to the "agriculture world" so he sincerely thinks about leaving agriculture. These pluriactive farmers were often forced to keep the off-farm job because farm incomes were (at the time of the farm takeover) and still are insufficient. All these farmers therefore put forward a financial motivation that sometimes seems to be the only reason for pluriactivity which partly explains their dissatisfaction: "*I use my income from job of educator to invest in the farm*" (individual A10). Their dissatisfaction is often mixed with anger towards an economic and political context for which they cannot do anything but which has a huge impact on their remuneration for agricultural work. "*I have the feeling of always working and not receiving much in return, telling myself that if I was bad, it's true that it would be normal for me not to succeed, but here I do my very best"* (individual A3)

Managerial strategy

5 farmers have developed a **managerial strategy and** have regular employees who manage a large part of the farm work, almost independently. This organisation of the farm makes the farmer appear as "a manager" who delegates a part of the work to one (or more) trusted person, the family of course but also employees. "*Today it is the employee who does all the work ... for the anecdote I address him with the courtesy "vous" because he is my employee but he knew me from my childhood ... I do not need to see him every day, there must also be trust and he agrees to be autonomous* "(individual A1). An essential element of this "managerial" organisation of pluriactivity seems to be related to the ability to adjust the off-farm work schedule in order to free up time to be present on the farm. The flexibility of the other job and the choice of an agricultural production with less time constraints reduce the stress related to absences on the farm and mitigate the workload by limiting the "double days". This "managerial" governance combined with an optimal organisation of the time spent on the farm allows them to consider the future of their pluriactivity with greater serenity. Indeed, they all want to stay pluriactive. In addition, when they do not have an employee, their parents or spouse might keep an eye on the farm. *"I can easily arrange things with my employee. I avail myself in winter for stand-by duties that I compensate in the summer at the time of the harvest. So there are no worries .... my tractors return in October in the buildings and leave in February for fertilizers. I have six months, I can disconnect the batteries* "(individual A8). Most of those farmers became pluriactive in order to keep the family farm so they are proud to have kept the family farm despite their other job *"I managed to set up a system that allows me to get my own farm, to manage the farm without constraints, so I am very happy with what I did* "(A9).

Responsive strategy

Most of the farmers have adapted the farm to their pluriactivity but they keep on investing in the farm and they still develop farm activities and have projects. Some of them have changed farm organisation or production in in order to reduce time constraints as individual A4 who has oriented his agricultural activity towards an automated production which requires little work force and if necessary this farmer uses occasional supports. Others have an agricultural production that requires lots of work force and presence on the farm but the off-farm job is flexible so they can free up time when needed like individual A5 who is a cattle farmer, and clearly indicates that the workload is important and that he has "big time constraints" but thanks to the flexibility of his other job he can manage the farm, for the moment at least.

For most of them, the other job is qualified and they like it and they are convinced that their agricultural activity improves their off-farm-work efficiency because it provides entrepreneurial and business skills and for some of them being a farmer enhances networks and gives them a better legitimacy in their work. *"(about the farming activity) As part of my job, it brings me a lot of things, both professionally, also socially, somewhere, because I am in contact with other farmers, social networks that are different. I have contacts with my fellow* *farmers as part of my CUMA, with the new owners. There are many circles of exchange that are, in my opinion, positive, that I would not have if I were only an employee of the Chamber of Agriculture" (Individual A27).*

They are still engaged in the farm and continue to invest and create new activities such as direct sales. These farmers have a positive image of the farmer's work: famers get their own business, which give them independency and a freedom of satisfaction. Farmers have multiple functions and diverse skills: *"A farmer is a business leader, (he decides). I am a farmer, a business leader who takes into account different dimensions: technical dimension, economic dimension and then environmental dimension" (*A20). They think that pluriactivity gives them the possibility to be in « both worlds », it opens their mind. Some farmers are convinced that their agricultural activity improves their off-farm-work efficiency because it provides entrepreneurial and business skills and for some of them being a farmer enhances networks and gives them a better legitimacy in their work. *"(about the farming activity) As part of my job, it brings me a lot of things, both professionally, also socially, somewhere, because I am in contact with other farmers, social networks that are different. I have contacts with my fellow farmers as part of my CUMA, with the new owners. There are many circles of exchange that are, in my opinion, positive, that I would not have if I were only an employee of the Chamber of Agriculture" (Individual A27).* As individual A25 who has created a direct selling activity and uses the off-farm job to improve his skills and bring in new consumers to his business. *"Being multi-active reinforces the development of my direct sales workshop of Angus.... my job of teacher is open-mindedness, it is openness to technique, training, meetings that I can make, it helps the development of my direct sales clientele, it's really complementary*" (Individual A25)

They seem satisfied about their situation and want to continue. They see lots of advantages for having two jobs. Financial incentives and profitability do not seem to be a main condition for going on with the farm but they do not want to finance the farm with their other activity. However, it does not mean that they do not invest themselves on the farm. In fact, those farmers seem to be more confident in the future and in their capacities, and most of them are in a proactive entrepreneurial logic: they maintain the family patrimony, remaining open on possible evolutions of their farm and their career and without being limited to the technical conceptions, or cultural and legal aspects of the profession (Lagarde, 2006). *"On the heritage side, I am very proud of me. I have carried out two activities and maintained this farm that may be passed down to my children. I am also very proud somewhere to maintain an agricultural fabric …."* A27. But even when pluriactivity seems to be pleasant, many farmers put forward the overload work and time constraints *"The disadvantages (of pluriactivity) are double organization, double stress. We combine two different professions and therefore two different stresses. We also have different deadlines. (Individual A26).* Indeed, most of those would to be willing to leave their off-farm job to become someday "just a farmer". They admit that one day the work overload will be too hard so that they will have to make a choice, which often means stop the off-farm job, if the farm is profitable. *"I like it. Satisfied, yes. After that, I'm not saying it's easy every day. Some days when you have to run, you have to run. That's why I put it into perspective. Today, I'm young, it's okay. Maybe in ten years from now, I will not be willing to run like this anymore. There is, I think, an evolution over time, with age, that will make priorities elsewhere. Pluriactivity works great for a while, but not forever I don't see myself multiactive until I'm 65."* (Individual A22)

Discussion

Our results seem to indicate that satisfaction and sustainability of pluriactivity are closely linked to the expectations of pluriactivity and its origins, but organisational constraints and work overload are also very present. In addition, it appears that pluriactivity is more sustainable when the farm has been designed and organised in order to complement the other activity and to reduce time constraints. In particular, the presence of regular or even permanent labour force appears highly discriminating in terms of sustainability because it allows farmers to be less present on the farm which limits not only the workload but especially the "competition" between jobs, generating stress (Keating, 1987). The "partial" presence of the farmer on the farm which is compensated by a non-family labour force necessarily raises the question of the identity of the pluriactive farmer, his managerial skills and his position as executive director (Legagneux and Salvagnac, 2017). Indeed, the farmers we interviewed consider themselves farmers-entrepreneurs, they often have investment projects, or even expansion plans, but their vision of the job is different from that of their parents and grandparents. This new way of being a farmer can be related to the increase of the use of salaries on farms since the 2000s (Legagneux and Salvagnac, 2017) and the restructuration of work and work organization within farm (Harff and Lamarche, 1998).

Hiring of permanent employee(s) also raises the question of financial profitability of the farm. During our interviews, many farmers expressed the will to get an employee on the farm, but they cannot afford it. Indeed, pluriactive farmers who employ someone on the farm are the only ones to consider that the financial situation of their exploitation is good. Finally, unsatisfied farmers are often in a precarious financial situation, leading them to increase their working hours in the hope of getting back on their feet. Unfortunately, they rarely see their efforts rewarded and it follows a negative spiral: a bad financial situation requiring them to work more which causes a lot of stress, fatigue and psychological tension and with, unfortunately results, in general, far from their expectations which can even be a real brake for family transmission.

Conclusion

They can be called "slashers", professionals doing several activities at once, trades interspersed with a slash: computer scientist / baker, photographer / craftsman ... etc. and the agricultural world is not immune to this way of life that is increasingly present in society. Based on this observation, we conducted a qualitative study on agricultural pluriactivity in NPdC and in particular on the satisfaction and sustainability of such a strategy. Our results seem to indicate that the durability of pluriactivity is closely linked to the expectations of this strategy and to the role of farmer. In addition, satisfied farmers often have patrimonial and social motivations and the off-farm job seems to have a strong identity role. However, these farmers also consider themselves as farmers-entrepreneurs whose functions are varied and qualified. The flexibility of the off-farm job and the good organisation of the farm around the pluriactivity contribute to the success of this strategy. However, the durability of the pluriactivity also depends on the possibility of hiring regular or even permanent workforce which will guarantee serenity for the farmer. But the possibility to get regular employees depends on the financial situation of the farm, which then appears as an important condition for the success of pluriactivity in the long run. At the end of this work, a number of factors related to the satisfaction and sustainability of pluriactivity were highlighted. Among these factors, the financial situation, the organisation of the farm and in particular the presence of labour and the flexibility of the other job are issues of pluriactivity on which public actors can position themselves. However, it's important to remember that during this study we were interested in a restricted geographical area (part of the north of France) and a future extension (this is planned soon) of this area as well as an enrichment of the database of farmers interviewed will improve the validity of the current study. Therefore, a reflection on the support of pluriactive farmers is necessary to integrate the particularities related to their dual profession: time management, lack of manpower in the short and long run, organisational difficulties. This consideration is important because it would improve the pluriactive farmer's situation and make this strategy more sustainable and more attractive for young farmers who want to combine activities while reducing financial constraints and risk.

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A Review of Olive Oil Price Relations through a Systematic Map

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Extended Abstract

Olive oil is probably the most characteristic product of the Mediterranean and is considered to be the healthiest edible fat deriving from vegetable origins. With a steady upward trend in the demand for olive oil globally due to its health benefits and the fact that the EU accounts for 69% of the world's olive oil production (European Commission, 2020), it is interesting to see how principal olive oil markets interact in such a dynamic environment. The most important markets for olive oil are Spain, Italy and Greece, and in recent years Portugal and France have also increased their production for olive oil, even though they are still falling behind.

Several policies have been undertaken on behalf of the European Commission aiming to integrate national markets. Thus, the Single Market established in 1993, encouraged the free movement of people, goods, and capital (Borchert & Reineke, 2007). Although policies have been undertaken to empower competition, there is evidence that the prices for same products in neighbouring countries differ (Emmanouilides & Fousekis, 2012). Therefore, price relations between different markets and/or actors across the supply chain have gained considerable attention by policy makers and researchers (Conforti, 2004). This is because the intensity and pattern of price transmission reflect the degree of market integration or market segmentation respectively (Fackler & Goodwin, 2001). In highly integrated markets, a shock in one market will cause a shock to the other due to price dependence (Meyer & von Cramon-Taubadel, 2004). Thus, price transmission is a prerequisite for markets to achieve economic efficiency and to maximise benefits from spatial arbitrage (Serra et al, 2006).

The majority of existing research focus on agricultural commodities consumed and produced mainly in Northern European countries. To the best of knowledge, a very limited number of studies has analysed price relations regarding olive oil within the Mediterranean countries. To find evidence of price mechanisms related to the olive oil markets, a systematic mapping process was performed. The search was expanded on vegetable edible oils to reduce the likelihood of missing any evidence relating to the topic of interest.

This study was based on a systematic search of past research relating to price transmission in edible oil markets worldwide, published after 1993. The database search was conducted on the following databases: AgEcon, CAB abstracts, CABI, Emerald, Food Science Source, ProQuest, Science Direct, Scopus, Web of Science, Wiley Online and World Bank, based on set inclusion and exclusion criteria. This search resulted in 8019 documents and 107 more documents were identified through other online sources such as

Google Scholar. During the first stage, screening of Title-Abstract-Keyword was conducted, where 185 articles progressed to full-text eligibility. Only 34 articles met the inclusion criteria and were included for qualitative analysis. 29 of the articles studied price transmission in edible oil markets and 5 investigated both price transmission and volatility. All the included studies were analysed in detail and were categorised based on the type of price transmission they studied. 10 studies analysed vertical price transmission, 10 focused on spatial price transmission and the final 14 examined horizontal price transmission. The most studied types of edible oils were palm oil, soybean oil and rapeseed oil. This may be due to the fact that these are some of the most commonly used vegetable oils that are used for biofuels, and a total of 15 articles studied price transmission in relation to energy markets specifically (Yu et al, 2006; Campiche et al, 2007; Busse and Ihle, 2009; Rifin, 2009; Busse et al, 2010; Peri and Baldi, 2010; Busse et al, 2012; Hassouneh et al, 2012; Nakajima, 2012; Thomas et al, 2013; Serra and Zilberman, 2013; Vacha et al, 2013; Bergmann et al, 2016; Salami and Haron, 2018; Mohantya and Mishra, 2020). Noteworthy is the fact that only 2 of the included studies examined price transmission in Mediterranean olive oil markets (Fousekis and Klonaris, 2002; Emmanouilides et al, 2014).

