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Technology adoption and upscaling of detailed farm-level models

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Kurzfassung

Die Annahme digitaler Technologien in der Landwirtschaft kann ein wichtiger Treiber für die Steigerung der landwirtschaftlichen Produktivität und die Transformation hin zu einem nachhaltigen Landwirtschaftssystem sein. Das Verständnis der Entscheidungen der Landwirte zur Nutzung von Technologien und die Bewertung ihrer wirtschaftlichen und ökologischen Auswirkungen sind von entscheidender Bedeutung für die politischen Entscheidungsträger, um den Annahme- und Verbreitungsprozess solcher disruptiver Technologien zu steuern.

Diese Dissertation zielt darauf ab, zur Modellierung der Annahme digitaler Technologien in der Landwirtschaft beizutragen und Methoden für die Bewertung der Auswirkung solcher Technologien zu entwickeln. Zunächst konstruieren wir einen konzeptionellen Rahmen für agentenbasierte Modellierung hinsichtlich der Annahme und Verbreitung digitaler Technologien in der Landwirtschaft. Dieser Rahmen basiert auf den bestehenden empirischen Studien zur Annahme von Präzisions- und digitalen Technologien auf Farmebene sowie der agentenbasierten Modellierung landwirtschaftlicher Innovationen. Weiterhin vergleichen wir die Bedeutung verschiedener kontextueller und technischer Spezifikationen (Landwirtschaftssysteme, Arbeitskosten, Technologieattribute und Parzellenmerkmale) bei der Bestimmung der Zahlungsbereitschaft von Landwirten und damit ihrer potenziellen Akzeptanz digitaler Technologien am Beispiel von Unkrautrobotern. Schließlich untersuchen wir die Machbarkeit der Verwendung modernster neuronaler Netze als Surrogat-Modelle für detaillierte landwirtschaftliche Betriebsmodelle, um deren Hochskalierung zu erleichtern.

Die Ergebnisse zeigen, dass die Entscheidungen der Landwirte zur Annahme digitaler Technologien von verschiedenen Faktoren beeinflusst werden, darunter Betriebs- und Nutzermerkmale, Interaktionen, Technologieattribute sowie institutionelle und psychologische Faktoren. Außerdem spielen kontextbezogene und technische Spezifikationen eine große Rolle für die Zahlungsbereitschaft der Landwirte und die potenzielle Akzeptanz digitaler Technologien. Beispielsweise könnte die Annahme von Unkrautrobotern zuerst in Bio-Betrieben beginnen, während die hohe Überwachungskosten von Unkrautrobotern ein wichtiger Faktor bei der Nutzungsentscheidung konventioneller Betriebe

sein könnten. Wenn Saisonarbeit kostspieliger wird und der Einsatz von Herbiziden stark eingeschränkt ist, könnten Unkrautroboter sowohl für biologische als auch für konventionelle Betriebe attraktiv sein. Die Ergebnisse zeigen auch, dass neuronale Netze bei der Annäherung detaillierter Betriebsmodelle effizient sind und als Surrogat-Modelle verwendet werden können, ohne dass die Genauigkeit der Simulation in relevanter Weise eingeschränkt wird. Diese Dissertation trägt zur Verbindung zwischen Betriebsmodellen und agentenbasierten Modellen bei und ebnet den Weg für zukünftige Forscher, die Annahme von Technologien, insbesondere Technologien für die digitale Landwirtschaft, in großem Maßstab zu modellieren und zu bewerten.

Schlüsselwörter: *Technologieannahme, digitale Landwirtschaft, Betriebsmodelle, agentenbasiertes Modell, neuronale Netze*

Abstract

Adoption of digital farming technology can be an important driver for agricultural productivity enhancement and transformation towards a sustainable farming system. Thus, understanding farmers' technology adoption decisions and evaluating their economic and environmental impacts are crucial for policy-makers to steer the adoption and diffusion process of such disruptive technologies.

This thesis contributes to the modelling of digital farming technologies adoption and develops modelling tools for impact evaluation of such technologies. First, we develop a conceptual framework for Agent-based Models (ABMs) that simulate the adoption and diffusion of digital farming technologies based on the existing empirical farm-level adoption studies of precision and digital farming technologies and ABMs of agricultural innovations. Second, we compare the importance of different contextual and technical specifications (farming systems, labour costs, technology attributes and plot characteristics) in determining farmers' investment limits and their potential adoption behaviour of digital farming technologies, using the example of weeding robots. Finally, we explore the feasibility of using state-of-the-art Neural Networks (NNs) as surrogate models of detailed farm-level models to facilitate the upscaling of those models.

The results show that farmers' adoption decisions of digital farming technologies are influenced by various factors including farm and operator characteristics, interactions, technology attributes, and institutional and psychological factors. Further, contextual and technical specifications matter a lot in farmers' investment limits and adoption decisions of digital farming technologies. For example, adoption of weeding robots might first start among organic farms, while high supervision costs of weeding robots could be an important factor in the adoption decision of conventional farms. When seasonal labour becomes more costly and the use of herbicide is severely restricted, robotic weeding can be attractive to both organic and conventional farms. It also proves that NNs are efficient in approximating detailed farm-level models and can be employed as surrogate models without losing accuracy in relevant perspectives. This thesis contributes to the connections between farm-level models and ABMs and paves

the way for future researchers to model and assess technology adoption, especially digital farming technologies, on a large scale.

Keywords: *technology adoption, digital farming, farm-level model, surrogate model, agent-based model, neural networks*

Contents

List of Figures

List of Tables

List of Abbreviations

ABM	**A**gent-**B**ased **M**odel
AgriPoliS	**Agri**cultural-**Poli**cy **S**imulator
AI	**A**rtificial **I**ntelligence
APE	**A**bsolute **P**ercentage **E**rror
BiLSTM	**Bi**-directional **L**ong **S**hort **T**erm **M**emory
CNN	**C**onvolutional **N**eural **N**etwork
DOI	**D**iffusion **o**f **I**nnovation
GAN	**G**enerative **A**dversarial **N**etwork
GPU	**G**raphics **P**rocessing **U**nit
HFH	**H**ands **F**ree **H**ectare
HFT	**H**uman **F**unctional **T**ypes
IoT	**I**nternet **o**f **T**hings
KTBL	**K**uratorium für **T**echnik und **B**auwesen in der **L**andwirtschaft e.V.
LHS	**L**atin **H**ypercube **S**ampling
LSTM	**L**ong **S**hort **T**erm **M**emory
MAV	**M**aximum **A**cquisition **V**alue
MIC	**M**aximum **I**nformation **C**oefficient
MIP	**M**ixed-**I**nteger **P**rogramming
MLP	**M**ulti**l**ayer **P**erceptron
MSE	**M**ean **S**quared **E**rror
NN	**N**eural **N**etwork
PAT	**P**recision **A**griculture **T**echnology
ReLU	**Re**ctified **L**inear **U**nit
ResNet	**Res**idual **Net**work
RMSprop	**R**oot **M**ean **S**quare **prop**agation
RNN	**R**ecurrent **N**eural **N**etwork
SGD	**S**tochastic **G**radient **D**escent
TAM	**T**echnology **A**cceptance **M**odel
TPB	**T**heory of **P**lanned **B**ehaviour

Chapter 1

Overview of the thesis[1]

1.1 Motivation and structure

Global agriculture faces various challenges to meet the demand for food and fibres in the coming years because it needs to maintain overall productivity without further polluting soil, water and other agroecological systems (Finger et al., 2019). Adoption of more efficient agricultural technology is believed to be an important driver for productivity enhancement and transformation towards a sustainable farming system (Ruzzante et al., 2021). Over the past decades, the development of information communication technology, robotic and sensing technology, and artificial intelligence is leading the agricultural sector into the era of digital farming (Ehlers et al., 2021). Digital farming technologies cover a broad spectrum, from small mobile apps for decision support, to in-field sensors and remote sensing technologies for data collection, and to drones and robots for the automation of processes (OECD, 2019). Digital farming is expected to transform agricultural systems to be more sustainable by reducing the use of agrochemicals and using less of other farming inputs such as land and labour (Khanna et al., 2022).

The rise of digital farming technologies and their potential disruptive impacts make it particularly important for agricultural economists and policy-makers to understand

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farmers' adoption decisions and their economic, social and environmental impacts. However, since the adoption and diffusion of digital farming technologies are still at the early stage, empirical adoption studies of such technologies are still rare in the literature, not to mention the impact evaluation studies of them. This makes it challenging to model the adoption of digital farming technologies and thus evaluate their impacts at this stage. Therefore, the overarching aim of this thesis is to contribute to the modelling of digital farming technologies adoption and to develop modelling tools for the impact evaluation of these novel technologies.

Modelling technology adoption requires an understanding of the mechanism for farmers' adoption decisions not only at the farm level but also at the system level (Rasch et al., 2017). The system refers to the collection and organisation of entities (e.g. farmers, technology providers, and government) relevant to the technology adoption and diffusion. It evolves over time based on farmers' behaviour and their interactions with the environment and one another (Alexander et al., 2013). As examples, farmers might adopt labour-saving technologies to cope with the shortage of seasonal labour (Bochtis et al., 2020; Gallardo and Sauer, 2018), or adopt environmentally friendly technologies due to new environmental requirements or the increasing prices of fertiliser (Barnes et al., 2019; Guo et al., 2022; Hassen and El Bilali, 2022; Merrigan, 2022). Further, their technology adoption decisions may also be influenced by the opinions in their social network (Crudeli et al., 2022; Massfeller and Storm, 2022). It is the system interaction in combination with, and depending on, individual farm decision-making that will ultimately determine technology adoption and its economic and environmental impacts.

These system dynamics among heterogeneous agents and with the environment can be well captured by Agent-based Models (ABMs). They are "bottom-up" social simulation approaches, consisting of "agents", representing entities in the social world, and an "environment" in which agents act (Gilbert, 2007). In ABMs, agents can perceive the environment, make decisions autonomously, and interact with each other (Bonabeau, 2002). Thus, ABMs can capture the heterogeneous decision-making of local agents and their interactions, as well as the emergent phenomena from local interactions and their feedback to each agent (Zhang and Vorobeychik, 2019). In terms of agricultural technology adoption and diffusion, ABMs have been employed to simulate various interactions and system feedback. Examples include social network effects on the use of mechanical weed control and herbicide (Huber et al., 2022), collective actions of farmers' community in adopting irrigation technologies (Perello-Moragues et al., 2019), the impact of agricultural extension and policy instruments on farmers' adoption of beneficial water management practices (Sun et al., 2022), and the feedback from markets for crops and carbon allowances on farmers' behaviour in crop production and best management practice (Ng et al., 2011).

ABMs have not been employed for simulating the adoption and diffusion of digital farming technologies. This is largely due to a lack of data on the topic since the widespread use of these technologies is still at an early stage. Therefore, the first section in the body of this thesis (Chapter 2) aims to build an empirically grounded, conceptual modelling framework for the adoption and diffusion of digital farming technologies. Due to the lack of both farm-level and ABM studies on such technologies, Chapter 2 links empirical farm-level evidence of precursor technologies (i.e. Precision Agricultural Technologies, PATs) and system interaction simulated by current ABMs of agricultural innovations. It directly contributes to the research goal of the thesis by laying out a holistic picture of farmers' decision-making regarding technology adoption and system interactions in the context of digital farming technologies.

Robotic weeding is one of the digital farming technologies that is commercially available (see e.g. FarmDroid, 2022; Naïo Technologies, 2022) but not yet widely adopted by farmers (Lowenberg-DeBoer et al., 2020; Spykman et al., 2021). As such, the lack of data prevents empirical studies on farmers' adoption behaviour. The second section in the body of this thesis (Chapter 3) uses a Monte Carlo simulation approach to improve our understanding of farmers' potential adoption behavior. The simulation systematically varies certain input parameters to capture contextual and technical specifications relevant for farmers' investment limits with respect to weeding robots. This is based on the existing farm planning data of German sugar beet farming extracted from KTBL (2020) (In German: Kuratorium für Technik und Bauwesen in der Landwirtschaft e.V.; In English: the Association for Technology and Structures in Agriculture) and the data of technical attributes from current weeding robot companies. The contextual and technical specifications varied include farming systems (organic farming vs. conventional farming), labour costs (wage rate of skilled and unskilled labour), plot characteristics (plot size and mechanisation level), and technology attributes (e.g. area capacity, weeding efficiency, required supervision intensity, etc.). The Monte Carlo simulation approach makes it possible to compare the importance of different input parameters in determining farmers' potential adoption behaviour and contributes to the research goal of this thesis by informing policy-makers and technology providers (a) under which conditions weeding robots are more likely to be adopted, and (b) which technology attributes to focus on during technology design and development.