The findings show that the frequency of data used in the articles depends on the type of price transmission studied. In vertical price transmission the most utilized frequency of data was weekly data, for spatial price transmission monthly data, and for horizontal price transmission daily data. Even though the frequency of data differs based on the form of price transmission, it is found that the most employed empirical models were Johansen cointegration analysis and VECM.

Testing for asymmetries is one of the main focus topics of these studies, where 56% of the articles test for asymmetries and 44% do not account for them. The results regarding the presence of asymmetries are mixed and depend on the type of edible oil and the type of price transmission. Market power appears to be the most common cause of asymmetries regardless of the type of edible oil or price transmission. Some other important causes of asymmetries appear in relation to the type of price transmission, such as stock-holding behaviours, transaction costs and lack of competitive market conditions, for vertical, spatial, and horizontal price transmission, respectively.

The results of the systematic mapping process indicate that there is a gap in the literature for studies that examine price transmission in olive oil markets, therefore further research is suggested to investigate price relationships in major EU olive oil markets.

Keywords

Price transmission, edible oils, olive oil, price asymmetries, systematic map

Presenter Profile

Pamela Theofanous is a PHD Candidate in Land and Agribusiness Management Department at Harper Adams University. Her research focuses in investigating price relations between major olive oil markets with particular focus on Mediterranean markets. Her interest lies in price asymmetries analysis and reasons that hinder market integration. The aim of her research is to understand the functioning of the markets thus determining market imperfections and subsequently proposing policies to tackle any form of inefficiency.

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Environmental impact of using EUR-size wooden and plastic pallets measured by generated carbon footprint and solid waste.

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Abstract

The paper addresses environmental impact of using pallets and compares the performance of plastic and wooden pallets regarding to carbon footprint and waste, they produce. Common wisdom has it, that wooden pallets are environmentally friendly. Plastic pallets, due to the material they are being made of, are regarded to be a potential source of pollution in land, air, and water. We have gathered, evaluated, extracted and/or calculated data showing how much CO_2, and solid waste is generated due to specific wooden and plastic pallet operations. The Life Cycle Assessment method has been used, with primary data extracted from our own studies and experience or taken from reputable sources we quote in our work.

Keywords

circular economy, carbon footprint, waste, pallets.

Presenter Profiles

Msc Krzysztof Witos, economist, logistician, inventor (holding patent for a plastic pallet system), entrepreneur, and researcher interested in resource management and network efficiency, PhD student in Warsaw School of Economics. Participating in research and development projects, e.g., "Local government level support instruments for SMEs, based on the model of multi-level regional management (REGIOGMINA)", “Conditions enhancing creation and development of the so-called "smart society”. Involved in issues related to reverse logistics, waste management, recycling, reusing, and remaking. Follows and readily quotes professors Kaplan’s statement “if you can’t measure, you can’t manage”.

Professor Zbigniew Grzymała and Doctor Agnieszka Wójcik - Czerniawska are employees of the Warsaw School of Economics. As employees of the Department of Economics and Finance for Local Government, they deal with the issues of sustainable development in a very broad sense.

Introduction

Pallets are common assets in the range of logistic tools, applied to maintain efficiency in storage and transportation of goods. They are used across all industries, and all means of transportation. Pallets made of wood have prevailed in the market. They are standardized, easy to manufacture, common to use and swap, and - until recently - relatively cheap. Timber has been regarded as environmentally friendly material obtained from seemingly inexhaustible source: trees growing without any limitations in our forests. Common wisdom has it, that wooden pallets withdrawn from operations, can be burned, or can rot without adversely affecting nature.

Plastic (and metal) pallets have also been used for quite some decades by now, though on smaller scale than their wooden counterparts. They vary in construction and performance characteristics. Generally, they have been regarded as more durable and simultaneously more expensive than wooden ones. Manufacturing plastic pallets requires relatively high investment in moulding machines and high material costs of oil and/or gas-derived plastic granulate. Public opinion is not in favour of plastics, accusing it to be the source of pollution in land, air, and water. Pictures of plastic items floating on ocean surface, or black smoke coming from plastic incineration, we can find in the media are all too common, not to be addressed, unless we agree that sustained development, and the need to care for environment are just empty phrases.

We have come across common judgements of plastic goods adversely affecting our environment, based on opinions with often limited if any data to back them. We, instead, wanted to check and present data, refraining from expressing our opinion, let alone a firm judgement, ready to accept critics and corrections to the method we applied and results we have achieved. Should the results stand the critics and appear generally correct, we would be glad to proceed and participate in implementing advantages of plastic pallets, reflected by the outcome of our research.

Our intention has been to gather, check, extract and/or calculate data showing how much CO_2, and solid waste is generated due to specific wooden and plastic pallet production and operations. We have been relaying on our personal experience and research, as well as literature available. We accept that others' experiences may be different; all are welcomed to test our model with their own scenarios and compare results.

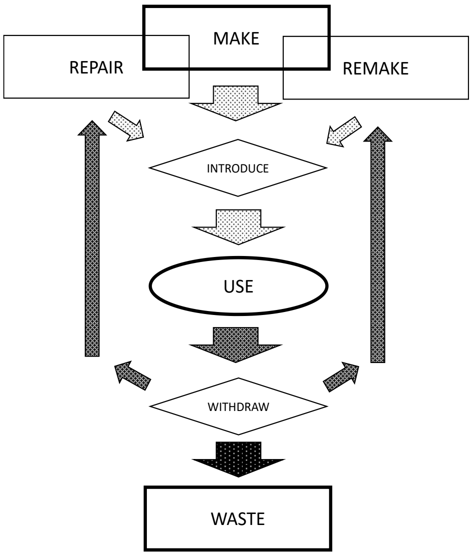
Methods

Pallets are “made to work” - facilitate storing and transporting of goods. Our goal is to provide a transparent account of the environmental impact of making, using, and wasting different pallets, along their lifetime, in relation to the work they have done. Sourcing raw materials, manufacturing elements, assembling pallets, working with them, and finally disposing of them, requires energy, and generates emissions and waste. Ultimately, we want to compare total CO_2 emissions and solid waste generated by pallets, against the number of trips completed with their use.

Our model is based upon LCA[3] approach. We have cumulated the energy needed to source materials and the energy to assemble/mould a Ready to Use (R2U) object – the pallet. All energy in the **MAKE** process has been treated as electrical energy and denominated in kWh. Generating electricity produces carbon dioxide: 0.7733 kg CO_2 / 1 kWh (data for Poland). The CO_2 emissions of the **USE** phase are function of pallet weight, distance driven and fuel (diesel oil) consumption. **WASTE** is seen in two dimensions: CO_2 emissions deriving from material decomposition, and solid waste, both in kg.; they make up for the whole waste.

Model

Figure 2.1



The **MAKE** phase yields a Ready to Use pallet (R2U). A pallet will be assigned the R2U status, following one of the processes: manufacturing from original/virgin materials or elements, repairing - using both new and/or recovered elements, and remanufacturing - using materials from previously used, recycled items.

Each of these processes may require different inputs and result in specific waste generated volumes. When R2U state is observed, action: INTRODUCE is executed, and pallets are made available for the Use phase.

The **USE** phase embraces all activities that pallets have been made for. Pallet life cycle and their "productivity" vary, depending, among others, upon the way they are being used. For the Reference Service Life (RSL), a synthetic measure of pallet productivity, durability, and longevity, we have adopted the average number of trips (issues) executed within pallet's lifetime. The USE phase CO_2 emissions volumes are a function of pallet weight, distance driven and fuel (diesel oil) consumption. Different conditions and pallet type could produce different RSL levels. A pallet that cannot be used due to technical reasons is regarded as defected - DFC. When DFC state occurs, action WITHDRAW is executed. DFC pallets, withdrawn from use are redirected to repair, or to remanufacture, or to waste.

The **WASTE** phase embrace: recycling - resulting with materials that would be applied in industries other than pallet manufacturing, incineration – burning for heat and/or energy production, landfilling – using time and space for wasted product/material to biodegrade.

Scope

Pallet choice

Pallets, we find in the market, vary substantially. Materials used, the construction concept, load capacity, current condition, etc. determine if and where we can use them safely. Many of them are used only once. Some are earmarked for light weights only. We limit our interest to returnable pallets, used in the **FMCG and Retail Goods** industries. These require relatively

[3] Life cycle assessment or LCA (also known as life cycle analysis) is a methodology for assessing environmental impacts associated with all the stages of the life cycle of a commercial product, process, or service. For instance, in the case of a manufactured product, environmental impacts are assessed from raw material extraction and processing (cradle), through the product's manufacture, distribution and use, to the recycling or final disposal of the materials composing it (grave)- http//:www.wikipedia.org; [access: 01/07/2021]

high weight capacity, and robust pallets, that can stand multiple handling operations with different goods bestowed on the way from a Manufacturer to a Sales Point, which may be hundreds of kilometres away, along the supply chain system. Saving precious warehouse space, palletized goods are stored in high racks. Low quality, low capacity, and one-way pallets are out of scope of our study.

Pallet circulation

Palletized goods are sent from Manufacturer to Distribution Centre and ultimately delivered to Sales Point. It is common for Manufacturer and Distribution Centre to keep goods in high storage racks, demanding adequate capacity and quality from pallets used. Various types of vehicles are used for transport and distribution; however, our model is based on commonly used transport unit: a truck tractor and 13.6 m trailer, that can carry 33 pallets with approximately 24.000 kg load, stowed 2.60 m high. This type of vehicle offers favourable ratio of fuel consumption to carried load weight. We assume this transport unit consumes, as per 100 km, 21 litres of fuel - empty, plus 0.4 litres - for every ton of load carried. Considering the maximum authorized vehicle weight[4], we assume an average single pallet load as 800 kg, carried from a Manufacturer's location to a Distribution Centre - a 100 km drive, and from a Distribution Centre, further to a Sales Point - another 100 km. One full working cycle consists of a pallet loaded and carried 200 km, then empty returned same 200 km back. While real life scenarios may vary, the proportions of energy (fuel) consumption for transportation of wooden and plastic pallets, remain. Using discrete measure of 100 km may be helpful to make individual calculations. We assume that burning 1 litre of diesel fuel generates 2.64 kg CO_2 emissions[5]. Apart from the transport itself, no other activities e.g., using forklift /crane, generating emission, have been taken into consideration in the model.

Data

Data, concerning the energy needed for production of materials, have been estimated using Inventory of Carbon & Energy (ICE) Version 2.0[6] - for lumber and steel wire (nails), Eco-profiles of the European Plastic Industry[7] - for polypropylene.

The emissions due to electric energy production and diesel oil combustion were adopted from PARP (Poland) conversion tables[8].

Data, concerning manufacturing of plastic pallets studied, road transport fuel consumption, used in the model, are based on hands on experience. Data concerning Reference Service Life of pallets are mainly based on experience; we have chosen high values for wooden, and low values for plastic pallets.

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[4] European COUNCIL DIRECTIVE 96/53/EC

[5] Polska Agencja Rozwoju Przedsiębiorczości, https://www.parp.gov.pl/storage/grants/documents/103/Wytyczne-dotyczce-konwersji---emisje-gazw-cieplarnianych_20200225.pdf

[6] Hammond, G.P; Jones, C.I. (2011) *Embodied energy and carbon in construction materials*. Geoff Hammond & Craig Jones Sustainable Energy Research Team (SERT) Department of Mechanical Engineering University of Bath, UK (2011)

[7] Eco-profiles of the European Plastic Industry, Polypropylene (PP), 11, (2005)

[8] Polska Agencja Rozwoju Przedsiębiorczości, https://www.parp.gov.pl/storage/grants/documents/103/Wytyczne-dotyczce-konwersji---emisje-gazw-cieplarnianych_20200225.pdf

Pallets surveyed

We surveyed two specific 1200 x 800 mm pallet models: wooden – EPAL EUR-1, and plastic – AGP-S. Both models can be used for storing loads in high racks and fulfil foodstuff transport requirements: wooden pallet - for a limited time, and plastic pallet - for life. Other differences, existing between the two models, are not directly relevant for the study.

Wooden Pallets

MAKE

EPAL[9] EUR-1 wooden pallets are made of wooden boards and blocks, joint with steel nails. The weight of the EPAL EUR-1 pallet is stated at approximately 25 kg[10]. We assume the material input at 25 kg of kiln dried softwood lumber (e.g., pine) and 0.38 kg of steel nails per pallet. Each material carries energy, and emissions deriving from processes prior to arriving at the pallet assembly point: wood 7MJ/kg, nails 30 MJ/kg. We assume the energy input of 0.7 kWh for the assembly process[11] and 4 kWh for heat treatment per pallet, which is to initially protect it against pests and fungi, according to International Phytosanitary Measure IPSM-15[12]. We do not take eventual paint, anti-pest chemical agents, clips, inhouse transport, nor transport to the first user, etc., in our model, into account.

USE

EUR-1 type wooden pallets are commonly used in Europe[13] being sold with the goods, exchanged within the so called “open” pool systems (white pallets), or close pool systems (colour pallets)[14]. Reference Service Life (RSL) – number of work cycles before withdrawal from usage – vary case by case. Calculations based on pallet stock count, number of trips covered, and numbered of pallets acquired to substitute for those withdrawn from operations, at a given time, show that a wooden pallet, used intensively in FMCG and Retail Goods distribution sector, e.g., within supermarket networks, lasts 5 - 8 trips. These findings correspond to some data found in literature. The fuel used and CO_2 emission per EUR-1 EPAL pallet, due to transport for the distance of 100 km has been calculated respectively: 0.045354 l. and 0.119733 kg CO_2.

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[9] EPAL - THE EUROPEAN PALLET ASSOCIATION - founded in 1991, EPAL has focused on developing and safeguarding l open pooling system for load carriers (wooden pallets) worldwide.

[10] The EN-13698 presents the weight of wooden elements at 21,9 kg, however e.g., EPAL, CHEP, IPP, that manufacture and use compatible pallets, state 25 kg as an approximate weight in their product descriptions. Our experience confirms 25 kg to be correct for pallets “out of the manufacturing process”, due to low moisture level. Otherwise, they may weight substantially more.

[11] Deviatkin, I; Hortanainen, M. (2020) Carbon Footprint of an EUR-sized wooden and plastic pallet. E3S Web of Conferences 158, 03001 (2020)

[12] IPSM-15 https://www.ippc.int/en/core-activities/standards-setting/explanatory-documents-international-standards-phytosanitary-measures/

[13]EPAL alone claims over 600 million pallets in use https://www.epal-pallets.org/eu-en/news/news/details/article/production-of-epal-pallets-at-a-high-level-in-2019-again.

[14] CHEP, IPP, etc. pallet providers on rental basis

Repair

It is commonly understood that wooden pallets can be repaired, increasing RSL value, before final withdrawal. Deviatkin [15], assumed 20 trips in total and 2 repairs per wooden pallet before final withdrawal, at the end-of-life. This might be true in some cases but cannot be considered as average for the market. According to EPAL, in 2020, for over 600 million pallets that had been in use, 97.5 million new pallets had been introduced, and 26.2 million repaired pallets reintroduced into the system[16]. No more than 5% of the total number of pallets in the EPAL system were subject to repair. Should we count for 10 pallet trips before the need of first repair, and additional 5 trips afterwards (no "space" left for the second repair to occur) the RSL of an average wooden pallet would be up by 0.25 trip. **Remake process does not apply.**

The question could be asked whether it is possible to increase the number of wooden pallets repaired and by how much. As simple as the pallet construction may look like, it should be assembled with a high degree of precision and consistency, using strictly defined materials, of size and quality. The holes in boards and blocks of disassembled pallets remain. You would not hammer nails into or close to these holes, understanding that the pallet might be used at high racks with a load of close to 1000 kilograms on the top.

Taking above into consideration, we assume wooden pallet RSL for 10 trips in our model before being withdrawn from service. We disregard repairs.

WASTE

Should we assume that the number of pallets used in trade as constant, all new pallets introduced compensate for the pallets withdrawn permanently form operations. In case of EPAL it can be therefore approximately 100 million pallets withdrawn from the system in 2020. There are three methods of dealing with withdrawn wooden pallets:

- incinerate – that some claim to be a welcomed process of "recovering energy" [17],
- mulch and use as live-stock bedding or soil fertilizer,
- landfill.

All these scenarios lead to CO_2 emission due to energy applied for "forced" process of dismantling, segregating, mulching, and transporting of wasted pallets, and "natural" process of wood decomposition resulting with biogenic carbon. Wood decomposition varies in time: burning takes minutes, decomposition of mulched wood can last months, decomposition of wooden elements left to rot, may last years. Whatever scenario we chose, 1 kg of wood upon complete decomposition will release 1,65 – 1,80 kg CO_2[18] . Disregarding energy costs and carbon emissions of different methods of pallet disassembling and waste treatment, we take

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[15] Deviatkin, I; Hortanainen, M. (2020) *Carbon Footprint of an EUR-sized wooden and plastic pallet.* E3S Web of Conferences 158, 03001 (2020)

[16] EPAL-PALLETS, https://www.epal-pallets.org/eu-en/news/news/details/article/epal-pallet-production-increases-despite-covid-19-pandemic

[17] Carrano, A.L; Thorn, B.K; Woltag, H. (2014) *Characterizing the Carbon Footprint of Wood Pallet Logistics*. Forest Products Journal 64(7):232-241

[18] Carbon storage using Tibber, https://www.accoya.com/app/uploads/2020/04/Carbon-Storage-Using-Timber-Products.pdf

into our model the amount of 1.7 kg CO_2 emission per every kg of wasted pallet wood - biogenic carbon, and weight of nails - solid waste.

Plastic Pallets

MAKE

AGP-S plastic pallets are made of polypropylene (PP). Prime Energy Demand for PP is estimated at 73 MJ/kg[19]. Each pallet weights 11.7 kg; weights and dimensions are consistent. AGP-S pallets are rackable and nestable. The pallet production line has been based upon YIZUMI UN 2300 DP moulding machine, consuming 2.5 kWh of energy per single pallet manufacturing process. Polypropylene PP is fully recyclable and reusable in consecutive injection cycles, maintaining strength and durability of the products made[20].

Each AGP-S pallet is identified with unique code, beneficial when pallets are in the use and ultimately, when they are withdrawn from operations, preventing uncontrollable landfill which happens all to often in case of unidentified objects no more needed.

USE

Plastic pallets in general are noticeably more durable and long-lasting then their wooden counterparts[21]. They can be cleaned and disinfected, yet another advantage. AGP-S pallets maintain these features alike. Basing on tests and proven record, we assume AGP-S pallet RSL at 80 trips in our model. The fuel used and CO_2 emission per AGP-S pallet, due to transport for the distance of 100 km has been calculated respectively: 0.030255 l. diesel and 0.079872kg CO_2.

Remake

We assume that due to adopted model of operations, and EU "plastic tax"[22] regulations, the risk of intentional landfill is minimalized, and 100% of initial material used for constructing pallets is returned by the users, back for remanufacturing.

After withdrawal from service, pallets and their parts are fragmented with Hammerman HR 1000 crusher using 1 kWh energy per pallet. To compensate for potential quality loss up to 20% of virgin material is added to the batch of recycled plastic. As the recycled plastic comes only from original AGP pallets, process efficiency and product quality are maintained. Remaking a pallet ultimately requires 3.5 kWh energy and 2.34 kg of virgin PP. **Repair process does not apply.**

WASTE

Unlike wooden pallets, 100% of the material from withdrawn plastic pallets can be reused in consecutive remanufacturing processes. Polypropylene is virtually non-biodegradable, does not easily come in chemical reaction with the environment, should not and needs not to be

[19] Eco-profiles of the European Plastic Industry, Polypropylene (PP), page 11, 2005.

[20] Kloziński, A; Jakubowska, P. (2009) *Chosen Properties of Multiple Recycled PP/PS Blend* Mechanika, Wydawnictwo Politechniki Krakowskiej, 2009.

[21] It's not uncommon for a plastic pallet to serve 100-200 trips before withdrawal.

[22] COUNCIL DECISION (EU, Euratom) 2020/2053 of 14 December 2020 *on the system of own resources of the European Union* and repealing Decision 2014/335/EU, Euratom

landfilled or incinerated. In our model, excessive 20% of recycled material is used for manufacturing items other than AGP-S pallets.

Results

Life Cycle Inventory

According to our study a single EUR-1 wooden pallet production process, "from cradle to gate", generates 43.67 kg CO_2, while AGP-S plastic pallet manufacturing is responsible for 186.33 kg CO_2. Should we use each pallet one-time, plastic pallet would add to **environmental burden over four times** as much as wooden counterpart.

Table 4.1:

measure unit	MATERIALS	PED (MJ/kg)	kWh	kg CO2/ measure unit	
kg	softwood lumber kiln dried (pine)	7			
kg	steel nails (HDG steel)	30			
kg	polypropylene PP	73,37			
	PROCESSES				
1 pallet	wooden pallet assembly		0,70		
1 pallet	wooden pallet heat treatment (IPSM-15)		4,00		
kg	wood decomposition			1,6	
1 pallet	plastic pallet injection molding		2,50		
1 pallet	plastic pallet recycling (crushing, washing)		1,00		
	ENERGY				
1 MJ	MJ/kWh		0,2778		
1 kWh	emission due to electrical power production (PL mix)			0,7733	
1 liter	diesel fuel			2,64	
	MAKE	**WOODEN PALLET**		**PALSTIC PALLET**	
	MATERIALS				
kg	wood	25		-	
kg	nails	0,38		-	
kg	plastic PP	-		11,7	
	ENERGY				
kWh	assembly/pallet	0,70			
kWh	heat treatment/pallet	4,00			
kWh	injection molding/pallet			2,50	
kWh	CUMULATIVE ENERGY Ready to Use	56,4778		240,9525	**PP/WOOD**
kg	CUMULATIVE kg CO2 Ready to Use	43,6743		186,3286	**426,63%**

Replacing withdrawn pallets

Remaking and replacing plastic pallet generate 39.59 kg CO_2. Our assumption is that wooden pallet replacement is always done with a new item. Wooden pallet replacement generates slightly higher carbon footprint than its plastic counterpart.

Table 4.1.1:

	REMAKE/REPLACE	WOODEN PALLET		PALSTIC PALLET	
	virgin added to recycled			20,00%	
kg	plastic - PP			2,34	
kWh	energy		3,50		
	REPLACE	56,4778		51,1905	**PP/WOOD**
		43,6743		39,5856	**90,64%**

Polypropylene recycling process seems not to adversely affect its mechanical characteristics. Khademi, F. et al[23] conclude "…using a higher percentage of recycled material will not have a significant effect on the mechanical properties of polypropylene. This finding is the main contribution of this research because of its potential benefit to plastic industries and to the environment. That means, to reduce costs, more recycled material can therefore be used without a significant reduction in material performance….".

Reference Service Life and CO_2 emissions in transport

Due to the weight difference in favour of plastic pallet, it generates some 30% less CO_2 emissions than wooden pallet. Regarding the design the material used, AGP-S plastic pallet can cover 8 times more trips – RSL = 80 trips, than wooden pallet – RSL = 10 trips.

Table 4.1.2:

	FEATURES			
trips	RSL - Reference Service Life (trips to withdrawal)	10	80	
liters	diesel fuel used to transport a pallet/ 100 km	0,0454	0,0303	PP/WOOD
kg	kg CO2 emission per pallet/100 km	0,1197	0,0799	66,71%

Life Cycle Assessment

Functional Unit: 1000 trips/1 pallet

Calculating the use of a single wooden and single plastic pallet in a process to cover 1000 trips, replacing any of them, when Reference Service Life is completed, shows the need to replace wooden pallets 99 times, and plastic pallet 12 times. CO_2 emission in transport alone is 30% lower, when using plastic pallets. Cumulating emissions due to transport and replacements, plastic pallets generate 80% less carbon footprint, than when wooden pallets are used.