In the context of European agriculture, modelling the impacts of agri-environmental policies and induced technology adoption behaviour increasingly requires accounting for detailed farm-level decision-making, spatial conditions, and interactions among heterogeneous farmers. For example, when evaluating the impact of newly introduced eco-schemes or collective agri-environmental payments (Kuhfuss et al., 2016; Šumrada et al., 2022), modellers must be able to not only capture the individual decision-making but also emergent phenomena from coordination and participation of local communities and system feedback to each farm . While using separate detailed farm-level models usually cannot capture the system interaction and dynamics, the current ABMs of agricultural technology adoption can hardly fulfil the requirement either, due to their limited complexity of the embedded farm decision-making models (Bradhurst et al., 2016; Murray-Rust et al., 2014). However, simply combining the two types of models to take advantage of both could become computationally expensive as the number of agents or regional coverage increases (Sun et al., 2016). In recent years, the availability of highly flexible deep learning (Goodfellow et al., 2016) tools offers the opportunity to build surrogate models (Jiang et al., 2020) for computationally demanding simulation models (Storm et al., 2020). In spite of the rapid evolution of deep learning in the past decades, it is still rarely employed in agricultural economics. Therefore, the last chapter of this thesis (Chapter 4) aims to develop surrogate models approximating detailed farm-level models within different contexts using deep learning tools. This chapter contributes to the research goal of the thesis by facilitating the upscaling of detailed farm-level models into system-level models for future large-scale impact evaluation of novel farming technologies.

The general research objectives of the three chapters in this thesis are:

1. To develop a conceptual modelling framework that allows us to build empirically grounded ABM to study the adoption and diffusion of digital farming technologies by synthesising the knowledge from farm-level studies of precursor technologies

and ABMs of agricultural innovations (Chapter 2).

2. To conduct a cost-based investment analysis of weeding robots and identify the most important factors (including farming systems, technology attributes, labour costs, and plot characteristics) in determining farmers' investment limits and their potential adoption decisions (Chapter 3).

3. To develop surrogates of detailed farm-level models using deep learning tools and develop evaluation criteria to assess their performances (Chapter 4).

In the remainder of this introduction, the contributions and main results of the thesis are highlighted. Afterwards, a conclusion section summarises the thesis and its limitations and proposes directions for future research.

1.2 Contributions of the thesis

This section summarises the three chapters of the thesis, including research gaps identified in the literature, how they were addressed, and the main results of each chapter. The contribution of each chapter to the overarching research goal of the thesis is also highlighted.

1.2.1 Adoption and diffusion of digital farming technologies - Integrating farm-level evidence and system interaction

Chapter 2[2] gives a holistic picture of farmers' decision-making in technology adoption. It consists of a systematic literature review of empirical farm-level studies on the adoption of precision and digital farming technologies and ABMs of agricultural innovations. It then builds a conceptual modelling framework for the adoption and diffusion of digital farming technologies based on the empirical findings.

While the research of technology adoption has a long tradition in agricultural economics in general, adoption studies of digital farming technologies only started to emerge in recent years (see e.g. Drewry et al., 2019). To understand the mechanism of farmers' adoption decisions of digital farming technologies, we must refer to the lessons of

[2]Chapter 2 is published as Shang, L., Heckelei, T., Gerullis, M. K., Börner, J., and Rasch, S. (2021): Adoption and diffusion of digital farming technologies - integrating farm-level evidence and system interaction, *Agricultural Systems*, Vol. 190. 103074. https://doi.org/10.1016/j.agsy.2021.103074

the precursor technologies, i.e. PATs, since the similarities between them could be useful for us to gain insights into the potential adoption determinants of digital farming technologies. So far, our understanding of the mechanisms of technology adoption and diffusion mainly comes from empirical farm-level studies on individual adoption and ABMs simulating systemic diffusion mechanisms. Farm-level adoption studies usually use regression-type analysis (e.g. Logit, Probit, Poisson models) estimating the effect of different variables on adoption (such as farm size and farmers' age) or qualitative descriptive approaches (e.g. descriptive summary of interviews with farmers) focusing on technology attributes (such as compatibility of a technology and data safety) (Klerkx et al., 2019). While farm-level adoption studies usually do not consider system interaction among farmers or with other entities (Heckelei, 2013), ABMs can capture system interaction among heterogeneous entities (Zhang and Vorobeychik, 2019). However, existing ABMs of agricultural innovations have not covered the adoption and diffusion of digital farming technologies yet. Most importantly, current ABMs are not well connected with empirical farm-level evidence on the adoption and diffusion of digital farming and are thus lacking the empirical foundation needed for applications beyond the toy-model stage so far (Matthews et al., 2007).

We therefore need to establish the connection between empirical farm-level evidence and ABM studies to explore (a) how farmers' adoption behaviour influences the system, and (b) how changed system conditions affect what is happening at the farms. This dynamic and spatially differentiated process ultimately determines the diffusion of digital farming technologies, and understanding them can help us to identify effective pathways for sustainable agricultural systems.

To this end, the objective of this chapter is to connect the dots between the two strands of literature and build an empirically grounded, conceptual framework for modelling the adoption and diffusion of digital farming technologies. Chapter 2 first reviews 32 farm-level adoption studies of precision and digital farming technologies and 27 ABMs studies of agricultural innovations. We classify the determinants of farmers' adoption decisions into six categories: 1) farm characteristics, 2) operator characteristics, 3) interactions, 4) institutions, 5) attributes of technology, and 6) psychological factors. The importance of the factors is standardised for a fair comparison across factors and studies. We also find that the majority of farm-level studies focus on farm and operator characteristics, while only a few recent studies highlight the importance of the attributes of technology, institutions, and psychological factors. Similarly, ABMs are quite limited with respect to modelling various types of agents and are largely characterised by profit maximisation while rarely modelling farmers' knowledge/capacity, psychological factors, attributes of technology and institutional arrangements. Based on the identified gaps, a conceptual framework integrating farm-level evidence on adoption with a systemic perspective on technology diffusion is developed.

Chapter 2 contributes to the research goals of this thesis by developing a concept on how to improve the modelling of adoption and diffusion of digital farming technologies. Our empirically grounded modelling framework is the first holistic approach to connect the dots between the wealth of empirical research on technology adoption with a more model-driven investigation of innovation diffusion in ABMs. It can serve as a reference for future ABMs capable of integrating empirical evidence and system dynamics holistically. Applying this framework can increase the empirical and theoretical foundation, as well as improve model coherence and comparability of future ABMs. Furthermore, this framework can be the basis for contextual applications to inform policy-makers trying to foster the diffusion of suitable digital technologies through interventions, such as subsidies and extension services, as it highlights where policy can impact important aspects of adoption via relevant processes of diffusion.

1.2.2 How much can farmers pay for weeding robots? A Monte Carlo study

Chapter 3 focuses on the importance of the contextual and technical specifications in determining farmers' investment limits thus their potential adoption behaviour in digital farming technologies, using the example of weeding robots.

Despite the rapid advancement on the engineering side of digital agricultural technologies, our economic understanding of agricultural robots has lagged due to the limited adoption and data availability from farm trials of such technologies (Lowenberg-DeBoer et al., 2020; Spykman et al., 2021). The review of Lowenberg-DeBoer et al. (2020) could only identify 18 studies that include economic analyses of agricultural automation and robotics. Profitability is one of the key determinants of technology adoption (Kolady et al., 2021), which is highly impacted by the investment cost of the technology. Thus, it is necessary for us to understand how contextual and technical specifications influence farmers' maximum investment and their potential adoption behaviour. Such analyses are highly relevant for farmers' adoption decisions, technology providers' machine design (Shockley et al., 2019), and policy-makers' strategies to promote adoption.

Therefore, Chapter 3 conducts a cost-based investment analysis with the example of weeding robots in German sugar beet farming. Specifically, it calculates the Maximum Acquisition Values (MAVs) (Shockley et al., 2019; Sørensen et al., 2005) of weeding robots and their determinants for both organic and conventional sugar beet farming in Germany. The MAV of a weeding robot is defined as the break-even price of the robot that renders the same net profit as the current weeding methods. It uses empirical data from KTBL (2020), assumptions about different robotic characteristics (based on existing literature and information provided by technology development firms), and a Monte Carlo simulation approach. The Monte Carlo approach systematically varies the input parameters, including technology attributes (area capacity, weeding efficiency, required supervision intensity, repair and energy cost, and setup time per plot)[3], labour costs (wage rate of skilled and unskilled labour), and plot characteristics (plot size and mechanisation level) for both organic and conventional sugar beet farming. This approach makes the comparison across different contexts and technical specifications possible.

The results show that the MAVs of mechanical weeding robots for organic farming are substantially higher than that of spot spraying robots for conventional farming. Therefore, the adoption and diffusion of weeding robots might also start among organic farms. Another implication is that the availability of weeding robots (and generally agricultural robots) might change the conversion decision of conventional farms, for whom the high labour requirement could have been an obstacle so far. The importance of different factors in determining the MAVs of weeding robots differ in the two farm systems: In organic farming, area capacity and weeding efficiency impact the MAVs of mechanical weeding robots the most. The wage rate of unskilled labour, relevant for manual weeding, plays a more important role in determining the MAVs than the wage rate of skilled labour, relevant for supervision of the robot. This implies that a shortage of seasonal workers and hence increases in the wage of low-skilled labour could be important drivers in the adoption of mechanical weeding robots. Further, full autonomy of the mechanical weeding robot might not be critical, as supervision costs are less

[3]See Chapter 3 for detailed definitions of these technology attributes.

relevant in determining farmers' potential adoption decisions; In conventional farming, supervision costs and the robot's ability to save herbicides are the most influential factors in determining the MAV of a spot spraying robot. Plot characteristics such as plot size and mechanisation level only have limited impacts on the MAVs.

Chapter 3 contributes to the research goals of this thesis because it explores the impacts of contextual and technical specifications on how much farmers can pay for novel technologies and what factors matter the most for farmers' potential adoption behaviour. The results of this study could be enlightening for technology providers and policy-makers who intend to promote the adoption of weeding robots. In the case of technology providers, total weeding capacity and weeding efficiency are the two most important technology attributes for mechanical weeding robots, while supervision intensity and weeding efficiency are the most important for spot spraying robots. Policy-makers can learn under what circumstances farmers are more likely to adopt. When seasonal workforce becomes more costly, mechanical weeding robots would save more labour costs thus become attractive to organic farms. When herbicide use is severely limited, conventional farms would have more incentives to convert to more profitable organic farming because the high seasonal labour cost could be alleviated by mechanical weeding robots. Therefore, not only the spot spray robots could massively reduce the negative environmental impacts, but also mechanical weeding robots could bring new opportunities for conventional farms to convert to organic farms.

1.2.3 Surrogate modelling of detailed farm-level models using state-of-the-art neural networks

Chapter 4 develops computationally efficient surrogates of the detailed farm-level model FarmDyn (Britz et al., 2016). The surrogate models can be later integrated into large-scale ABMs to simulate technology adoption and diffusion with high resolution on details of farm-level decision-making and to capture system dynamics.

Computational demands have been limiting the complexity of the embedded farm decision-making model within an ABM for upscaling purposes, i.e. if the number of agents and the regional coverage of an ABM shall be increased (Bradhurst et al., 2016; Murray-Rust et al., 2014; Sun et al., 2016). While modelling the impacts of agri-environmental policies increasingly requires accounting for detailed farm-level decision-making, heterogeneous local conditions, and interaction among farmers, the computational challenge remains a barrier to developing such large-scale ABMs. In addition, farm-level models and ABMs, developed by different research teams and for different purposes, have their own advantages and disadvantages in modelling. Detailed farm-level models can represent individual decision-making with a rich representation of input choices, investments, and environmental indicators, but do not account for interaction among farmers and market feedback on larger scales (Heckelei, 2013). ABMs, on the other hand, capture system interactions and market feedback, but the embedded decision-making model of farm agents is usually simpler than detailed farm-level models. Therefore, Chapter 4 addresses this issue by using the surrogate modelling approach, which allows us to combine the strengths of both types of models and overcome the computational constraints.