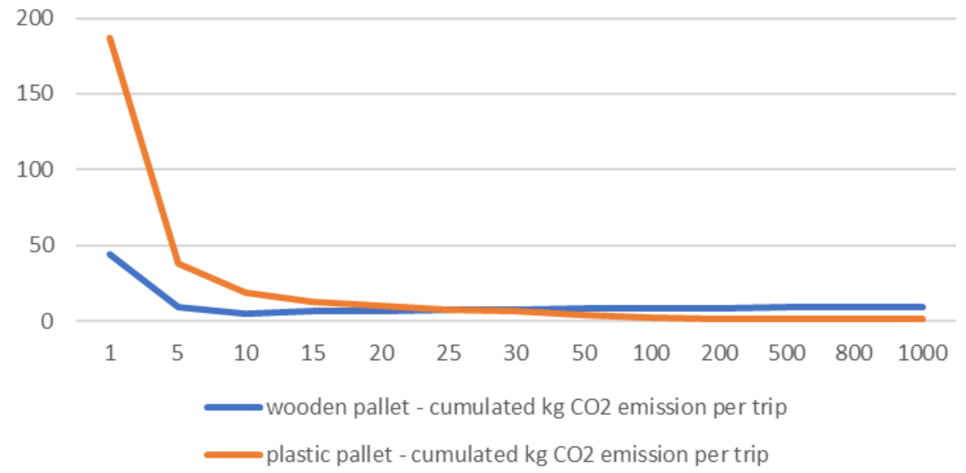

Figure. 4.2.1: Cumulated kg CO_2 emissions related to number of trips

[23] Khademi, F; Ma, Y; Ayranci, C; Choi, K; Duke, K. (2016) *Effects of Recycling on the Mechanical Behavior of Polypropylene at Room Temperature Through Statistical Analysis Method* POLYM. ENG. SCI., 00:000–000, 2016. VC 2016 Society of Plastics Engineers

Table 4.2.1:

	SCENARIO				
trips	FU - Functional Unit	1 000		trips total number	1 000
pallets	PC - Pool Count ("pool pallets")	1		periods	1
km	trip distance (from loading to loading)	400		standard trip distance	100
		WOODEN PALLET		PALSTIC PALLET	
	POOL'S PRIME ENERGY NEED AND CO2 EMISSION				PP/WOOD
1 kWh	energy	56,48		240,95	
1 kg	CO2	43,67		186,33	426,63%
	FEATURES				
trips	RSL - Reference Service Life (trips to withdrawal)	10		80	PP/WOOD
liters	diesel fuel used to transport a pallet/ 100 km	0,0454		0,0303	
kg	kg CO2 emission per pallet/100 km	0,1197		0,0799	66,71%
	USE				
	TRANSPORT				PP/WOOD
liters	Transport - diesel fuel consumption	181,41		121,02	
kg	Transport - kg CO2 emission	478,93		319,49	66,71%
	POOL MAINTENANCE - REPLENISHMENT				
life	RSL's per "pool pallet"	100		12,5	
pallets	number of pallets withdrawn	99		12	
pallets	numbers of pallets repaired	0	0,00%	0	
pallets	number of pallets remade	0		12	100,00%
pallets	number of pallets replaced with new pallets	99,00		0,00	
pallets	number of pallets wasted	99,00		0,00	
kg					
	REMAKE				
1 kWh	energy			588,69	
kg	CO2 emission			455,23	
	REPLACE				
1 kWh	energy	5 591,30			
kg	CO2 emission	4 323,75			
	SUBTOTAL				PP/WOOD
kg	CO2 emission	4 846,36		961,05	19,83%
	WASTE				
kg	wood	2 475,00			
kg	CO2 wood decomposition	3 960,00			
kg	plastic recycled to be used in other products or industries			26,91	
	CO2 plastic decomposition				
kg	nails	37,62			
kg	CO2 nails decomposition				
	TOTAL				PP/WOOD
kg	CO2 emission	8 806,36		961,05	10,91%

Adding CO_2 emissions due to wood decomposition on the top, we find plastic pallet operations generating 10% carbon impact comparing scenario when wooden pallet is used. As for solid waste, 37.62 kg of nails fall into wooden pallet account, and 26.91 kg of Polypropylene PP recycled is to debit plastic pallet account. Both can be reused, however recovering, and reusing nails seems to be more problematic, than reusing plastic scrap.

Functional Unit: 15,000,000 trips / 500,000 pallets – 1 year

Real life scenarios require a significant number of pallets allowing to serve wide stream of supplies, starting from "day one". Creating a pool of half a million plastic pallets generates, naturally, far more CO_2 emissions, than the respective pool of wooden pallets. However, comparing the total emission of CO_2 already at the end of the "year one" shows, that using plastic pallet should lead to limiting CO_2 emissions by 13% in comparison to wooden pallets. No solid waste, while replacing wooden pallets would find us with 380 tons of nails to be recycled, provided they are not scattered around.

Table 4.3:

	SCENARIO				
trips	FU - Functional Unit	15 000 000		trips total number	15 000 000
pallets	PC - Pool Count ("pool pallets")	500 000		periods	1
km	trip distance (from loading to loading)	400		standard trip distance	100
		WOODEN PALLET		PALSTIC PALLET	
	POOL'S PRIME ENERGY NEED AND CO2 EMISSION				
1 kWh	energy	28 238 888,89		120 476 250,00	PP/WOOD
1 kg	CO2	21 837 132,78		93 164 284,13	426,63%
	FEATURES				
trips	RSL - Reference Service Life (trips to withdrawal)	10		80	
liters	diesel fuel used to transport a pallet/ 100 km	0,0454		0,0303	PP/WOOD
kg	kg CO2 emission per pallet/100 km	0,1197		0,0799	66,71%
	USE				
	TRANSPORT				
liters	Transport - diesel fuel consumption	2 721 212,12		1 815 272,73	PP/WOOD
kg	Transport - kg CO2 emission	7 184 000,00		4 792 320,00	66,71%
	POOL MAINTENANCE - REPLENISHMENT				
life	RSL's per "pool pallet"	3		0,375	
pallets	number of pallets withdrawn	1 000 000		0	
pallets	numbers of pallets repaired	0	0,00%	0	
pallets	number of pallets remade	0		0	100,00%
pallets	number of pallets replaced with new pallets	1 000 000,00		0,00	
pallets	number of pallets wasted	1 000 000,00		0,00	
kg					
	REMAKE				
1 kWh	energy			0,00	
kg	CO2 emission			0,00	
	REPLACE				
1 kWh	energy	56 477 777,78			
kg	CO2 emission	43 674 265,56			
	SUBTOTAL				PP/WOOD
kg	CO2 emission	72 695 398,33		97 956 604,13	134,75%
	WASTE				
kg	wood	25 000 000,00			
kg	CO2 wood decomposition	40 000 000,00			
kg	plastic recycled to be used in other products or industries			0,00	
	CO2 plastic decomposition				
kg	nails	380 000,00			
kg	CO2 nails decomposition				
	TOTAL				PP/WOOD
kg	CO2 emission	112 695 398,33		97 956 604,13	86,92%

Discussion

Functional Unit: 15,000,000 trips / 500,000 pallets / years 1-10

With the exception of initial fabrication, the incremental value of each use and renewal parameter is significantly higher for wooden pallets. It's already the first year-end showing environmental advantage of using plastic pallets against wooden pallets.

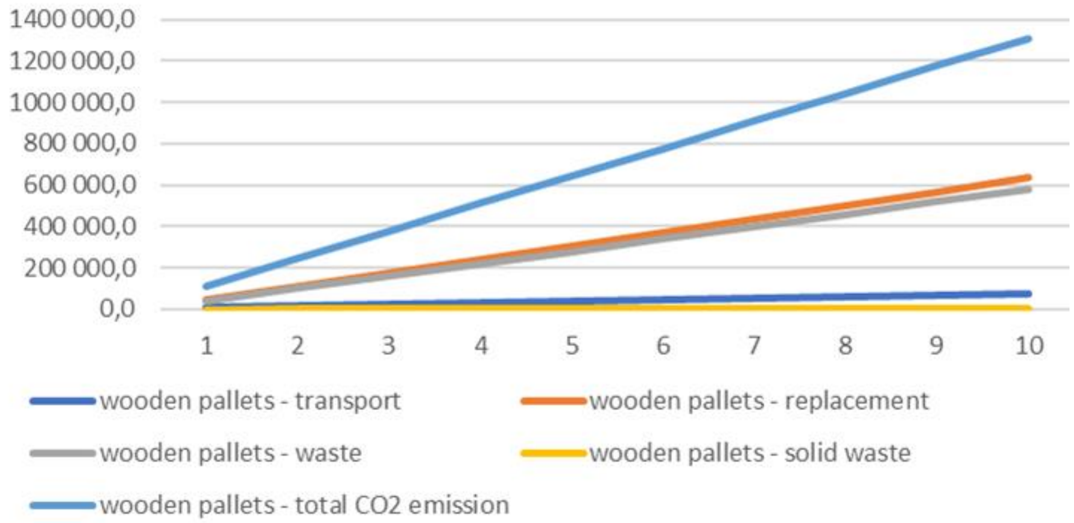

Figure 5.1: Wooden pallets CO2 and solid waste (metric tons – cumulative 10 years)

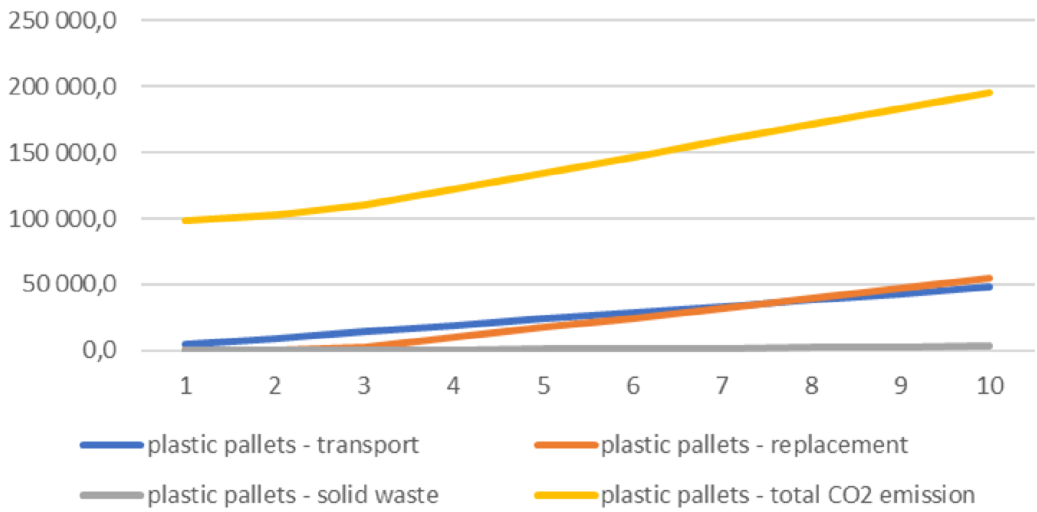

Figure 5.2: Plastic pallets CO_2 and solid waste (metric tons – cumulative 10 years)

In 10 years accumulated CO_2 emissions with wooden pallets will exceed the emissions created by plastic pallets operations by 6 times.