The state-of-the-art Neural Networks (NNs) (Goodfellow et al., 2016) are used as surrogate models of FarmDyn in Chapter 4. These include Multilayer Perceptron (MLP), Residual Networks (ResNets) (He et al., 2016), Long Short-term Memory (LSTM) (Hochreiter and Schmidhuber, 1997), and Bidirectional Long Short-term Memory (BiLSTM) (Graves et al., 2005). In addition to their ability to capture the underlying linear and nonlinear relationships between input and output data, these highly flexible deep learning tools are also much more computationally efficient to run than detailed farm-level models (Razavi, 2021; Storm et al., 2020). In agricultural economics, however, NNs are rarely used as surrogate models compared to other disciplines, such as engineering and water resource modelling (Jiang et al., 2020; Razavi et al., 2012). With the exception of Audsley et al. (2008) and Nguyen et al. (2019) who have employed the classical MLPs as surrogate crop and biogeochemical models, respectively, the advantages and disadvantages of state-of-the-art NNs as surrogate models are not yet studied in our discipline. Thus, Chapter 4 aims to develop surrogates of the detailed farm-level model FarmDyn using state-of-the-art architectures of NNs and evaluates their performances from different perspectives.

The results show that NNs are efficient in approximating detailed farm-level models. All tested NNs achieve a high fit (R^2) but differ substantially in inference time. The best BiLSTM achieves an average R^2 of 0.99, while the lowest average R^2 is 0.93 by ResNet. BiLSTM and LSTM achieve better performance than other types of NNs. In terms of inference time, all trained NNs are much faster than FarmDyn. MLPs are about

30,000 times faster, and the best performing BiLSTM regarding R^2 is still 45 times faster. Furthermore, we provide generic evaluation metrics to assess the performance of surrogate models, which can offer future modellers additional help in designing surrogate modelling approaches in applied modelling. The evaluation metrics consist of four dimensions: (1) Goodness of fit; (2) Consistency of bivariate relationships; (3) Accuracy in capturing corner solutions; and (4) Accuracy in holding constraints. They are calculated for different sizes of samples used for training to understand the effort needed in data generation. In our specific case, increasing the sample size from 1,000 to 50,000 significantly improves the performance of all types of models. Once the sample size reaches 100,000, adding more data points for training does not improve the performance of the surrogate models in any relevant way as defined by the evaluation metrics.

Chapter 4 contributes to the research goals of this thesis because it develops modelling tools to upscale detailed farm-level models to enable large-scale simulation of technology adoption and diffusion. Future studies can construct an integrated modelling system that consists of a detailed farm-level model, a surrogate model, and an ABM. Such an integrated modelling system can be used to enable comprehensive analyses of agri-environmental policies that are targeted at the individual farm level. Besides, the evaluation metrics in this study are generic and can be extended for other applications in the future.

1.3 Conclusion

1.3.1 Summary of results

This thesis contributes to the modelling of technology adoption and its impact evaluation on a large scale. It proposes an empirically grounded modelling framework for the adoption and diffusion of digital farming technologies and compares the importance of different contextual and technical specifications (farming systems, labour costs, technology attributes and plot characteristics) in determining farmers' investment limits, thus their adoption behaviour of digital farming technologies, using the example of weeding robots. It further explores the feasibility of using NNs as surrogates of detailed farm-level models to facilitate the upscaling of those models. This thesis builds the connections between farm-level models and ABMs and paves the way for future researchers to model and assess technology adoption on a large scale.

We find that farmers' adoption decisions of digital farming technologies are influenced by various factors including farm and operator characteristics, interactions, technology attributes, and institutional and psychological factors. To model technology adoption, both farm-level and system-level elements must be covered. Furthermore, our cost-based investment analysis of weeding robots reveals that contextual and technical specifications are an important consideration: Organic farms are able to pay significantly more for weeding robots than conventional farms, and technology attributes and labour costs play an important role in determining the economic value of such novel technologies. We also proved that NNs are efficient in approximating detailed farm-level models and can be employed as surrogate models without losing accuracy in relevant perspectives.

1.3.2 Limitations and outlook

Despite the contributions this thesis has made, there are several remaining limitations. Here, the general limitations and an outlook for future research are summarised. The more detailed shortcomings are left to each individual chapter of the thesis.

First, the proposed conceptual modelling framework for the adoption and diffusion of digital farming technologies has not yet been employed for real-world applications. The fairly broad conceptual framework contains factors that might not be relevant for some specific technologies. Similarly, there might be factors that are not included yet in our framework because it is only based on a limited number of studies available at this time. Future researchers can start from this general framework and adjust it to their own research goals by specifying the contextual relevance of the adoption determinants.

Second, the contextual specifications represented in the cost-based investment analysis of weeding robots are limited to the German sugar beet farming system and its socioeconomic and technological settings. When switching to other contexts (e.g. another country with much lower labour costs and different policy settings), the results from our analysis might not be suitable anymore. Further, due to the characteristics of the KTBL dataset, we could only perform the analysis per plot instead of per farm. In reality, when a farmer decides on investing in a new technology, the whole farm production activities of various crops and plots with different characteristics might be considered.

Third, the surrogate models developed in this thesis using different NNs have not been integrated into ABMs for concrete simulations of technology adoption and policy analysis yet. To assess the impact of digital farming technologies or related agricultural policies on a large scale, we need to first achieve the technical coupling of the surrogate model and the ABM, which are usually written in different programming languages and by different research teams. Therefore, updating and debugging the integrated modelling system could be challenging. Finally, calibration and validation of such an integrated modelling system could also be demanding because even a slight deviation of the surrogate model on the farm level can cause crucial divergence on the regional level, where heterogeneous farms interact with each other in both the short and long run.

Going beyond what the thesis has achieved and the limitations of each chapter, as digital farming technologies become more widely adopted in different contexts, future researchers would have more opportunities to conduct empirical studies contributing to the modelling of technology adoption and its impact evaluation. For example, the availability of real-world data on the costs and profitability of using digital farming technologies or farmers' acceptance or actual adoption behaviour of such novel technologies can improve the parameters of our farm-level models as well as ABMs. The upscaling of detailed farm-level models in large-scale ABMs simulating the adoption and diffusion of digital farming technologies would also benefit from the increasing data availability, thus being more sophisticated to evaluate agri-environmental policies.

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Chapter 2

Adoption and diffusion of digital farming technologies - Integrating farm-level evidence and system interaction[4]

Abstract: Adoption and diffusion of digital farming technologies are expected to help transform current agriculture towards sustainability. Our current understanding of the mechanisms of adoption and diffusion mainly comes from empirical farm-level adoption studies and by agent-based models of systemic diffusion mechanisms. To build an empirically grounded conceptual framework for adoption and diffusion of digital farming technologies, we synthesise the knowledge from 32 farm-level studies on the adoption of precision and digital farming technologies and 27 agent-based models on the diffusion of agricultural innovations. We show farm-level studies focus on farm and operator characteristics but pay less attention to attributes of technology, interactions, institutional and psychological factors. Agent-based models, despite their usefulness for representing system interaction, only loosely connect with empirical farm-level findings. We then develop a conceptual framework integrating farm-level evidence on adoption with a systemic perspective on technology diffusion.

Keywords: *technology adoption, innovation diffusion, digital farming, agent-based modelling, farm level, systematic review*

JEL classification: Q16; Q12; C61

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2.1 Introduction

Digital farming has the potential to transform agricultural systems to be more sustainable by reducing the use of agrochemicals. Global agriculture faces various challenges to meet the demand for food and fibres in the coming years because it needs to maintain overall productivity without further polluting soil, water and other agroecological systems (Cole et al., 2018; Finger et al., 2019). Digital farming (also referred to as smart farming or agriculture 4.0) is expected to address these challenges using information communication technologies to collect and analyse data to support efficient farming processes (Bacco et al., 2019; OECD, 2019). Digital farming technologies cover a broad spectrum, from small mobile apps for decision support, to in-field sensors and remote sensing technologies for data collection, and to drones and robots for the automation of processes (see OECD (2019) for detailed categories of digital farming technologies). A sustainable agriculture in the future will need digital farming technologies (Walter et al., 2017), which use Artificial Intelligence (AI), cloud computing, Internet of Things (IoT), and blockchain among others (Klerkx et al., 2019; Torky and Hassanein, 2020). The rise of these technologies and the potential disruptive impact of digital agriculture make it particularly important to understand the mechanisms of adoption and diffusion of digital farming technologies.

The mechanisms of adoption and diffusion of digital farming technologies must be understood on both farm and system level, where system refers to the collection and organisation of entities relevant for the adoption and diffusion. Adoption behaviour not only depends on farm and operator characteristics but is also influenced by structural, political and economic conditions of the agricultural system. The system evolves over time, based on the behaviour of the farmers and their interactions with their environment and one another (Alexander et al., 2013). It is the system interaction in combination with, and depending on, individual farm characteristics that will ultimately determine technology diffusion and its impact on the sustainability of agriculture. Therefore, it is necessary to understand not only individual adoption but also system interaction in the process of adoption and diffusion.

So far, our understanding of the mechanisms of technology adoption and diffusion mainly comes from separate empirical farm-level studies on individual adoption and Agent-based Models (ABMs) simulating systemic diffusion mechanisms. Other equally important system approaches like system dynamics (Reinker and Gralla, 2018) are beyond the scope of this study. Farm-level adoption studies of digital farming technologies start to emerge in recent years, like Michels et al. (2020), Salimi et al. (2020), Caffaro and Cavallo (2019), Drewry et al. (2019), Pivoto et al. (2019), and Zheng et al. (2018), but they are still few compared to the large amount of adoption studies of other agricultural practices (e.g. sustainable farming practice (Dessart et al., 2019) and precision farming (Pathak et al., 2019)). This lack of information requires us to also refer to the lessons of precursor technologies, i.e. Precision Agriculture Technologies (PATs). Farm-level adoption studies usually use regression-type analysis (e.g. logit, probit, poisson models) testing the effect of different variables on adoption (such as farm size and farmers' age) or qualitative descriptive approaches (e.g. descriptive summary of interviews with farmers) testing less measurable factor (such as compatibility of a technology and data safety) (Klerkx et al., 2019). These studies usually do not consider system interaction. When considering the process of adopting a potentially transformative technology like digital farming, feedback processes may speed up or dampen the technology diffusion. This requires us to look at mechanisms and models beyond the farm level.

ABMs are gaining popularity in modelling adoption and diffusion of innovations as they capture system interaction among heterogenous entities (Zhang and Vorobeychik, 2019). In an ABM, a system is modelled as a collection of autonomous decision-making entities, i.e. agents (Bonabeau, 2002). An agent can be an individual (e.g. a farmer) or a collective entity (e.g. an organisation). It assesses its environment and behaves based on rules defined by modellers. ABMs enable researchers to create, analyse and experiment with models composed of agents that interact with each other and with their environment (Gilbert, 2007). Nevertheless, our review on ABMs of agricultural innovations (see section 2.3) shows that existing ABMs have not covered adoption and diffusion of digital farming technologies yet. Most importantly, we find that current ABMs are not well connected with empirical farm-level evidence on the adoption and diffusion of digital farming and are thus lacking the empirical foundation needed for applications beyond the toy-model stage so far (Matthews et al., 2007).

The objective of this chapter is to build an empirically grounded conceptual framework for modelling adoption and diffusion of digital farming technologies. To this end, we synthesise literature from empirical farm-level adoption studies of precision and digital farming technologies with ABMs simulating systemic diffusion mechanisms. We need to establish this connection to later explore how farmers' (adoption) behaviour influences the system and how changed system conditions in turn affect what is happening at the farms. This dynamic and spatially differentiated process ultimately determine diffusion of digital farming technologies, and understanding them could help us to identify effective pathways for sustainable agricultural systems. Such a conceptual framework can be the basis for contextual applications to inform policy-makers trying to foster implementation of suitable digital technologies through interventions, such as subsidies and extension services. Our empirically grounded conceptual framework may generally serve as a reference for those studying the adoption and diffusion of digital farming technologies beyond farm scale, and it may more specifically interest ABM modellers aiming to simulate such processes in different contexts. The results of structured – and in parts quantitative – review of both strands of literature are by themselves relevant contributions for the respective communities.