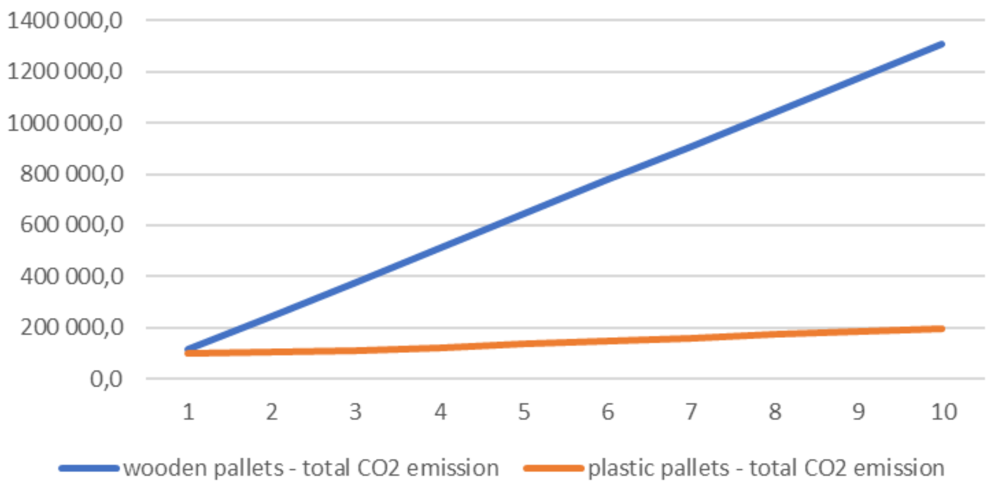

Figure 5.3: Wooden and plastic pallets CO_2 emission compared (metric tons – cumulative 10 years).

In year 10, the gap between single transport CO_2 emissions when we compare plastic and wooden pallets would have reached 85%.

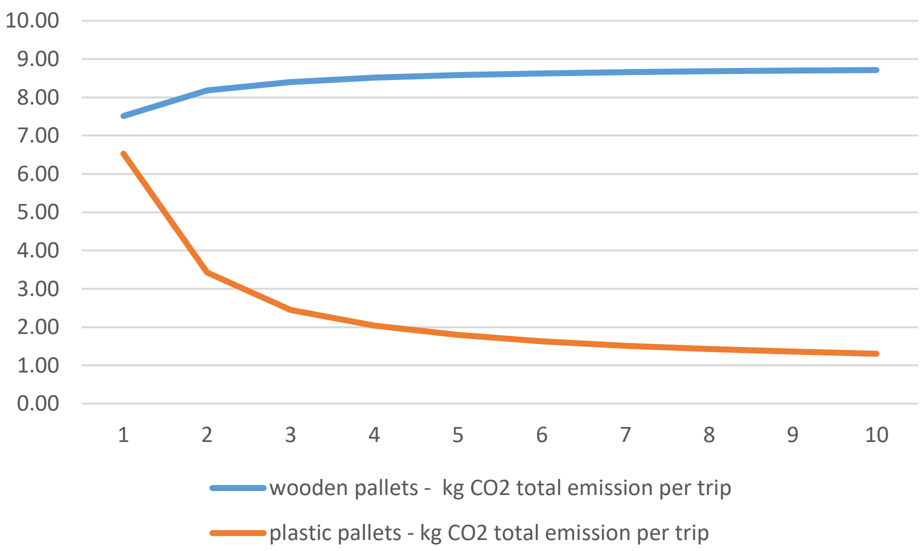

Figure 5.4: Total calculated emission per trip (kg CO_2) wooden and plastic pallet comparison (10 years)

Conclusions

Plastic pallets have already proven their performance: durability and longevity, when used in the market. Our study shows, that quite contrary to common feeling, they may be a welcomed alternative to wooden pallets in terms of environment as well. Substantially lower carbon footprint and no solid waste generated in comparison to wooden pallets, should at least rise interest and boost research as to wider implementation of plastic pallets. Study shows that multiple use, both the items and material they are being made of, is the key factor in reducing the burden on the environment. The impact of initial production is an important element of the LCA; however, all other elements must be considered as well. Finally, we seem to have far too much “plastics” available, more than we would have wished for, and not that many trees left to cut and take away from our forests.

As mentioned above, we see the results of our work, and the way we share it, as our contribution to paving further activity, which we hope could be agreed upon, aiming at limiting CO2 emissions, and limiting deforestation, due to replacing wood (scarce resource) , with plastic (recycle “waste” in excess, as for now, into raw material). This is the direction of further research and practical implementation of plastic pallets into existing supply chains.

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How will regulation influence commercial viability of autonomous equipment in U.S. production agriculture?

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Abstract

Autonomous equipment for crop production is on the brink of commercialization in the United States but federal, state, and local policies could affect commercial viability and hinder adoption. While there are no federal policies on autonomous farm equipment in the United States, precedent has been set at the state level by the current restrictions in California. Under California code, the operator must monitor and supervise the tractor and surrounding workers at all times, and the autonomous equipment cannot exceed two miles per hour. While California's code was developed for worker safety under the technology available at the time, sensor technology, intelligent controls, safety measures, advanced guidance systems, and artificial intelligence have rapidly advanced. This presentation will illustrate the farm-level impact of both a speed restriction and on-site supervisory regulation on the economic viability of autonomous equipment for a U.S. corn and soybean farm.

Presenters profile

Dr. Shockley is an Associate Extension Professor and Farm Management Specialist within the Department of Agricultural Economics at the University of Kentucky. His areas of expertise include the economics of precision agriculture technologies, post-harvest management, machinery management, the economics of soil quality, and poultry economics. His research on the economics of precision agriculture and robots spans the past 15 years publishing his work in renown precision agriculture journals and presenting results nationally and internationally, while educating producers around the U.S. on the proper techniques for evaluating the profitability of precision agriculture technologies.

Keynote Presentation: Precision Conservation in Arable Crop Systems

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Abstract

"Precision conservation" (PC) describes the application of precision farming technologies to achieve environmental benefits from perennial conservation areas within crop fields. Recent research highlights environmental benefits from incorporating strips of native plants into agricultural fields. Native plant strips planted along topographic contours have reduced soil erosion and nutrient loss to waterways in Iowa, USA, leading to a creation of an official U.S. agricultural conservation practice for prairie strips.

Precision conservation potentially offers farmers lower opportunity cost than strips of native plants, because the conserved areas need not run linearly across a field. New guidance systems enable farmers to practice PC at lower costs than in past by devoting low-profit areas to conservation in perennial, native plants. New sensing and modelling technologies enable public agencies to make spatially explicit estimates of environmental benefits at lower cost than previously. The emerging feasibility of PC challenges traditional agricultural conservation policy based on whole-field management. Several important questions face policy designers who wish to enable precision conservation

Presenter Profile

Scott Swinton is a University Distinguished Professor at Michigan State University in the Department of Agricultural, Food, and Resource Economics. His research examines agriculture as a managed ecosystem, focusing on decision analysis for enhanced ecosystem services. He concentrates on problems involving crop, pest, pollination, and nutrient management; precision agriculture; resource conservation; and bioenergy production. Throughout his career, Scott has worked on multidisciplinary teams (mostly with biologists) seeking ways to make agriculture more sustainable via improved technology, information, and incentives. His research has been cited over 11,000 times (Google Scholar). Scott currently teaches undergraduate managerial economics and graduate research design & writing.

Scott is a past president of the Agricultural and Applied Economics Association (AAEA), which AAEA named him a Fellow in 2020. He served as Case Study Editor of Review of Agricultural Economics, as well as associate editor of the American Journal of Agricultural Economics, Precision Agriculture, Frontiers in Ecology and the Environment, and Journal of Production Agriculture, and as a member of three panels of the National Academies of Science, Engineering, and Medicine. Scott received Michigan State University's William J. Beal Outstanding Faculty Award in 2015 and was named an Aldo Leopold Leadership Fellow through Stanford University in 2008. He holds degrees in Economics and Political Science (BA, Swarthmore) and Agricultural and Applied Economics (MS, Cornell; PhD, Minnesota).

Digital nutrient management decision support and environmental footprints of maize intensification: A Randomized evaluation from Nigeria

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Abstract

Agricultural intensification associated with increased use of external inputs, such as inorganic fertilizer is widely considered relevant to improving farm income and welfare of smallholder farmers in Sub-Saharan Africa. The emphasis on increased use of inorganic fertilizer will likely be associated with increased greenhouse gas emissions, especially nitrous oxide, as with the Asian Green Revolution. Yet, traditional agricultural extension systems typically provide generalized 'blanket' fertilizer recommendations that are not tailored to the plot-specific growing conditions of individual farmers, which could lead to negative environmental externalities. Within this context, a digital nutrient management decision support tool 'Nutrient Expert' has been co-developed in Nigeria to enable the extension system to transition from provision of generalized to plot-specific fertilizer recommendations. Using a three-year randomized controlled trial in northern Nigeria, this paper analyses the impact of farmers' access to site-specific nutrient management recommendations, provided through the Nutrient Expert tool on environmental sustainability of maize intensification. The primary outcome of interest is global warming potential (greenhouse gas emission per unit maize yield), measured using the Intergovernmental Panel on Climate Change Tier 1 method. The preliminary results show that the provision of tailored recommendations to the treatment group led to a reduction in global warming potential compared with the control group, who were exposed to blanket recommendations. However, the observed effect size is small, and the effect is not statistically significant at the conventional significance levels. A plausible reason could be due to the on average, low fertilizer application rates in the study area compared with the often cited over application of fertilizer in most parts of Asia. Overall, this paper finds weak evidence of the causal effects of farmer-tailored nutrient management extension advice on mitigating the environmental impacts of fertilizer intensification under farmers' conditions and management in maize-based farming systems of northern Nigeria.

Keywords

Extension advice, environmental sustainability, fertilizer recommendations, greenhouse gas emissions, Nutrient Expert, randomized controlled trial.

Presenter Profile

Oyakhilomen Oyinbo is an agricultural and development economist affiliated with the Department of Agricultural Economics, Ahmadu Bello University, Nigeria. His research focuses on the economics of agricultural development, with a particular focus on agricultural technology adoption under imperfect markets, digital agriculture, sustainable agricultural intensification, risk management and household resilience to shocks.

Introduction

Agricultural intensification associated with increased use of external inputs, such as inorganic fertilizer is widely considered relevant to improving farm income and reducing rural poverty and food insecurity in Sub-Saharan Africa (SSA). The emphasis on increased use of external inputs, such as inorganic fertilizer will likely be associated with increased greenhouse gas (GHG) emissions, especially nitrous oxide, as with the Asian Green Revolution (Graham et al., 2017; Albanito et al., 2017). This is expected as Nitrogen-based fertilizer application accounts for the largest share of N_20 emission from agricultural production (Venterea et al., 2012; Gerber et al., 2016). Yet, traditional agricultural extension systems in SSA typically provide generalized or 'blanket' fertilizer recommendations that are not tailored to the plot-specific growing conditions of individual farmers, which could lead to negative environmental externalities (Xu et al., 2009; Shehu et al., 2018; Theriault et al., 2018; Burke et al., 2019). A potential intervention for plot-specific fertilizer use is site-specific nutrient management (SSNM). This entails 4Rs of nutrient management, which includes the right fertilizer application rate, the right fertilizer source, the right application time, and the right application method, and allows adjusting fertilizer application based on crop-, plot- and season-specific conditions (Pampolino et al., 2012; Johnston and Bruulsema, 2014; Singh, 2019).

In light of the rapid advancement in digital technologies, decision support tools (DSTs) are increasingly considered to allow better tailored extension services. Within this context, a digital nutrient management extension tool for maize 'Nutrient Expert' has been co-developed in Nigeria to enable the extension system to transition from provision of generalized to SSNM-based fertilizer recommendations. Yet, little is known about the effectiveness of such farmer-tailored nutrient management extension advice on mitigating the environmental impacts of input intensification in maize-based farming systems in SSA. To my knowledge, there is limited empirical studies that relate relaxing information constraints via extension interventions to environmental impacts of agricultural intensification. In addition, the few previous studies that have attempted to show the potential of SSNM in reducing environmental externalities of input intensification are agronomic studies under researcher-managed trials and mainly from Asia (Dobermann et al., 2002; Pampolino et al., 2007; Xu et al., 2014; Sapkota et al., 2014; Banayo et al., 2018). This may not reflect real-world farm settings, where conditions are quite different, and farmers have full control over their resource allocations and management decisions (Barrett et al., 2004; Duflo et al., 2008; Beaman et al., 2013; Vandercasteelen et al., 2018; Jayne et al., 2019; Macours, 2019).

In this paper, I analyse the impact of farmers' access to site-specific nutrient management recommendations, provided through an ICT-enabled tool 'Nutrient Expert' on environmental sustainability of maize intensification. The paper contributes to different strands of literature, including the literature on digital agricultural extension, environmental dimension of sustainable intensification, soil fertility management and randomized evaluations in SSA.