This chapter is organised as follows. In section 2.2, we review farm-level adoption studies of precision and digital farming technologies and summarise determinants of farmers' adoption decisions. In section 2.3, we review ABMs of adoption and diffusion of agricultural innovations and their limitations for modelling adoption and diffusion of digital farming technologies. Section 2.4 presents the empirically grounded conceptual framework for modelling adoption and diffusion of digital farming technologies. Section 2.5 concludes the chapter and points out its limitations and directions for future research.

2.2 Empirical farm-level studies of technology adoption

2.2.1 Selection of farm-level studies

The literature search was conducted a final time on 14 April 2020 using the Web of Science database. Search terms used and numbers of studies identified are presented in Table 2.1. Search terms of group 1 require that studies must investigate adoption or diffusion of agricultural technologies/innovations. Group 2 requires that the investigated technologies must be either precision or digital (including autonomous) farming technologies. The combination of group 1 and 2 (by logical "AND") resulted in 1,266 identified studies.

After reading all 1,266 abstracts, we selected 32 studies that focus on determinants of farmers' decision to adopt technologies in crop production (see Appendix 2.A.1). We only focus on crop production because only two studies of livestock production (Abeni et al., 2019; Lima et al., 2018) are found by the structured literature search. Nearly half of the selected studies (14) was conducted in the USA; 12 studies in European countries; and the rest in Canada (2), Australia (1), Brazil (1), China (1), and Iran (1). In terms of methods, 26 studies used regression-type analysis (e.g. logit, probit, poisson models), and 6 studies used qualitative descriptive approaches (like descriptive summary of interviews with farmers or experts). Among regression-type studies, 21 studies modelled the adoption decision as a binary outcome (yes/no), and 8 studies modelled intensity of adoption (e.g. number of PATs used). Some studies included both cases, and some regression-type studies also included qualitative descriptions.

Table 2.1: Search terms used and number of farm-level studies identified

Group	Search terms	Number of studies
1	TS = (agricultur* OR farm*) AND TS = (technolog* OR innovation*) AND TS = (adopt* OR diffusion)	6,694
2	TS = (precision OR digital OR "smart farming" OR robot* OR autonomous OR automa* OR "unmanned aerial vehicle*" OR drone OR "cloud computing" OR "site specific" OR "variable rate" OR "GPS" OR "remote sensing" OR "soil sampling" OR "yield mapping" OR "yield monitor*" OR "autosteer" OR drip OR irrigation OR water saving)	1,389,788
	Combine 1 and 2 (by logical "AND")	1,266

Source: own results

Note: TS = Topics, referring to the title, abstract, or keywords of an article.

In this study, we consider not only the significance of factors but also their importance for explaining adoption. Figure 2.1 illustrates the frequencies with which factors are considered and identified as significant (significant at least at a 10% level if it is a regression-type analysis; identified as important if it uses qualitative approach) or as insignificant. Some studies modelled the binary adoption decision and adoption intensity of multiple technologies. Thus, we count the number of cases (in total 54 cases reported in 32 studies, as shown in x-axis of Figure 2.1) instead of the number of studies. Factors are grouped into 6 categories: farm characteristics (e.g. farm size), operator characteristics (e.g. age of the operator), interactions (e.g. get information from consultants), institutions (e.g. regulations), attributes of technology (e.g. relative advantage) and psychological factors (e.g. attitude towards the technology). Figure 2.2 summarises partially standardised coefficients of factors representing their importance (i.e. effect size) in farmers' adoption decisions.

2.2.2 Significance of factors

Farm characteristics

Farm characteristics get a great deal of attention in farm-level studies. 1) **Farm size** is identified to be positively related to adoption in 33 out of 43 cases. Large farms can take advantage of economies of scale and are more likely to be able to afford the high initial investment of new technologies (Tamirat et al., 2017). One may speculate that large farms are more targeted by technology providers for their potential of a higher sales volume. 2) **Biophysical conditions** like yield variability and locations are found significant by 15 out of 26 cases. Farmers with higher quality land might anticipate greater potential benefits from adoption than farmers with lower quality land (Isgin et al., 2008). 3) **Land use** like the share of arable land or share of a certain crop determines if the technology meets the farms' needs and is found relevant by 11 out of 18 cases. Barnes et al. (2019) find that farms with a high share of arable land tend to adopt more PATs. Paustian and Theuvsen (2017) find producing barley negatively influences the adoption of PATs. 4) **Use of complementary technologies** positively contributes to the adoption of other PATs as shown in 18 out 19 cases. For instance, farmers who already use a variable rate technology are more likely to adopt yield mapping technologies (Isgin et al., 2008). 5) **Land ownership** might influence the adoption of technologies requiring investments tied to the land such as precision irrigation (Abdulai et al., 2011; Moreno and Sunding, 2005). However, none of the 8 cases that include this as an explanatory variable find it statistically significant. 6) **Labor availability** like the number of regular employees is statistically significant in 3 out of 8 cases. Pivoto et al. (2019) find that the lack of skilled labour operating the new technology is a constraint for the adoption. On the other hand, labour availability and cost could be the main drivers of robotic farming technologies. 7) **Livestock ownership** is considered in 6 out of 54 cases, but only Lambert et al. (2015) find a positive relationship between owning livestock and adoption of computerised cotton management system with digital maps. 8) **Farm succession** could be an important factor influencing farmers' adoption decision in digital farming technologies that require high investment, but only Paustian and Theuvsen (2017) consider this factor and find it statistically insignificant.

Operator characteristics

Features of farm operators are often researched in farm-level studies. 1) **Education level** is found significant in 15 out of 39 cases. Farmers with a high level of education could better comprehend the application of new technologies (Aubert et al., 2012). 2) **Age** is found significant in 12 out of 31 cases, and 11 cases report a negative impact of age on adoption. The complexity of digital farming technologies is perceived as a barrier to adoption for older farmers. Moreover, fewer working years until retirement reduces the planning horizon regarding technology use (Barnes et al., 2019). However, Pivoto et al. (2019) observe that older farmers tend to adopt autopilot spraying. 3) **Farming** as the main occupation is reported to be significant in 3 out of 13 cases. The more important the farm to the household, the higher the willingness to adopt (Zheng et al., 2018). 4) **Income** impacts adoption as shown in 4 out of 13 cases. This might be due to high initial investments required by digital farming technologies. 5) **Computer use** for farm management is examined by 11 cases and 7 of them observe a positive impact on adoption. Being familiar with computers makes farmers comfortable in using PATs (D'Antoni et al., 2012). 6) **Off-farm income** is only found significant by Schimmelpfennig and Ebel (2016) in the case of adoption of a bundle of technologies (yield monitor, GPS and variable-rate technologies). 7) **Farming experience** (in years) is explored by 6 cases but only 2 cases imply a positive impact (Asare and Segarra, 2018; Paustian and Theuvsen, 2017). 8) **Innovativeness** of a farmer is found significant for adoption by 5 of 6 cases, e.g. Pino et al. (2017) and Aubert et al. (2012). 9) **Knowledge capacity** are crucial as 4 out of 5 cases point out. Lack of knowledge in new technologies (especially in software and data transfer) is a barrier to adoption (Takácsné György et al., 2018). 10) **Risk preference** has been rarely investigated (2 out of 54 cases). Farmers with a higher ratio of debt to asset (a proxy of risk preference) tend to adopt more PATs (Isgin et al., 2008).

Interactions

Although interactions within social networks are found influential for adoption of agricultural innovations (Ramirez, 2013; Sampson and Perry, 2019), they have not become a focus of adoption studies of precision and digital farming technologies (Figure 2.1). 1) **Having consultants** is found by 10 out of 16 cases to be significantly associated with adoption. Lack of advisory services and the negative opinion on PATs from advisors influence farmers' adoption decisions (Pivoto et al., 2019). 2) **Extensions** connect researchers and farmers by introducing innovations to farmers, and they are found to be influential by 3 out of 9 cases. Asare and Segarra (2018) report a negative impact of having contact with university extensions on adoption of soil sampling technology, while in Larson et al. (2008) farmers who believe that information from extensions are helpful tend to be adopters of remote sensing technology. The interview of Kutter et al. (2011) considers private extension service the most important promoter of PATs. 3) **Farmers' associations or other organisations** are often believed to be an information source for farmers, but only 2 of 11 cases affirm their impact on farmers' adoption decisions (Barnes et al., 2019; Takácsné György et al., 2018). 4) **Technology providers** offer farmers pre-adoption trials and training, farm system advice and post-installation technical support. More technical support and training from technology providers are believed to promote adoption (Barnes et al., 2019; Drewry et al., 2019). 6 out of 8 cases find a positive effect of having access to technical support and training from technology providers on farmers' adoption decisions. 5) **Other farmers** can influence farmers' decisions through information exchange. However, the 6 regression-type studies we reviewed have not found the statistical significance of exchanging information with other farmers. But the interviews conducted by Pivoto et al. (2019) and Kutter et al. (2011) emphasise the impact of neighbours' negative opinions on PATs and the importance of obtaining information from other farmers. 6) **Contractors** provide machinery services to farmers. 4 out of 6 cases emphasise the impact of getting information from contractors or paying them for related farming activities, e.g. Gallardo et al. (2019) and Larson et al. (2008). Especially for small farms, contractors will be a major driver behind the adoption (Kutter et al., 2011). 7) Attending **Events** (trade shows, workshops) is identified as influential by Lambert et al. (2014), Tamirat et al. (2017) and Kutter et al. (2011). 8) **Information sources** in general play a role in farmers' adoption decisions as shown in 5 out of 12 cases.

Institutions

Institutions are “the rules of the game in a society” (North, 1990, p.3) and devise constraints that shape human interactions. They consist of formal and informal rules, norms, beliefs, and potentially organisations. Institutional theories are expansive (see Ostrom, 2005), thus we only focus on what we found in the literature. 1) Accessibility of **subsidy/credit** is believed to have a positive effect on adoption by 6 out of 8 cases. Reichardt and Jürgens (2009) point out that financial support is a prerequisite for diffusion of PATs. Lambert et al. (2015) discover that farmers who participate in conservation easement programs are more likely to adopt PATs. 2) **Laws and regulations**: 2 cases (Barnes et al., 2019; Kutter et al., 2011) find that increasing environmental requirements (e.g. stringent laws on pesticide and nitrogen application) are one of the forces for adoption of PATs that can significantly reduce chemical use. In the context of digital farming, regulations that ensure data ownership and prevent misuse of farms’ data can promote adoption of digital farming technologies (Barnes et al., 2019).

Attributes of technology

Regarding attributes of technology, the theory of Diffusion of Innovation (DOI) of Rogers (2003) and the Technology Acceptance Model (TAM) of Davis (1985) are often applied by empirical studies. We organise attributes of technology according to the DOI because it covers a broader range than TAM. According to the DOI, the perceived attributes of an innovation (relative advantage, complexity, compatibility, trialability, and observability) are important explanations of adoption (Rogers, 2003). Surprisingly, they seem to be less researched regarding adoption of precision and digital farming technologies. 1) **Relative advantage** (perceived usefulness in TAM) like increasing productivity promotes adoption, while high cost and time required for handling data are barriers (Adrian et al., 2005). Only 10 out of 46 regression-type cases consider this attribute, and 7 cases identify it as significant, e.g. Walton et al. (2008) and Zheng et al. (2018). Qualitative descriptive studies pay more attention to attributes of technology than regression-type studies. They explore the exact advantages and disadvantages of adopting precision and digital farming technologies. In 7 out of 8 descriptive cases, better information for farm management, reduction in input-use, and high yield are the most often mentioned motivations for farmers to adopt such technologies. “High initial investment” and “time consuming” are the two most often mentioned disadvantages

(Reichardt and Jürgens, 2009). 2) **Complexity** (perceived ease of use in TAM) was considered by 12 cases. Studies using interviews with farmers and experts convey that complexity in manipulating data and machines is a constraint for adoption (Pivoto et al., 2019). 3) **Compatibility** of new farming technologies to existing machinery, poor telecommunication infrastructure and data interoperability are constraints of adoption of precision and digital farming technologies, pointed out by 7 qualitative cases, while only 1 regression-type analysis considers this attribute (Aubert et al., 2012). 4) **Trialability** actualised in a positive exploratory experience can facilitate the adoption. However, the only study that considers this attribute (Aubert et al., 2012) reveals a negative relationship between trialability and adoption. As they interpret, this might be because non-adopters have a too optimistic prior impression about the ease of use of new technologies. 5) **Observability** of the technology by peers is not examined by any of the studies we have reviewed. This constitutes stark negligence of its stated importance for adoption in the DOI. 6) We add a sixth attribute, **data safety**, which is especially relevant for digital farming. Issues of data safety have been stressed by 4 descriptive cases (Drewry et al., 2019; Kutter et al., 2011; Pivoto et al., 2019; Reichardt and Jürgens, 2009). They stress that concern about the misuse of digital data by commercial service providers makes farmers more cautious. Besides the papers we reviewed, recent studies (e.g. Klerkx et al., 2019; Pfeiffer et al., 2020; Wiseman et al., 2019) highlight the urgent need for legal and regulatory frameworks of data collection and use in the context of digital farming.