Methods

I use a three-year clustered randomized controlled trial (RCT) to cleanly identify the causal effects of DST-enabled site-specific nutrient management on global warming potential associated with input intensification. The RCT includes two treatment groups of farmers who are exposed to SSNM information interventions, the first group (T1) without and the second group (T2) with additional information on variability of expected investment returns, and a control group (C) of farmers who do not receive an SSNM information intervention. Specifically, T1 were exposed to SSNM information including a site-specific fertilizer application rate to obtain a target yield, optimal fertilizer management practices (sources, timing, placement), the rationale behind the recommendations and a detailed explanation on how to implement them as well as the expected return from uptake of the recommendations. The latter is a naïve estimate based on the prevailing maize market price at the time of providing the information, before planting. This is akin to most agronomic recommendations and to the uncertainty farmers face due to the time lag between planting decisions and outcomes at harvest time. Farmers in T2 were exposed to the same information as T1 farmers but received additional information on the variability of expected returns. This is a more robust estimate based on the 25th, 50th and 75th percentiles of the distribution of the monthly real maize price during post-harvest months over the last eight years in the research area. The SSNM extension interventions were provided to farmers using the Nutrient Expert tool prior to planting in the 2017 and 2018 farming seasons (April to May) by public extension agents.

I use panel datasets from a three-period panel survey known as Agronomy Panel Survey, which was implemented across Nigeria, Ethiopia and Tanzania by the Taking Maize Agronomy to Scale in Africa (TAMASA) project. The panel survey was conducted in three states in northern Nigeria (Figure 1) as part of the randomized controlled trial. The baseline survey was conducted in 2016 before the introduction of DST-enabled SSNM intervention and two follow-up surveys in 2017 and 2018, after a first and second DST-enabled SSNM intervention. The surveys were conducted during the maize harvest season (September to October). The questionnaire includes general household information, production data and detailed agronomic data for the focal plot, and community-level information on prices and access to institutions and services. At baseline, data were collected from the full sample of 792 households while this dropped to 788 and 786 households in the first and second follow-up rounds. This implies a very low attrition of 0.5% and 0.8% in the first and second follow-up rounds respectively. The data were collected by means of digital data collection using the Open Data Kit (ODK) software on tablets.

I use difference-in-difference (DiD) and analysis of covariance (ANCOVA) specifications in equations (1) and (2), respectively to estimate the intent-to-treat (ITT) effect. While DiD accounts for possible imbalances in pre-treatment outcomes and time-invariant unobserved heterogeneity not controlled for by randomization, ANCOVA can improve statistical power when outcomes of interest have low autocorrelation (McKenzie, 2012).

$$y_{ijt}=\beta_0+\beta_1 T1_{iJt}+\beta_2 T2_{iJt}+\beta_3 Post_t+\beta_4 T1_{iJt}*Post_t+\beta_5 T2_{iJt}*Post_t+\beta_6 X_{iJ(t-1)}+\varepsilon_{ijt} \quad (1)$$

$$y_{ijt}=\beta_0+\beta_1 T1_{iJt}+\beta_2 T2_{iJt}+y_{ij(t-1)}+\beta_6 X_{iJ(t-1)}+\varepsilon_{ijt} \quad (2)$$

where y_{ijt} is the global warming potential (GWP) for focal plot of household i in village j at year t (Scaled GHG emissions – GHG emissions per unit maize yield in carbon dioxide equivalents), $T1_{iJt}$ and $T2_{iJt}$ are binary indicators for farmers in treatment one and two respectively, the coefficients of interest that captures the effects of treatment one and treatment two interventions are β_4 and β_5 in equation (1) and β_1 and β_2 in equation (2) respectively, $Post_t$ is an indicator equalling zero for observations in the baseline year and one for observations in the follow-up round, X_{iJ} is a vector of baseline control variables, $y_{ij(t-1)}yij(t-1)$ is the lagged value of the dependent variable, $\varepsilon_{ijt}\varepsilon ijt$ is a random error term clustered at the village level to account for both the cluster design and heteroscedasticity, $\beta_0\beta 0$ is the average value of the outcomes of interest for the control group at the baseline. The measurement of GWP associated with N_20 emissions was carried out using the Intergovernmental Panel on Climate Change (IPCC) Tier 1 method (IPCC, 2019). It considers the direct emission of N_20 from fertilizer application and the indirect emission form volatilization, leaching and run-off as well as the carbon dioxide emissions in the production of fertilizer.

Preliminary Results

The results of the summary statistics of household and plot characteristics of the sampled farmers show that across the treatment groups, the farmers are on average 44 years old, have about 5 years of formal schooling and 19 years of maize farming experience. They live in households with an average of about 9 members, 3 ha of farmland and 2 tropical livestock units. Also, about 39% of the farmers have access to extension, 23% have access to farm input credit and 31% belong to a farmer association. For plot-level characteristics, the size of the maize focal plot of farmers is on average 0.9 ha, majority (98%) of the plots is owned by the farmers and the plots are on average, 15 minutes walking distance from the homestead. Most (97%) of the plots are cultivated with inorganic fertilizer, 29% with improved maize seeds, 78% with organic manure and the plots produce an average yield of around 2 tons ha^{-1}.

The results of summary statistics on fertilizer use and yields at the baseline show that across the treatment arms, the majority (95%) of farmers apply nutrients rates below the recommended rates (95% of farmers in treatment one and 91% of farmers in treatment two). In general, there is low nutrient application rates, pronounced nutrient and yield gaps despite the long history of fertilizer use in the research area. This suggests that improving maize yield and closing the yield gap will require an improved nutrient application especially for farmers with sub-optimal application among other yield-limiting biophysical and socioeconomic factors that needs to be addressed.

The preliminary results of the ITT effects of farmers' exposure to SSNM information show that the provision of SSNM recommendations to the treatment group led to a reduction in GHG emissions per unit maize yield compared with the control group, who were exposed to blanket fertilizer recommendations. However, the observed effect size is small, and the effect is not statistically significant at the conventional significance levels. While the few agronomic studies in Asian contexts (Dobermann et al., 2002; Pampolino et al., 2007; Xu et al., 2014; Sapkota et al., 2014; Banayo et al., 2018) that have attempted to show the potential of SSNM in reducing environmental externalities of input intensification under researcher-managed trials report substantial effects, this paper does not lend strong credence to the agronomic studies. A plausible reason could be due to the on average, low fertilizer application rates in the study area compared with the often cited over application of fertilizer in most parts of Asia. Overall, this paper finds weak evidence of the causal effects of farmer-tailored nutrient management extension advice on mitigating the environmental impacts of fertilizer intensification under farmers' conditions and management in maize-based farming systems of northern Nigeria. In addition, the findings of this paper suggest that while the use of SSNM recommendations can contribute marginally to promoting sustainable intensification through efficient fertilizer use, the GHG emissions-reducing effects of SSNM are likely to be substantial with increased use of fertilizer among smallholder farmers in the study area. More rigorous empirical research may help to test whether and to what extent digital advisory support for farmers can reduce negative environmental externalities associated with input intensification in other developing country context.

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Ecological and Economic Potentials of Digital Technologies in Weed Management

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Abstract

The European Commission's Farm-to-Fork Strategy aims to halve the use and risk of chemical pesticides and to further develop and expand organic farming by 2030. Digital technologies can help reduce conflicts of interest between ecological sustainability and productivity. As part of the ‘Networking and Transfer Project on Digitalisation in Agriculture ("DigiLand")’, funded by the German Federal Ministry of Food and Agriculture, various applications of digital technologies are being subjected to a technology assessment. Thus, ecological and economic potentials can be estimated and prerequisites for implementation on commercial farms can be identified. The use case "precise, individual plant-specific weed management" is examined in more detail below.

As the technologies for precise weed management are still largely at the prototype stage, valid information from practical agricultural application is lacking. Therefore, an iterative process of expert interviews, literature research, economic model calculations and a workshop for validation and collection of additional information was used for the analyses. The main focus of the analyses was targeted at sugar beet, as this was expected to have the greatest economic potential due to the high herbicide costs. In addition, mechanical technologies that are more suitable for organic farming were investigated. Due to the different time window and the lower herbicide costs for weed management oilseed rape was also included for comparison. Further, as oilseed rape is of less importance for organic farming, we therefore completed the analysis for chemical technologies only.

For the chemical methods of precise weed management, an average herbicide saving potential of 50 to 70% per pass was determined. In sugar beet, the cost of weed management can be reduced by between 42 and 77 € ha^{-1} compared to the current standard practice (four herbicide applications, total process cost 355 € ha^{-1}). With winter oilseed rape, on the other hand, the cost of precise weed management is at a similar level as the standard practice. In the context of chemical methods, possible yield advantages thanks to (partial) avoidance of herbicide damage to the crop were also discussed. From this a greater economic advantage might arise than from the herbicide savings. However, this has yet to be confirmed in further research.

For the mechanical methods of precise weed management, a cost advantage of 1,146 € to 1,348 € ha^{-1} compared to standard practice (total process cost 2,521 € ha^{-1}) was determined, because of saving 70% of the input of manual weeding. Therefore, the use of precise, individual plant-specific weed management methods in organic farming can provide a considerable economic advantage. This is not yet the case, at least to this extent, for the chemical methods in conventional agriculture.

For a broader implementation of precise weed management in agricultural practice, it is necessary that the still very new technologies become more efficient, reliable, and cost-effective. For example, when using field robots, a considerable amount of time is currently still required for troubleshooting. In addition to these fundamental prerequisites, it also became clear in the discussions and workshops that there is still no clear legal framework for some technologies (e.g. field robots). For the chemical methods of precise weed management, it is also important that suitable foliar-active herbicides continue to be available in the future.

The implementation of precise weed management technologies in other crops is limited not only by economics but also by technological limitations. For example, precise weed control in cereals was considered by the experts to remain technically difficult to implement in the future. Overall, however, it appears that the use of digital technologies in weed management can contribute to achieving the goals of the Farm-to-Fork Strategy through herbicide savings and cost reduction potential (the latter especially in organic farming).

Keywords

Precise weed management, digital farming, autonomous field robot, spot spraying, sugar beet

Presenter Profile

Marwin Hampe studied agricultural sciences at the Georg-August University of Göttingen and graduated as a Master of Science in Agribusiness. Since 2019, he has been working at the Thünen Institute of Agricultural Technology as a research associate focusing on the economics of agricultural technology and technology assessment.

The Use of Blockchain Technology in the Environment

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Abstract

The purpose of the article is to show how new technology can be use in the Environmental sector. Nowadays, everything that is ecological attracts more and more attention. This is due to developing environmental awareness. In this way, we have ecological cities, ecological food, ecological cars, green technologies are being developed, as well as ecological investments. The ecology boom began a few years ago. Since then, it has accelerated every year. It can be noticed by the fact that the issue of environmental protection, which has become one of the foundations of modern civilization, is not subject to discussion. It is logical, after all, we all want to live on an Earth that will provide good living conditions. Blockchain is the shared database technology that underlies Bitcoin and Ethereum and is expected to be ground breaking for many industries in the decade to come. It is already used in banking and payments, but most people don't realize that the same technology can be used to solve the major environmental problems we face on our planet today. If adopted globally, it could even help halt or reverse climate change. As persistent, tamper-resistant databases that are shared by a community without a centralized owner, they are of particular interest for environmental reasons. They enable the tracking and verification of transactions and interactions without a centralized authority. This can significantly increase the transparency, efficiency and accountability of environmental projects.

Keywords

Environment protection, ecology, technology, power engineering, waste management

Presenter Profiles

Professor Krzysztof Marecki, Professor Zbigniew Grzymała and Dr Agnieszka Wójcik - Czerniawska are employees of the Warsaw School of Economics. As employees of the Department of Economics and Finance of Local Government, they deal with the issues of sustainable development in a very broad sense. In the area of their research interests there is both sustainable development in the field of renewable energy and issues in the area of finances, including finance technology, in which innovative financial tools such as Blockchain are related both to finances in the strict sense, i.e. cryptocurrencies and in the broad sense, i.e. to influence a number of economy sectors, i.e. agriculture, industry, services.

Factors affecting British Farmer's adoption of carbon emissions reduction practices

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Abstract

Background: Agriculture is a significant contributor to greenhouse gas emissions in the UK. Therefore, numerous studies have assessed the factors motivating farmers to introduce environmental practices. However, the determinants of farmers' decisions to reduce carbon emissions in line with the new net-zero goal are not well-understood.