Psychological factors

Psychological factors are less investigated by models with binary outcomes and interviews, but more by models of adoption intensity. The Theory of Planned Behaviour (TPB), developed by Ajzen (1991), is a theoretical framework often used in examining the impacts of farmers' perceptions on technology adoption. The TPB states that a person's intention to do something is determined by his or her attitude, subjective norm and perceived behavioural control. 1) **Attitude** is a farmer's positive or negative evaluation of adoption. It is found to be statistically significant in 10 out of 12 cases. Farmers who believe the technology is beneficial tend to adopt it (Pino et al., 2017). 2) **Subjective norm** refers to the perceived pressure or expectation to adopt or not. 5 cases find that external pressure from the community and environmental organisations positively contributes to adoption of PATs (e.g. Aubert et al., 2012; Lynne et al., 1995). 3) **Perceived behavioural control** refers to a farmer's perceived ability to implement adoption. It contains self-efficacy and perceived controllability (Ajzen, 2002). 5 out of 6 cases confirm the importance of this factor. Lynne et al. (1995) declare a positive relationship between perceived behavioural control and technology adoption, while Pino et al. (2017) do not.

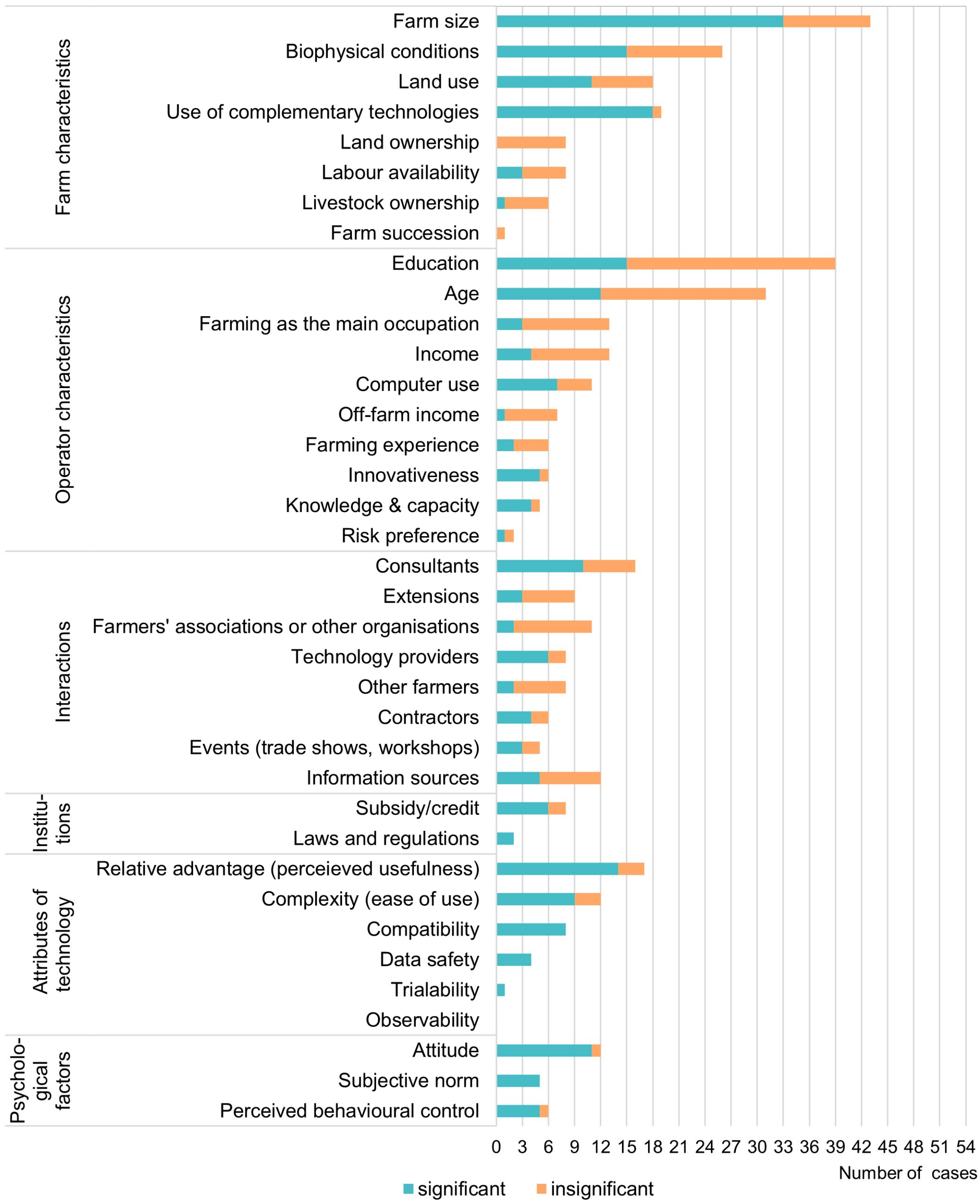

Figure 2.1: Influencing factors on farmers' technology adoption decision synthesised from 54 cases

Source: own results

2.2.3 Importance of determinants

Statistical significance of an explanatory factor neither tells anything about the size of the effect per unit change nor about the variability of variables in the data. Both are crucial elements to assess the *importance* of the effect for explaining adoption. As a consequence, we calculated the partially standardised coefficient of each factor from regression models. Standardised coefficients make it more meaningful to compare the relative influence of different independent variables on the dependent variable when these variables are measured in different scales or ways. Standardised coefficients transform the independent variables into variables measured in "standard deviation units" (sd_x) (Menard, 2004). However, calculating standardised coefficients also requires knowing the standard deviation of dependent variables (sd_y). In the case of logit models, standard deviation of transformed dependent variables using logit link ($sd_{logit(y)}$) is required (Menard, 2004), which can be calculated when pseudo R^2 and $sd_{logit(\hat{y})}$ are available. Given the limited data availability, we use partially standardised coefficients. They allow us to compare the importance of different independent variables assuming that the variances of the dependent variables from different models are similar. Following Agresti (2007), we calculate a partially standardised coefficient of an independent variable as:

$$\beta_x = b_x \times sd_x, \tag{2.1}$$

where b_x is the non-standardised coefficient of the independent variable x; sd_x is the standard deviation of the independent variable x.

The interpretation of a partially standardised coefficient, β_x, is that if the independent variable x increases by one standard deviation unit (sd_x), the dependent variable (y) or the transformed dependent variable using a logit or probit function ($logit(y)$, $probit(y)$) will increase by β_x unit(s).

A boxplot (Figure 2.2) presents partially standardised coefficients of independent variables in models with binary outcomes[5] (i.e. adopt or not adopt) following the same

[5]Synthesised partially standardised coefficients of independent variables in models of adoption intensity are shown in Appendix 2.A.2. We do not include them in the main text due to limited observations.

categorisation from section 2.2.1. It shows the minimum, maximum, first quartile, third quartile, mean, outliers, and the number of observations. The higher the number of observations (i.e. cases in this study), the more reliable the means of the partially standardised coefficients are. Thus, we try to interpret the results in the sequence of the reliability of the synthesised data and by the comparability of factors. Note that although some factors have no observations that enable us to calculate the partially standardised coefficients, they are not omitted in Figure 2.2 to keep the consistency with Figure 2.1. Another advantage of presenting all factors is that the unexplored factors can highlight potential directions for future research.

Among the most investigated factors i.e. farm size (18 observations), education (20 observations) and age (18 observations), the partially standardised coefficients of farm size have a higher mean value (0.35) than education (0.15) and age (-0.13). This implies that an increase by a standard deviation unit in farm size influences farmers' adoption decision more than that of education and age. Besides, farm size is consistently shown to have positive partially standardised coefficients, which means larger farms are more likely to adopt new technologies. Education also shows relatively consistent positive impacts with four exceptions. Age, on the contrary, does not seem to be a helpful predictor for adoption because of its varying and inconsistent pattern.

For biophysical conditions, we calculated the partially standardised coefficients of "yield" (6 observations, mean = 0.47). A change of one standard deviation unit in yield is shown to have a bigger impact on adoption than that of land ownership (5 observations, mean = 0.12) and farming as the main occupation (9 observations, mean = 0.27). Off-farm income (7 observations, mean = 0.01) is shown to have a smaller impact on adoption than total income (4 observations, mean = 0.313). Use of complementary technologies (8 observations, mean = 0.12) and computer use (6 observations, mean = 0.27) both have positive impacts on farmers' adoption decisions, with the latter showing overall larger importance.

Regarding attributes of technology, partially standardised coefficients of "perceived usefulness" (3 observations, mean = 0.47) and "complexity" (3 observations, mean = -0.20) were calculated. Together with attitude (3 observations, mean = 0.54), the importance of these three factors and their consistency remind us that attributes of technology and farmers' attitude towards the technology have the potential to be more useful predictors for adoption decisions than characteristics of farms and farmers. From the higher numbers of observations from farm and operator characteristics, we can see that adoption studies in the past have been focusing on social-demographics, while overlooking the importance of attributes of technology and psychological factors. Given the limited information, we do not discuss other factors any further but leave them for inspection by readers.

As we mentioned in section 2.2.2, the significance of interactions within social networks has not been investigated as often as one would expect according to researchers like Rogers (2003), Ramirez (2013), and Sampson and Perry (2019). In terms of their importance, surprisingly, interaction with other farmers seems less important for adoption than most of the other factors at first sight, but the evidence on this is very limited (2 observations, mean = -0.086). We also notice that interaction with other farmers can negatively impact a farmer's adoption decision (Pivoto et al., 2019). A possible interpretation is that this can happen when the attitude of other farmers towards the new technology is negative as negative opinions can diffuse in social networks as well (Deffuant, 2006). This highlights the role of social norms and their dissemination in farmers' adoption decision. In further investigations, we combined the search term of TS = ("social network analysis") with group 1 and 2 (Table 2.1), but no adoption studies of precision or digital farming technologies yet using the method "social network analysis" were found in the Web of Science.

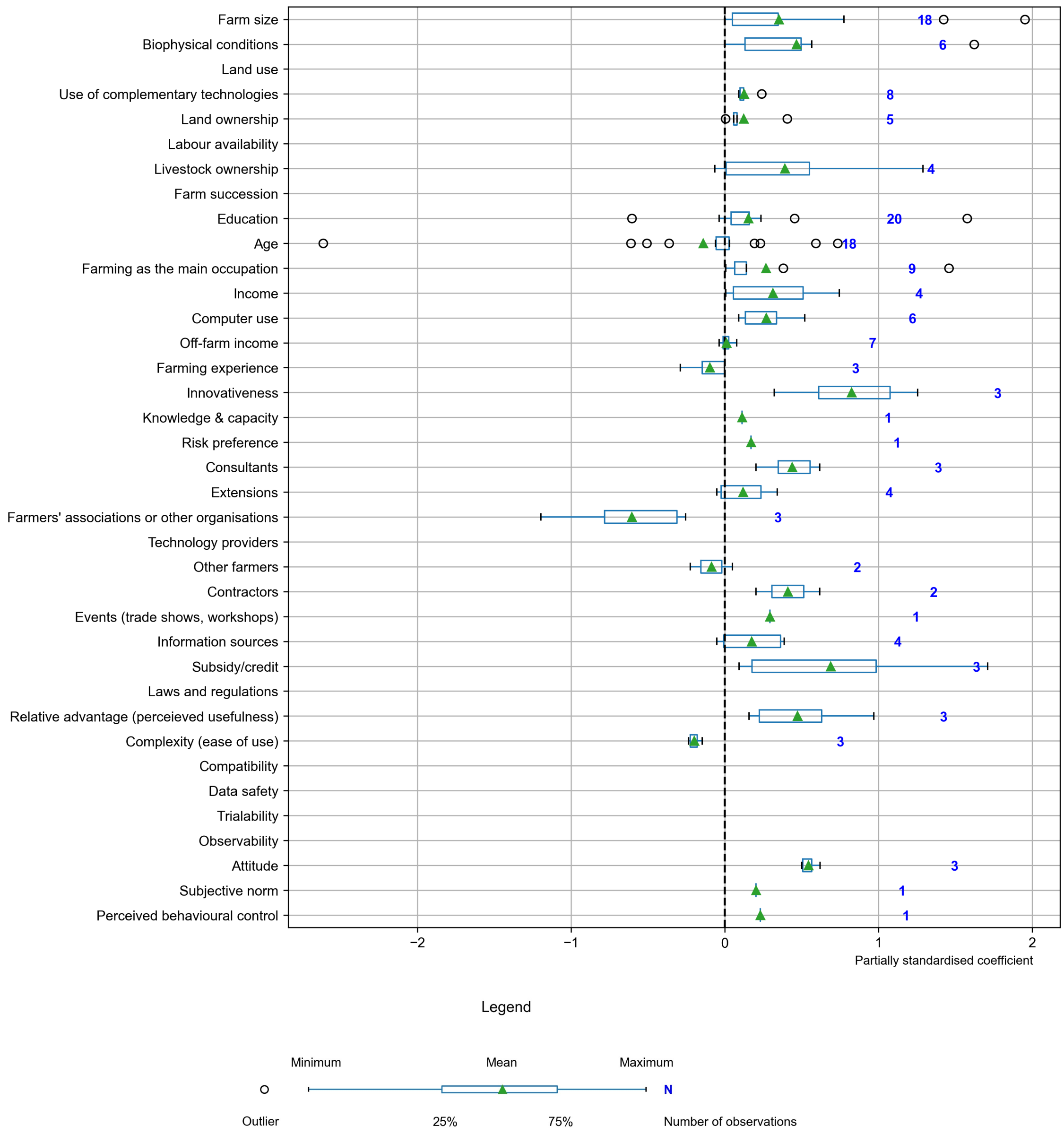

Figure 2.2: Partially standardised coefficients of factors from models with binary outcome

Source: own results

2.2.4 Limitations of farm-level studies

When considering the process of adopting digital farming technologies, which potentially can transform the agricultural system, factors determining each farmer's adoption decision change over time and across space. Farmers may learn about the technology from neighbours who already adopted it. This means farmers' awareness, knowledge and attitude may keep changing during the diffusion process of a new technology. Technology suppliers can offer more mature and/or cheaper versions based on feedback from users and economies of scale. Additionally, farmers may get more or better services by outsourcing technology implementation as the technology is spreading over time (Pedersen et al., 2020). Thus, feedback processes may speed up or dampen technology diffusion. However, as presented above, farm-level studies of complex technologies often assume variables to be exogenous and do not capture the interrelationship among variables. Thus, they do not account for the effects of endogenous feedback within a system. Consequently, the understanding of the processes leading to the diffusion of a new technology in the farm population requires us to look at mechanisms and models beyond the farm level.

2.3 ABMs of adoption and diffusion of agricultural innovations

As mentioned in the introduction, ABMs are gaining popularity in modelling adoption and diffusion of innovations as they capture system interaction among heterogenous entities in a temporal explicit manner (Zhang and Vorobeychik, 2019). For example, farmers (one type of agents) in Sun and Müller (2012) decide whether to convert cropland to forest (in response to a payment for ecosystem services) or not, based on not only their socioeconomic characteristics and features of their land but also on other farmers' behaviour. Once farmers have made their decision, macro-level phenomena (e.g. total amount of area converted by all villagers in this case) can be perceived by farmers. Those in return may influence farmers' decisions for the next simulation period (time-step), thus new macro-level phenomena emerge thereafter (Galán et al., 2009).

ABMs can easily model peer interaction as one of the central elements in the theory of DOI, which is rarely considered by farm-level studies as shown in Figure 2.1. ABMs have been used in various research fields such as geography, urbanisation, agricultural land-use and political science, etc. (Gilbert, 2007). In the field of agricultural economics, ABMs are used in modelling farmers' decisions on crop selection, use of natural resources, adoption and diffusion of innovations, etc. (see a review of Kremmydas et al., 2018). In this section, we will explore factors that are considered in current ABMs of agricultural innovations.

2.3.1 Selection of ABM studies

The literature research was conducted a final time on 05 May 2020 using the Web of Science database. Search terms used and numbers of studies identified are presented in Table 2.2. Search terms of group 1 require that ABM studies must investigate adoption or diffusion of technologies/innovations. Group 2 requires that ABM studies must be agriculture-related. So far, no ABMs of adoption and diffusion of precision or digital farming technologies are found. Thus, we did not limit our scope to this but also included other innovations (e.g. new practices, crops, etc.) to get a better picture of farmers' decision-making strategies of adoption and their limitations in current ABMs. The knowledge from farm-level adoption studies of precision and digital farming technologies and the knowledge from ABMs of diffusion of agricultural innovations are then combined to build the conceptual framework.

The combination of group 1 and 2 (by logical "AND") resulted in 265 identified studies. After reading all 265 abstracts, we selected only 27 ABM studies (Figure 2.3) that explicitly modelled adoption or diffusion of agricultural innovations. The innovations covered by these studies include conservation practices and programs (8 studies, e.g. Sun and Müller, 2012), innovative crops (7 studies, e.g. Alexander et al., 2013), innovative farming systems like organic farming and multifunctional agriculture (6 studies, e.g. Kaufmann et al., 2009), irrigation technologies (5 studies, e.g. Berger, 2001), fertilisers (2 studies, e.g. Beretta et al., 2018), and others. Note that the number of studies across all categories exceeds 27 because some articles include multiple innovations and are therefore counted as multiple times.

Table 2.2: Search terms used and number of ABM studies identified

Group	Search terms	Number of studies
1	TS = ("agent-based" OR "agent based" OR "abm" OR "multi-agent" OR "multi agent") AND TS = (adopt* OR diffusion OR innovati* OR technolog*)	5,129
2	TS = ("agent-based" OR "agent based" OR "abm" OR "multi-agent" OR "multi agent") AND TS = (agricultur* OR farm* OR water OR crop)	1,293
	Combine 1 and 2 (by logical "AND")	265

Source: own results

Note: TS = Topics, referring to the title, abstract, or keywords of an article.

2.3.2 Factors influencing adoption and adoption models in selected ABMs

To compare factors considered in ABMs and in farm-level studies, we keep using the six categories summarised from empirical farm-level studies (see section 2.2), but replace "information sources" with "other types of agents" in the category "interactions" to better fit the structure of ABMs. Figure 2.3 shows factors that directly affect the adoption decision process (i.e. triggers) and factors considered elsewhere (i.e. indirect factors) in the model, as well as the farmers' adoption model of each ABM. Modelled factors including triggers and indirect factors are to a large extent influenced by the adoption model applied by each study. In Figure 2.3, studies are ordered according to the similarity of their adoption models, so that the advantages and limitations of each type of adoption behavioural model can be clearly illustrated.

Pure economic models (Bell et al., 2016; Ng et al., 2011; Sorda et al., 2013) usually depend on data of farm characteristics to maximise farmers' profit or utility. This type of model has one trigger for adoption i.e. profit/utility (marked at relative advantage in the category of "attributes of technology") and ignores other aspects. Some studies (like Berger, 2001; Schreinemachers et al., 2007) combine economic models with the threshold model, which divides farmers into Rogers' five adopter groups (innovators, early adopters, early majority, late majority, and laggards) with percentages that work as "adoption thresholds" mimicking a contagion process (Rogers, 2003). Although this type of model allows for farmers' innovativeness triggering adoption in addition to economic determinants, it does not explicitly model direct interactions of farmers. Seven studies (e.g. Cai and Xiong, 2017; Huang et al., 2016) explicitly model the effects of neighbours' information or opinion on the adoption decision of a farmer as well as economic determinants. Farmers' psychological factors are usually investigated by cognitive models. Studies like Kaufmann et al. (2009) and Xu et al. (2018) use cognitive models where farmers' psychological factors like attitude and subjective norms are the only triggers, while farm characteristics are to a great extent ignored. Typology models of Daloğlu et al. (2014a)[6] and Sengupta et al. (2005) assign a probability of adoption according to some features (including farm size, farm income, age of the operator, land ownership, labour availability, information sources, etc.) of the agent, thus allow multiple triggers from different categories for adoption. However, assigning the probability of adoption assumes farmers' adoption decision is independent from each other once farmers' features are determined. Farmers might be able to still interact in other parts of the simulation (e.g. on the land market), but their adoption decision would not be affected anymore by the others. The other four ABMs at the end of the list are less typical: Beretta et al. (2018) only model the impact of social networks on adoption based on the attributes of the low requirement for investment and knowledge about the innovation – new fertilisers; Holtz and Pahl-Wostl (2012) model diffusion on an aggregated level using the Bass Model (Bass, 1969), in which the more widespread the technology is, the higher the probability that a farmer considers this technology, without any farm characteristics; the ABM of Schreinemachers et al. (2009) contains an econometric model that captures the influence of farm and farmer's characteristics on adoption; and Sun and Müller (2012) integrate a machine learning algorithm into the ABM, while farmers' perception (e.g. attitude) and the effect of neighbours are also captured.

2.3.3 Limitations of ABM studies

As can be seen from the shading patterns in Figure 2.3, the current ABMs of diffusion of agricultural innovations are only loosely connected to farm-level findings. Limitations

[6]See also Daloğlu et al. (2014b).

are listed by the following four observations.

(1) Agent types and their interactions: Most ABMs represent only a limited number of agent types. Other agent types highlighted in the theory of DOI (especially extensions and technology suppliers) are rarely considered. This is somewhat surprising given the general capacity of ABMs to explicitly model different agent types and heterogeneity within types (exceptions include Alexander et al., 2013; Cai and Xiong, 2017; Manson et al., 2016; Sorda et al., 2013). Rounsevell et al. (2012) propose a notion of human functional types (HFTs), which define an agent by three dimensions (i.e. role, preference and decision-making strategies), to generalise representations of actors and support the expansion of ABMs. The advantages of applying HFTs are demonstrated by Arneth et al. (2014). For example, based on HFTs, Holzhauer et al. (2019) further demonstrate how institutional agents at global and regional scales can be modelled to study the impact of institutions on land use change. Similar approaches can be adopted by ABM modellers who aim to study the impact of interactions among different types of agents on technology adoption.

(2) Operator characteristics and psychological factors: ABMs lack the attention to farmers' ability and confidence to handle the complexity of new technologies with respect to the adoption decision that farm-level studies show (exceptions include Holtz and Pahl-Wostl, 2012; Kaufmann et al., 2009; Schreinemachers et al., 2007; Sun and Müller, 2012). Likewise, considerations of substantial investments into complex technologies are bound to the current stage of farmers' life and farm succession, which can be well captured by ABMs, as the empirical findings regarding farmers' age showed. Due to the complexity and high requirement of investment of digital farming technologies, farmers' age, knowledge and self-efficacy[7] deserve more attention from ABMs.

(3) Attributes of technology: ABMs usually only consider the change in profit by adoption (relative advantage) and overlook other attributes of innovations, except for Olabisi et al. (2015). Since compatibility, complexity and issue of data safety are becoming concerns of farmers (Figure 2.1), modellers could integrate these attributes of digital farming technology into ABMs by considering existing farm equipment, farmers' knowledge and capacity, and risk preference.