Methods: This study aimed to explore factors affecting UK farmers' adoption of carbon emissions reduction practices using a mixed method approach based on 101 online survey responses. The survey questionnaire included a combination of closed and open-ended questions. Three additional in-depth interviews were conducted. No responses were obtained from farmers in NI. The respondents were from all farming sectors with majority being cereal growers and lowland livestock farmers. Factors explored include a range of motivating factors, perceived barriers to adoption of carbon emission reduction practices, farmers perceived behavioural control and farmers innovativeness. Attributes of farm and farmer such as location, farm type, farm size, age, and level of education

Results: Multiple linear regression analysis shows that 31.5% of farmer's adoption of carbon emissions reduction practices can be explained by five factors, which are farm size, financial incentives, farmers innovativeness, farmers perceived behavioural control and crop farming only. Further cluster analysis showed a typology of four categories of farmers with Early Adopters and Late Majorities reporting more actions in reducing carbon emissions than innovators, and Laggards taking fewest or no actions at all. Larger farmers and crop farmers are more likely to take more actions than animal and mixed farmers. Those who take less or no actions in reducing carbon emissions in farms were more likely to believe that there is not much farmers can do. Qualitative data analysis suggests that more accessible information and knowledge transfer should be provided to unlock the potential of achieving Net Zero target by 2050.

Keywords

Net zero, farmer's behaviours, factor analysis, multiple linear regression.

Presenter Profile

Dr Eric Siqueiros works as Innovation Specialist for the European Regional Development Fund project AGRI at Harper Adams University. He is also a visiting lecturer for the Food Land and Agribusiness Management Department. His main interests are in developing processes and strategies for the sustainability of the Food and Agricultural Sector. Eric holds a PhD focused in Sustainable Energy and Waste Recovery from Newcastle University.

Introduction

Climate change is one of the most prominent international crises, attracting the attention of global academic researchers, governments, and the wider population. The leading cause of climate change is the increasing concentration of carbon emissions (Abeydeera, Mesthrige and Samarasinghalage, 2019). Global emissions have increased 135%, from 14 billion tonnes in 1971 to 33 billion tonnes in 2017. The UK is responsible for 1.1% of emissions, making them the 16th largest contributor (OECD, 2020).

In the UK, agriculture accounts for 10% of carbon emissions, 70% of nitrous oxide emissions, 50% of methane emissions, and 1% of carbon dioxide emissions (DEFRA, 2020). Pressure has mounted on all industries to reduce carbon emissions. In particular, the Climate Change Act 2008 (2050 Target Amendment) Order 2019 made the target of net-zero carbon emissions by 2050 legally binding. Agriculture is uniquely placed to be part of the solution, as both an emissions source and a sink. There are several practices farmers can implement to reduce emissions, but adoption varies.

It was not until 2008, that the CCA made UK emission reduction targets law. The legislation binds the UK Government to reduce greenhouse gas (GHG) emissions by 80% by 2050 and to support adaptation to achieve this. It established the Committee on Climate Change (CCC) and the Adaptation Sub-Committee, to advise industries on adaptation, mitigation strategies and formulate 'carbon budgets' (Lorenzoni and Benson, 2014). In May 2019, the CCC recommended amending the CCA (2008) target to 100% reduction by 2050, now known as net-zero. From 27th June 2019, the Climate Change Act 2008 (2050 Target Amendment) Order 2019 introduced this new legally binding target.

The agricultural sector report focuses on non-CO2 abatement, with an emphasis on the potential for innovative or novel measures (Barnes *et al.*, 2019) . It suggests methods to reduce nitrate and methane emissions and analyses the cost-effectiveness of the suggested measures. The CCC (2019) reported that one-fifth of agricultural land must change to alternative land uses, afforestation, biomass production, and peatland restoration, to achieve emission reduction targets. The report notes 'the voluntary approach pursued so far for agriculture is not delivering reductions in emissions'.

In 2012, the Government established The Greenhouse Gas Action Plan (GHGAP) to deliver a reduction in agricultural-associated emissions. Reviewed in 2016, the GHGAP remains the main framework in place. It consists of ten performance indicators, including overarching indicators such as farmer 'attitude and knowledge' and sector-specific indicators such as 'manufactured fertiliser application on cereals'. A key indicator is mitigation method uptake, a reliable guide to whether farmers are being effectively motivated to reduce emissions. The 2016 Review confirms the Government's preferred method to motivate farmers' uptake remains the voluntary GHGAP.

Literature review

Environmental land management schemes

The most recent government action aimed at motivating farmers to reduce carbon emissions is the Environmental Land Management Scheme (ELMS). ELMS will pay farmers for managing their land in a way that delivers against key 25 Year Environment Plan goals and particularly supports the delivery of the net-zero target (DEFRA, 2020).

DEFRA is undertaking Phase 1 in a programme of tests and trials. So far, 42 trials are active, focussing on areas such as payments, advice delivery, and collaboration. A national pilot is expected by the end of 2021, with the scheme officially launching in 2024. A three-tier model is currently proposed. Tier 1 focuses on actions many farmers can take to improve environmental sustainability (for example, cover crops or wildflower margins), with an emphasis on practices that are most effective when delivered at scale. Tier 2 focuses on local priorities and relies on collaboration between local land managers. Tier 3 focuses on landscape-scale projects recognising that projects such as woodland creation, peatland restoration, and management of carbon-rich habitats are critical to achieving the ambitious net-zero target (DEFRA, 2020).

In 2020, the CCC raised concerns about ELMS with DEFRA. They agreed tiers 2 and 3 have potential to drive systemic change, and tier 3, in particular, could deliver carbon mitigation benefits through its focus on landscape-scale change. However, they noted that DEFRA has not explained how ELMS will sit within the wider suite of climate policies, including the current Environment Bill, the 25 Year Environment Plan and various policies for afforestation and peatland restoration, or how these different strategies worked together to support the Government's climate change goals.

A survey by the Country Land and Business Association (CLA) and Strutt & Parker, investigated farmers' concerns about ELMS. Over 50% reported they had already taken action to reduce GHG emissions. Four out of five said they are likely or very likely to join ELMS when it is launched in 2024.

However, apprehensions were raised about payments, with 76% concerned they will be insufficient (Bracken, Bulkeley and Maynard, 2014). The Rural Payments Agency currently pays farmers £86 per acre under the Basic Payment Scheme. DEFRA is yet to confirm if ELMS will be more or less generous (Vigani *et al.*, 2021). NFU (2019) cited productive farming as a key pillar to achieving net-zero. Farming more efficiently reduces emissions, and produces other carbon-reducing benefits, by ensuring fewer inputs to achieve the same production levels. DEFRA (2020) committed to providing grants for investment in equipment and infrastructure to drive improved productivity. The grants are due to open in 2021 and will be similar to the current Countryside Productivity Scheme.

Nevertheless, it is uncertain whether the ELMS scheme will motivate farmers to reduce their carbon emissions. Uptake of previous environmental schemes may be a good indicator. Studies have revealed that a complex combination of personal, business and external factors influence farmers' willingness and ability to participate in agri-environmental schemes(Gasson, R. and Potter, 1988). Lobley and Potter (1998) studied participants in Environmental Sensitive Areas (ESA) and Countryside Stewardship (CS) schemes in the southeast of England. This revealed ESA participants were predominantly motivated by financial gain, whereas those in CS were primarily motivated by conservation. Questioning the sustainability of schemes with financial incentives to engage otherwise disinterested farmers, suggesting that, while a short-term gain may be achieved, long term this may not be enough to continue good environmental practice (Lobley and Potter, 1998). These studies are limited in their usefulness due to their age, as farmers' motivations might have changed over time. However, they are still a helpful indication as to the general attitudes towards the uptake of good environmental practices, which is quite likely to translate to farmers' motivations today. More recent studies,(Wilson and Hart, 2001; Rosemarie Siebert, Mark Toogood, 2006), confirm Lobley and Potter's (1998) findings that economic considerations have been the main factors influencing participation in government environmental schemes. Jones *et al.* (2013) found that adoption of carbon emission reduction practices varied depending on the advice and support given to farmers, and there is a need for flexible policies to enable farmers to select measures best suited to their holdings (Jones *et al.*, 2013). Policies that provide help accessing financial support are considered beneficial to improving farm practice(Deressa *et al.*, 2009).

Farmer attitudes and knowledge

May (2019) found that a farmer's knowledge of the interaction between their business and the environment positively affected motivations to adopt beneficial environmental practices. These motivations could be reinforced if the investment made a reasonable return, but this was not the dominant motivation (May, 2019). In contradiction, Hornsey and Harris (2016) concluded climate change beliefs were marginally related to people's motivations to adopt new practices. This was supported by Lane *et al.* (2019) finding that although farmers were concerned about emissions, they experienced other pressures such as profitability, labour and regulations, which were more significant in their decision-making. Acceptance of knowledge increase if shared through farmer-to-farmer groups and the research is not only scientific but also based on experience (Burbi, Baines and Conway, 2016). Morris, Mills and Crawford (2000) confirmed this finding when stating that, while mass media is relevant to awareness creation, personal contact and demonstration are critical to action, with the best advocates for environmental schemes being farmers themselves.

Studies have suggested that farmers who were more willing to take risks, explore new ideas and adopt innovations were more likely to adopt new environmental sustainability practices (May, 2019). Rogers (2010) 'diffusion of innovations theory' categorised farmers into adopter categories: innovators, early adopters, early majority, late majority, and laggards. Moerkerken *et al.* (2020) found farmers' attitudes to innovation to be the strongest predictor for the uptake of climate change mitigation technologies. Farmers classified as innovators were more likely to be motivated to take up climate-friendly practices than farmers in the late majority and laggards categories, even if they had little knowledge about climate change. Moerkerken et al. (2019) found energy-saving measures were likely to be adopted by majority farmers but more complex renewable energy measures were more likely to be adopted by innovators and early adopters, with only innovators most likely to adopt complex non-CO_2 measures. Moreover, Barnes and Toma (2012) and Diederen *et al.* (2003) also concluded innovator farmers were more likely to be motivated to adopt carbon reduction methods. However, Niles and Mueller (2016) found that farmers who had climate change mitigation practices in place, and as a result were classed as innovators, were less likely to adopt further measures in the future.

DEFRA (2019b) measured farmer awareness of emissions, and intentions to change practice, as key indicators of mitigation method uptake. The survey results showed 13% of farmers felt it 'very important' to consider GHGs when making decisions relating to their farm, and a further 42% considered it 'fairly important'. However, 38% placed little or no importance on considering GHGs in their decision-making. Franks and Hadingham (2012) reported 38% of UK farmers believe climate change is already having an impact on their land, and 57% expect it to have an impact in the next 10 years. DEFRA (2019b) reported 61% of farmers were taking actions to reduce emissions. This is an increase from Franks and Hadingham's (2012) earlier data, which revealed 47% of farmers, had taken some action to reduce future climate change. When asked about their main motivations 84% of respondents believed it is 'good business practice'. Other strong motivating factors were the environment (71%), profitability (55%), and regulatory reasons (41%), whilst meeting market demands was only 19%.

The Theory of planned behaviour (TPB) has been widely used to understand human behaviour. It assumes that human behaviour originates from individuals' intentions to perform a specific behaviour (Ajzen, 1991). The TPB hypothesis is that intention is determined by three central psychological constructs: attitude, subjective norm and perceived behavioural control. In this study, the intention of a farmer is defined as the intention to adopt carbon emission reduction practices. The TPB has been used to explore behaviours in other related agricultural issues, like intension to diversify, pesticide handling and to perform agri-environmental measures (van Dijk *et al.*, 2016; Senger, Borges and Machado, 2017; Bagheri *et al.*, 2019).

Methods

In order to explore what factors affect UK farmers' adoption of carbon emission reduction practices, data were collected using a mixed-method approach involving semi structured in-depth interviews and online questionnaire survey with both closed and open questions.

Purposive but convenient sampling based on pre-determined criteria (to represent crops, animals and mixed farms) was applied to recruit study participants of the semi-structured interviews. Each interview lasted approx. 30 minutes. The interview participants are from different regions and different enterprises. Two interviewees are farm owners while the third one is a farm manager employed by a farming company. All interviews were recorded and fully transcribed. Thematic coding was used to explore participants' perspectives on barriers and attitudes to reducing carbon emissions. The thematic analysis showed three key barriers and four motivators to reducing carbon emissions in farms. These were used to inform the questionnaire design.