[7]A review of non-agricultural related technology diffusion ABMs revealed that psychological factors like perceived behavioural control and self-efficacy were modelled more frequently in those models.

(4) Lack of consideration of institutions: ABMs have shown to be capable of explicitly modelling institutions like regulations (Ng et al., 2011), social norms (Kaufmann et al., 2009) and beliefs (Sun and Müller, 2012) that govern agents' behaviour, but only a few studies have considered them as shown in Figure 2.3. Here, the failure of ABMs to cover institutions does match the lack of attention of empirical studies, although regulations, laws and norms are influential for the acceptance of digital farming technologies (Barnes et al., 2019). Modelling institutional agents allows important research questions related to the impact of governance structures and policy formulation (Rounsevell et al., 2012) in determining the adoption and diffusion of digital farming technologies.

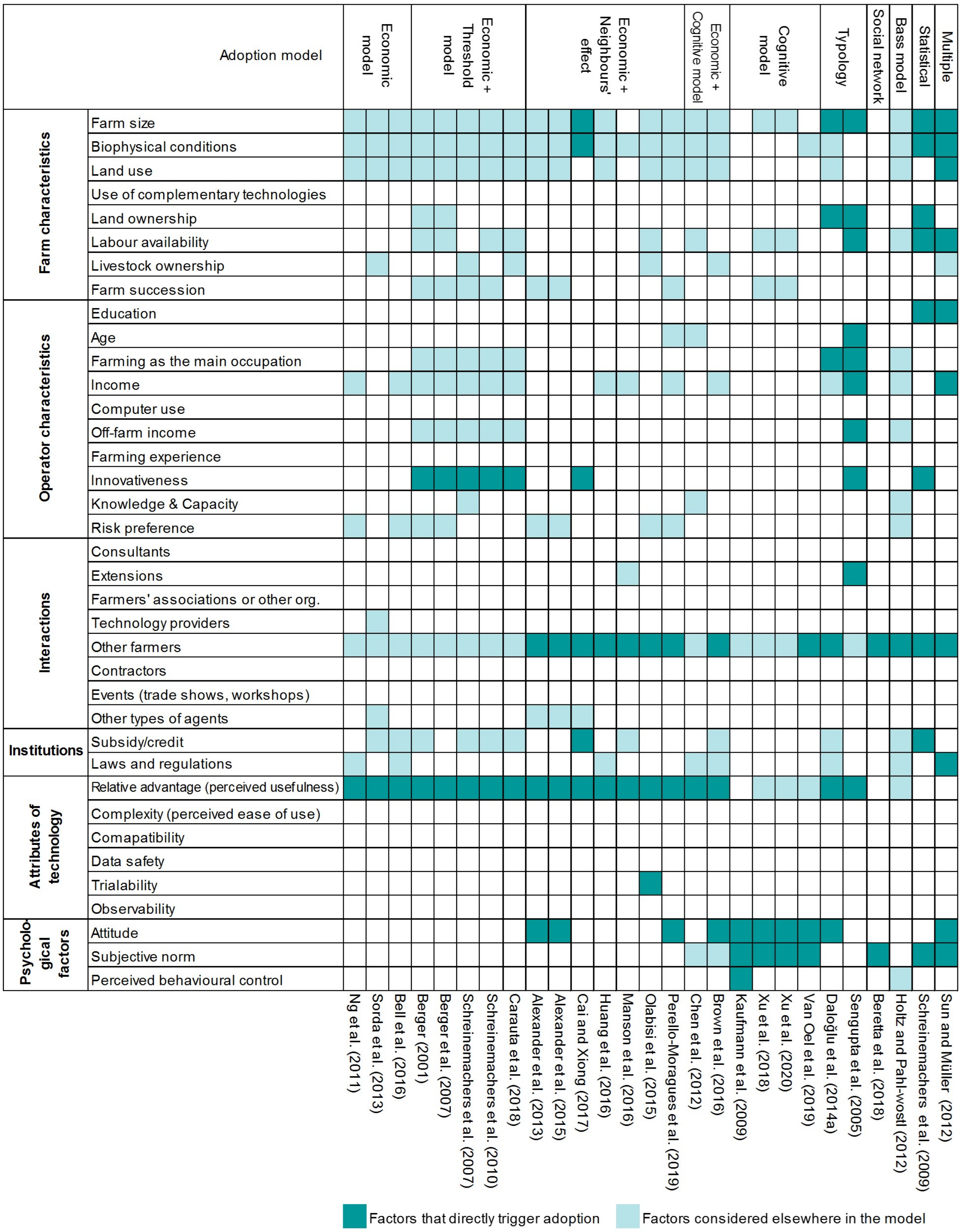

Figure 2.3: Factors influencing adoption and adoption models in ABMs of agricultural innovations

Source: own results

2.4 A conceptual framework for empirically grounded ABM

Having identified the loose ends of both strands of literature, we aim to build an empirically grounded conceptual framework for modelling adoption and diffusion of digital farming technologies of crop production. As suggested by Weersink and Fulton (2020), adoption should be understood as a process with multiple stages. We apply the model of five stages in the innovation-decision process from the theory of DOI (Rogers, 2003), i.e. knowledge, persuasion, decision, implementation and confirmation (see an example of Zheng and Jia, 2017). Because adoption of digital farming technologies is not a short-term commitment with potentially substantial changes in input use and farm management, a reasoned action approach is supposed to better capture farmers' decision mechanisms (Kaufmann et al., 2009). Thus, we apply the TPB to conceptualise intention formation due to its success on predicting human behaviour (Ajzen, 2012; Kaufmann et al., 2009). The TPB has been used in many ABMs of technology adoption outside the agricultural domain (see Jensen et al., 2016; Rai and Robinson, 2015; Schwarz and Ernst, 2009; Sopha et al., 2013). Furthermore, the TPB makes it possible to model farmers' intentions if actual adoption data is not available, which is a crucial factor for predicting the spread of new technologies via ABMs. In addition, our review of ABMs of adoption of agricultural innovations finds that only a few applications are motivated by social-cognitive theory (e.g. Kaufmann et al., 2009). Groeneveld et al. (2017) also attest a lack of such theories regarding ABMs of land use change. Thus, for ABM modellers, applying this framework can increase the empirical and theoretical foundation, model coherence and comparability of future ABMs.

2.4.1 Description of the framework

Figure 2.4 presents how the model of five stages in the innovation-decision process and the TPB can be combined as a useful tool to model adoption of digital farming technologies. Here, we aim at a balance of integrating empirical farm-level evidence and system interaction. Thus, we made a purposeful selection of empirical variables that are of importance and connect with system elements at the same time. In this way, our conceptual framework presents the holistic picture yet highlights important empirical factors (with red bold squares) that were shown to have considerable impacts by empirical studies. Evidence about impacts of other factors needs to be elucidated in future research. Different theories and categories of determinants are depicted in different colors (see the legend of Figure 2.4). We present the factors in the category "psychological factors" (i.e. core concepts in the TPB) and the category "attributes of technology" (from the DOI) in detail because of their theoretical foundations in the respective frameworks, which are directly linked with farmers' adoption decisions. Factors in the other four categories are collectively illustrated for clarity and simplicity. It shall be stressed here that it is not our intention to promote future models aiming to analyse adoption of digital farming technologies to explicitly represent all processes and factors depicted in our framework. It is rather meant as a systematisation for making conscious specification choices in view of own specific objectives. The conceptual framework is explained below.

(1) In the **knowledge** stage, a farmer becomes aware of a technology's existence and eventually gets interested in it. Knowledge (or awareness) about a new technology comes from "interactions" including learning from other agents and obtaining information from other sources (Rogers, 2003). Interactions themselves influence the observability of digital farming technologies by e.g. farm visits, which likewise impact a farmers' knowledge (Kuehne et al., 2017). The stage of knowledge can usually be modelled through the spreading of information in a social network (see Beretta et al., 2018).

(2) The **persuasion** stage is where a farmer ascertains the potential value of adoption. The TPB postulates that a person's intention is determined by attitude, subjective norm, and perceived behavioural control. **Attitude**, in our case, is a farmer's positive or negative evaluation of adoption. It is influenced by farmer's assumptions about the relative advantage, compatibility of the technology to the existing farm equipment (see Shiau et al., 2018), and data safety of the technology. Relative advantage (especially profitability) depends on the cost and benefit of the technology, farm characteristics and input and output markets (see the grey dotted box) from an economic perspective (Robertson et al., 2012). Compatibility refers to the technical adaptability of the innovation to the existing equipment and practices in the farming system (Robertson et al., 2012). **Subjective norm** is the perceived level of approval or disapproval of adoption by "important others" (Kaufmann et al., 2009). It does describe a receptiveness to normative sanctioning rather than the prescription or prohibition conveyed by a norm (Rasch et al., 2016). It is influenced by policies (connected with "institutions") and

social norms in farmers' social networks. Social norms are influenced by institutions and interactions (mainly with respected farmers and consultants) (Pino et al., 2017). **Perceived behavioural control** refers to a farmer's believed ability to implement adoption. It is influenced by a farmer's financial ability, complexity, and trialability of the technology. Farmers' financial ability depends on both incomes (included in operator characteristics) and subsidy/credit accessibility (included in "institutions") (Pino et al., 2017). Perceived complexity depends on operator characteristics, especially their knowledge and capacity, which might change through interactions in social networks.

(3) After the **persuasion** stage, where intention is formed, a farmer decides to adopt or reject at the **decision** stage. This can be done by setting a threshold of intention for adoption and using either deterministic or probabilistic decision models (Kaufmann et al., 2009; Ng et al., 2011). The latter might be constructed along observed adoption rates in farm populations.

(4) The **implementation** stage is where production activities of a farm are carried out based on the farmer's adoption decision. For example, a farm produces with the objective of maximizing the profit subject to farm endowments (including machinery) and environmental regulations. Farm-level production activities, potentially influenced by the new technology if it is adopted, largely depend on the input market and contribute to the output market. In the long run, changes in markets influence characteristics of farms and lead to structural change (Appel et al., 2016). The link between the input market and "interactions" refers to the fact that technology providers, suppliers and contractors are participating in the input market. Furthermore, production activities impact on the environment and type and severity of the impact depend on the technology used (Weersink and Fulton, 2020). Changes in the environment affect a farm's options of cultivation, for example by changing soil productivity (Aubert et al., 2012, see connection with "farm characteristics"). Environmental pressures may induce policy-makers to adjust regulations (Berger et al., 2007, see connection with "institutions"), and influence the behaviour of other agents in the system (Sun and Müller, 2012, see connection with "interactions").

Note that "implementation" stage is optional to model, depending on whether effect of adoption on production, market, or environment should be analysed or not. Some ABMs stop after observing adoption rate at "decision" stage (e.g. Kaufmann et al., 2009). But including "implementation" stage and next stage ("confirmation") completes the theoretical cycle of adoption.

(5) The **confirmation** stage refers to an evaluation based on whether the criteria initially set up for adoption/rejection has been met. The farmer confirms if the technology will be considered for the next simulation period according to the performance of the technology and the investment cost. This implies that dis-adoption and mal-adoption are allowed. Farmers' evaluations are input for technology providers (included in "interactions") such that they can improve some attributes of the technology (see the connection between the green dotted box and "interactions"). Xu et al. (2020) provide a good example illustrating how the confirmation stage can be modelled.