For the questionnaire-based survey, a snowballing technique using social media platforms such as Twitter and Facebook was used to distribute the questionnaire survey link. This method may be biased towards young farmers, which is not representative of the general farmer population with an average age of 60 (DEFRA, 2017).

The survey questionnaire's design was partly informed by the results of the thematic analysis of the interviews and partly informed by the literature reviewed. The questionnaire included items about relevant socio-demographic information, farmer's innovativeness, and carbon emission reduction practices adopted by farmers and influencing factors. Socio-demographic information included farmer's age, level of education, farm size, farm location and farming sector. Farmer's innovativeness was measured with the typology of innovation adoption (Rogers, 2010).

Carbon emission reduction **behaviour** was measured by the mean score of the summation of the applicable actions with binary answers as listed below:

- Increasing use of clover in grassland
- Improving nitrogen fertiliser application accuracy (e.g. using a fertiliser recommendation system, regularly checking and calibrating fertiliser spreaders)
- Increasing use of legumes in arable rotation
- Improving energy efficiency (reducing fuel use, producing own energy)
- Recycling of waste materials from the farm (e.g. tyres, plastic)

- Improving nitrogen feed efficiency, livestock diets (e.g. using ration formulation programme)
- Improving efficiency in manure and slurry management and application (e.g. covering stores)
- Other measures (e.g. planting hedgerows and trees on farm and no tillage)

Influencing factors includes attitudes towards carbon emission reduction by farmers, perceived behavioural control, perceived barriers to implementation, and key motivators.

Attitudes (Mean score)

- Own concern for environment (5-point scale)
- I consider it good business practice to reduce carbon emission (5-point scale)
- Importance of carbon emissions in decisions (5-point scale)

Neutralisation – denial of responsibility (MEAN SCORE)

- I don't believe there is much farmers can do to reduce carbon emission (binary)
- I have already done all I can to reduce carbon emission (binary)
- I don't believe my farm produces much emissions (binary)

Perceived behavioural control

- I am not sure what to do to reduce carbon emission (binary)

Motivators to reduce carbon emission

- To improve farm profitability (5-point scale)
- To meet market demand (5-point scale)

Multiple linear regression analysis was performed in order to determine which factors affected farmers' decisions to adopt carbon emission reduction practices. Moreover, cluster analysis identified the typology of the farmers and their motivations for implementing carbon emission

Results

Socio-demographic characteristics of the respondents

In total 101 valid responses to the online survey were collected. No responses were from the Northern Ireland. The majority of the respondents were based in England (79.2%). 48% of the respondents reported a farm size of 200 + hectares, which is bigger that the average farm size in England (87 ha) (DEFRA, 2021). Most participants (36%) are aged 18-30 years. Moreover, 46% have a degree (e.g. BSc, BA) with only two without qualifications. The respondents are from all farming sectors with 27.7% of the farms are crop only, 41.6% are animals only, and 30.7% of the farms have mixed farm activities involving both crops and animals. Majority are cereal growers (n = 54 of which 15 cereal) and lowland livestock farmers (n=49, of which18 were lowland livestock only).

Table 1: Socio-demographic attributes of the respondents

Age group	Frequency	Percent	Valid Percent	Cumulative Percent
18-30	36	35.6	35.6	35.6
31-50	26	25.7	25.7	61.4
51-65	30	29.7	29.7	91.1
65+	9	8.9	8.9	100.0
Total	101	100.0	100.0	
Education level				
No Qualifications	2	2.0	2.0	2.0
GCSEs or equivalent	7	6.9	6.9	8.9
BTEC or Diploma	16	15.8	15.8	24.8
A levels or equivalent	23	22.8	22.8	47.5
Degree (e.g. BSc, BA)	46	45.5	45.5	93.1
Higher degree (e.g. MA, PhD)	7	6.9	6.9	100.0
Total	101	100.0	100.0	
Farm size				
<20 ha	10	9.9	9.9	9.9
20-50 ha	13	12.9	12.9	22.8
51-200 ha	30	29.7	29.7	52.5
200 ha +	48	47.5	47.5	100.0
Total	101	100.0	100.0	
Farming sector				
Crops only	28	27.7	27.7	27.7
Animals only	42	41.6	41.6	69.3
Mixed	31	30.7	30.7	100.0
Total	101	100.0	100.0	
Location				
South-East England	29	28.7	28.7	28.7
South-West England	12	11.9	11.9	40.6
East Midlands	8	7.9	7.9	48.5
West Midlands	14	13.9	13.9	62.4
North of England	17	16.8	16.8	79.2
Wales	9	8.9	8.9	88.1
Scotland	12	11.9	11.9	100.0
Total	101	100.0	100.0	

Dependent variable: Farmers carbon emission reduction practices

Table 2 shows the responses to the carbon emission reduction practices. Three practices are not applicable to crop only farmers whilst one is not applicable to animal only farms. Three generic practices were reported by more farmers with the highest uptake reported being recycling of waste materials from the farm (n=70). The lowest up take of activities are improving livestock diets (n=25) and improving manure and slurry management and application (n=28).

Table 2: Carbon emission reduction activities practiced by farmers

Carbon emission reduction activities	Yes		No		Not applicable	
	n	Valid %	n	Valid %	n	% of total
Increasing use of clover in grassland	51	68.00%	24	32.00%	26	25.74%
Improving livestock diets (e.g. using ration formulation programme)	25	34.25%	48	65.75%	28	27.72%
Improving efficiency in manure and slurry management and application (e.g. covering stores)	28	38.36%	45	61.64%	28	27.72%
Increasing use of legumes in arable rotation	29	49.15%	30	50.85%	42	41.58%
Improving nitrogen fertiliser application accuracy (e.g. using a fertiliser recommendation system, regularly checking and calibrating fertiliser spreaders)	57	56.44%	44	43.56%		
Improving energy efficiency (reducing fuel use, producing own energy)	65	64.36%	36	35.64%		
Recycling of waste materials from the farm (e.g. tyres, plastic)	70	69.31%	31	30.69%		

To calculate the score for dependent variable of carbon emission reduction behaviour, the mean score of applicable items was used. The mean value of this calculated behaviour variable is 0.5655 (n=101, min = 0.00 and max. = 1.00, Std deviation= 0.27813).

Independent variables

Reliability of multi-item measures were tested. Table 3 reports the reliability (where applicable) and descriptives of the independent variables. Two items were removed from "denial of responsibility". One factor test (Harman) was conducted. The first factor accounted for 32.9% of the total variance indicating that common method bias was low.

Table 3. Descriptive statistics for the independent variables

	N	mean	min	max	SD
Attitude (Cronbach's Alpha = .732) • Own concern for environment • I consider it good business practice to reduce carbon emission • Importance of carbon emissions in business decisions	100	3.38	1	5	1.04
Business motivator • Financial incentives • To improve profitability (removed) • To meet market demand (removed)	101	4.11	1	5	1.019
Denial of responsibility – • I don't believe there is much farmers can do to reduce carbon emission. • I don't believe my farm produces much emissions (removed) • I have already done all I can to reduce carbon emission (removed)	100	.20	0	1	.40
PBC - I am not sure what to do to reduce carbon emissions	101	.35	0	1	.478
Innovativeness (stages of innovation adoption)	101	3.1	1	4	.889
Farm size	101	3.15	1	4	.994

What explains the difference in farmers' carbon emission reduction behaviour

Multiple linear regression was carried to find out what might explain the differences in farmers' behaviour in reducing carbon emissions on farm. Table 4 presents the test results.

Table 4. Regression model summary and coefficients

	Standardized (Beta)	t	Sig.
(Constant)		-2.155	0.034
Attitude	0.177	1.858	0.066
Denial - I don't believe there is much farmers can do	-0.219	-2.263	0.026
Financial incentive to reduce emissions	0.289	3.248	0.002
Farm size	0.256	2.82	0.006
Innovativeness	0.222	2.367	0.020

$R = 0.556$, R Square $= 0.309$, Sig. < 0.001

The regression showed five significant determinant factors: underlying belief about carbon emissions reduction, financial incentives, farm size and the farmer's innovativeness all positively influence the carbon emission reduction adoption whilst denial of responsibility has significant negative influence on adoption ($p = 0.026$). Financial incentive has the strongest influence of all (Beta = 0.289, $p = 0.002$). Together, the factors explain 30.9% of the differences in adoption behaviour by farmers.

Farmers' self-reported innovativeness was found to be a significant determinant factor. This was confirmed by the interviews. Thematic coding revealed interviewee 2 as an innovator. They had undertaken the most innovative measures, including two wind turbines, a hydro-generation scheme, solar panels and participation in a Climate Change Focus Farm Scheme. This supports Moerkerken *et al.* (2019) findings that only the most innovative groups are likely to adopt complex renewable energy measures and non-CO_2 measures. Interviewee 1 was classed in the majority category due to their cautiousness and cynicism of certain practices. However, they were recycling and improving fuel use, reinforcing the suggestion that these actions can be easily adopted regardless of farming enterprise (DEFRA, 2019b). Interviewee 3 have numerous plans to improve their farming practices, but were waiting to calculate a carbon basis before undertaking actions, placing them in the early-adopter category. Attitudes as an influencing factor was also confirmed by the interview results. All interviewees said they felt a moral responsibility to reduce carbon emissions but stated further knowledge and actions were needed before net-zero could be achieved.

Interviewees repeatedly chose the economic factors 'lack of incentive' and 'too expensive' as barriers to reducing emissions. This strengthens the pattern identified throughout the results that economic factors are influential, supporting Siedenburg *et al.* (2012), Swann and Richards' (2016) conclusions that financial incentives are required to motivate farmers and overcome barriers.

Discussion and Conclusions

The research aimed to understand what motivates farmers to reduce carbon emissions in line with the new net-zero target. From the results and literature, it was clear numerous factors influenced motivations. This study suggests economic factors are a significant motivation for reducing carbon emissions, however it also showed that between farmers different typologies can be identified that will respond differently to this motivation. The results showed that innovators are the least motivated by financial incentives. They also tend to be the larger farmers and their main enterprise is crop growing. Those who take less or no actions in reducing carbon emissions in farms were more likely to believe that there is not much farmers can do, this group was identified as passive resistors. Where they do not actively resist to actions to reduce carbon emissions nor are motivated by financial incentives, this group consist of the smaller farmers. When comparing attitude groups, it was shown that less innovative farmers (those more resistant to change) were more influenced by regulation. To achieve the net-zero target, a combination of factors to incentivise all farming groups is essential. For example, environmental incentive schemes will motivate the innovative farmers, whereas more unwilling farmers can be encouraged to reduce carbon emissions through stronger regulation. Qualitative data analysis suggests that more accessible information and knowledge transfer should be provided to unlock the potential of achieving Net Zero target by 2050.

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Agricultural Land as Natural Capital: Measurement, Data, and Public Policy

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Abstract

The stock of agricultural land can be viewed as natural capital that provides a flow of goods and services that benefit people. Changes in this stock of natural capital have implications for the long-term sustainable development of the agriculture sector. This study estimates a natural capital account for agricultural land in Quebec over twenty years. The natural capital account includes a physical inventory of the agricultural land and a valuation of this asset. Geospatial technologies were used to estimate the physical inventory of agricultural land in Quebec. The physical inventory was based on land cover, land use, and land capability information which provided the attributes of the asset. A spatial hedonic price model was estimated that provided implicit prices of the attributes that were included in the physical inventory. A well-defined and estimated natural capital account can assist public policy by (1) providing a better understanding of the evolution of the current level of the capital stock and (2) provide input into resource management.

Presenter Profile

Paul J. Thomassin is a Professor of Agricultural Economics at McGill University. His research areas include agricultural and environmental economics, macroeconomic analysis of food and agriculture policies, food safety, natural capital accounting, technological change, and the economics of climate change. He was the scientific director of Greenhouse Gas Management Canada, a SSHRC-BIOCAP national research network that investigated the social science dimensions of greenhouse gas management. He has been a Visiting Professor at the William S. Richardson, School of Law, at the University of Hawaii, Visiting Fellow at the National Centre for Development Studies at the Australian National University, and an Honorary Professor in the Division of Science and Technology at the University of Auckland.

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