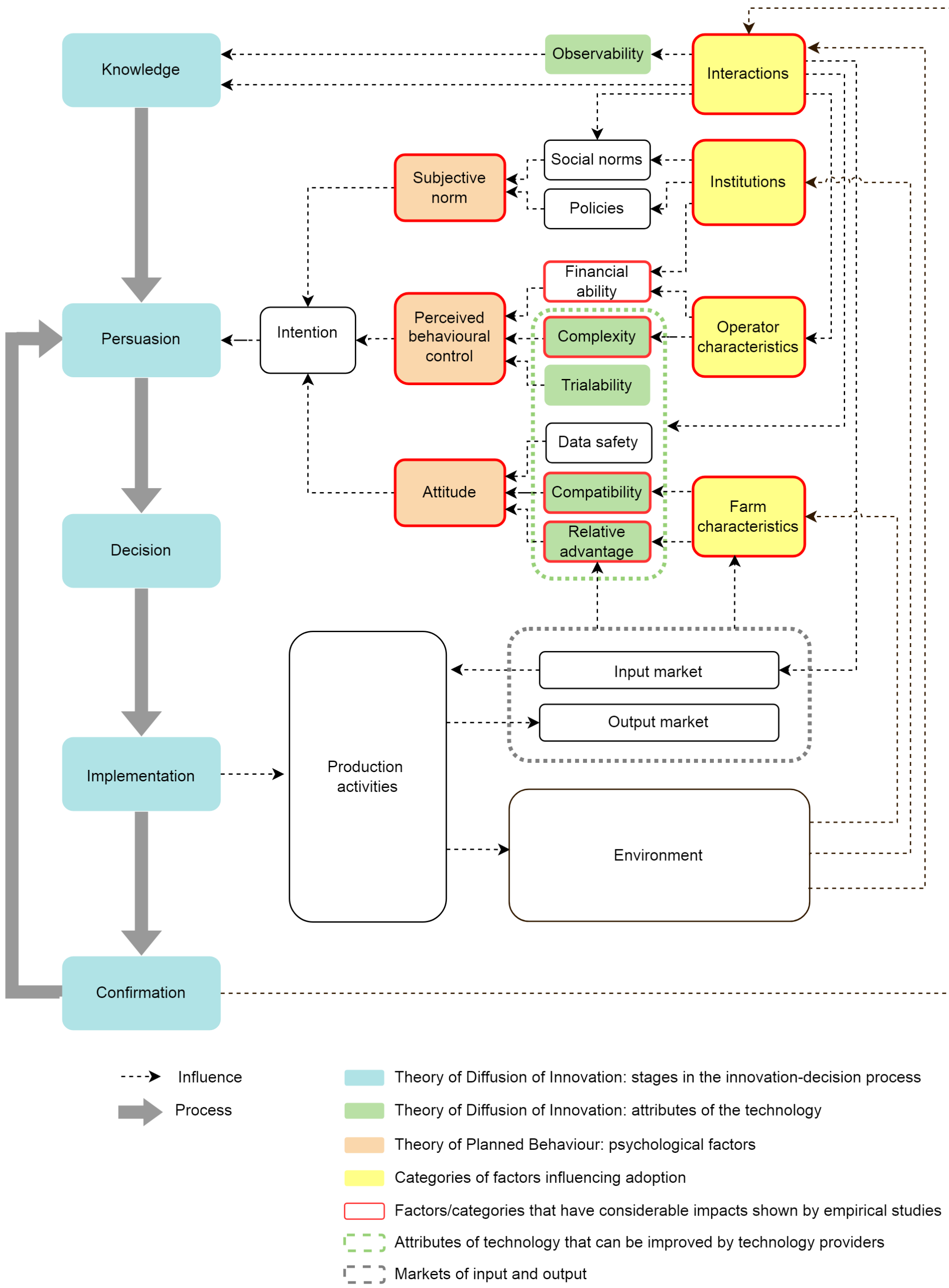

Figure 2.4: Conceptual framework for empirically grounded ABMs of adoption and diffusion of digital farming technologies

Source: own illustration

2.4.2 Applying the framework

This framework can be applied in studies investigating impacts of policy measures (such as subsidy to procure and regulations of data safety), technology attributes (such as price and compatibility), and interactions in social networks (such as extensions and contractors) on farmers' adoption decision on regional level. As results of such studies will not only improve our scientific understanding of the relevant processes, its application may also inform policy-makers about the potential impacts of policy intervention by scenario development or modelling outcomes. A specific application could be to assess the environmental and economic impacts of adoption and diffusion of mechanical weeding robots and how these are influenced by pesticide policies.

It is worth noting that the implementation of this framework will require a more detailed specification in the context of the specific technology, region, and policy to be analysed. Such more detailed specifications comprise the quantification and aggregation of farmers' attitude, subjective norm and perceived behavioural control (Schlüter et al., 2017), the identification of the main processes of interaction between farmers and other types of agents, and decisions on how other farmers' decisions (e.g. on production level and intensity) interact with the adoption and diffusion process and its impacts. A specific application benefits from the general setup of the framework but the context provides what matters more and what less.

2.5 Conclusion

To build an empirically grounded conceptual framework for modelling adoption and diffusion of digital farming technologies, this study combines knowledge of technology adoption generated from empirical farm-level adoption studies and ABMs simulating systemic diffusion mechanisms.

We first review 32 empirical farm-level studies on the adoption of precision and digital farming technologies. Results show that the majority of farm-level studies focus on farm and operator characteristics, while only a few recent studies highlight the importance of attributes of technology (e.g. compatibility to existing farming equipment, complexity and data safety), institutional and psychological factors. To compare the importance of determinants for adoption, we calculate their partially standardised coefficients. Our analysis shows that among the most frequently investigated factors, farm size has the largest average importance, followed by education, while age does not seem to be a linear predictor for adoption, because of its varying and inconsistent impacts found by various studies. Thus, further investigation is needed to find out whether age influences adoption of digital farming technologies through farmers' other characteristics (e.g. experience, innovativeness, and risk preference) or because of farmers' life stages. Although the observations of psychological factors and attributes of technology are limited, their consistency and high level of importance remind us that they could be useful predictors for farmers' adoption decisions. To obtain more evidence, future adoption studies of digital farming should explore the impacts of psychological factors and attributes of technology on adoption (especially the potential impact of data safety).

Due to the limitation of farm-level studies not capturing linkages between determinants and feedback within the complex adaptive system, we further review 27 ABMs of diffusion of agricultural innovations. We find that current ABMs of agricultural innovations only loosely connect with empirical farm-level findings, despite their usefulness for representing system interaction. They are quite limited with respect to modelling various types of agents, and are largely characterised by profit maximisation while rarely modelling farmers' knowledge/capacity, psychological factors, attributes of technology and institutional arrangements. While ABMs are well aligned with the theory in terms of endogenous macro-phenomena postulated by the theory of diffusion of innovation, they are not well-grounded in empirical details yet. This latter weakness might be a characteristic of ABMs of agricultural innovations just recently evolving from the early toy and proof of concept models to more empirically tuned ones. A natural next step in this evolution is to consider the wealth of research found in the empirical farm-level adoption studies.

Based on the loose ends between both literature strands, we present a conceptual framework integrating farm-level evidence and system interaction for modelling adoption and diffusion of digital farming technologies in crop production. The framework is aligned with the theory of diffusion of innovation and with the theory of planned behaviour. It uses well researched farm-level adoption determinants from a system perspective and connects important factors based on empirical evidence.

To the best of our best knowledge, this work constitutes the first proposal for a conceptual framework for adoption and diffusion of digital farming technologies in crop production. It improves our current understanding of mechanisms of adoption and diffusion of digital farming in this context. Our framework also serves as a reference for future ABMs capable of integrating empirical evidence and system dynamics holistically. Applying this framework can increase the empirical and theoretical foundation, model coherence and comparability of future ABMs. Furthermore, the framework provides structural hypotheses that can be examined by researchers who aim to understand farmers' decision-making of adoption using farm-level approaches or by those who investigate diffusion mechanisms of digital farming technologies using complex systems approaches.

There are some limitations in this study that could be addressed in future research. First, we reviewed adoption studies of generic precision and digital farming technologies in crop production. This leads to a fairly broad conceptual framework containing factors that might not be relevant for some specific technologies. Focusing on specific technologies (e.g. mechanical weeding robots) will allow to start from this general framework but require to specify the contextual relevance of the determinants.

Second, our conceptual framework is only based on a limited number of studies available at this time. This causes uncertainty regarding the importance of mostly unexplored factors such as institutions and social networks to farmers' adoption decision. We suggest to tackle these context-specific issues with the future development of diagnostic procedures (Cox, 2011) going hand in hand with our framework to deliver clear-cut interpretations for institutions and network types.

Last but not least, the proposed framework is largely based on the existing theories (i.e. DOI, TAM, and the TPB) applied in the reviewed studies. These theories have certain limitations. Lyytinen and Damsgaard (2001) question the completeness of the list of technology attributes defined by the DOI and whether all innovations should be characterised with the same set of attributes. TAM is criticised because it ignores the social influence on adoption (Beldad and Hegner, 2018). Frequently reported limitations of the TPB include its predictive validity, rationality assumption, and omitting the effect of habits and emotions among others (Ajzen, 2011). Therefore, these theories might need to be adjusted when dealing with different technologies in different social and political contexts.

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2.A Appendix

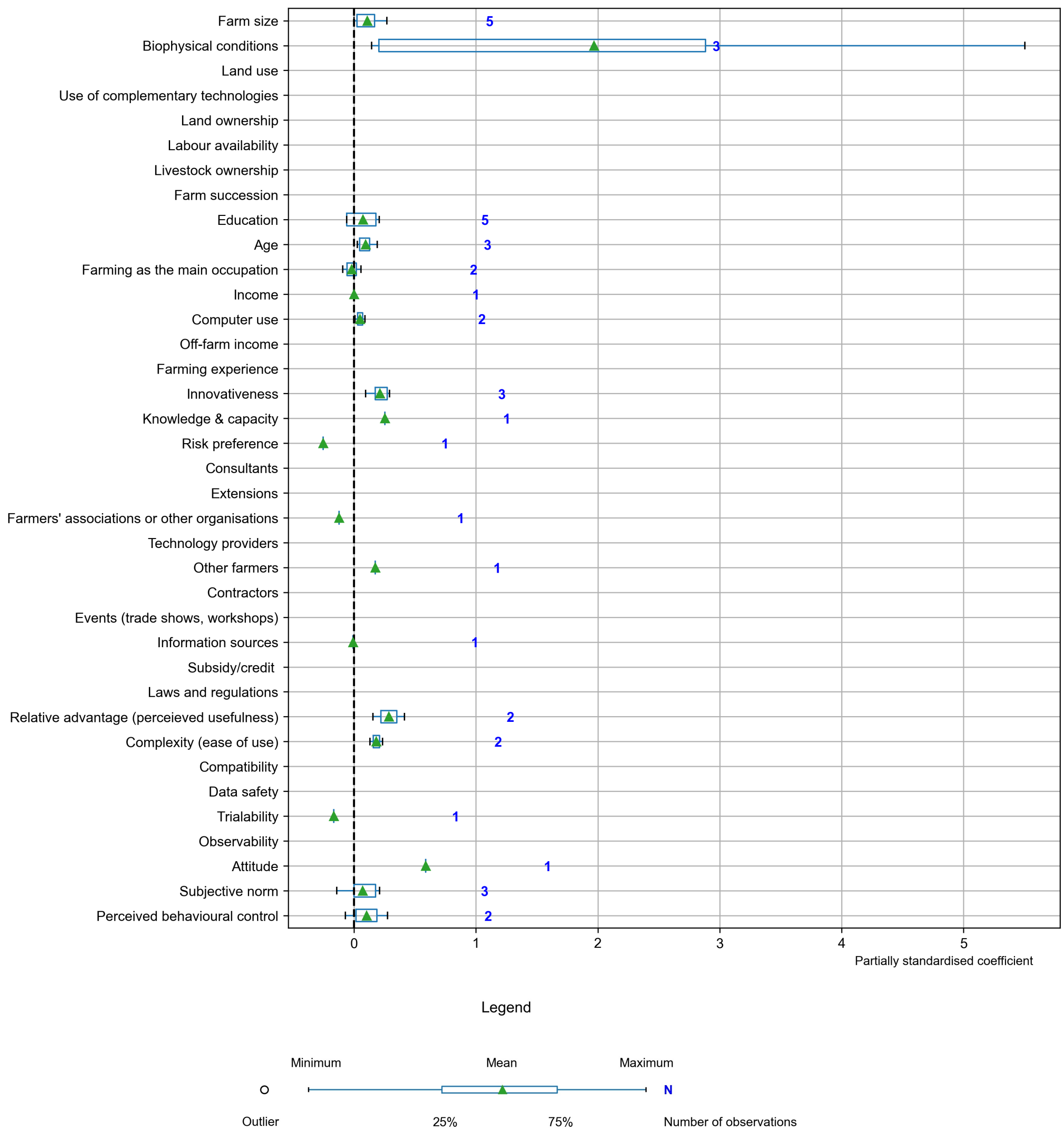
2.A.1 Selected empirical farm-level studies of technology adoption

No.	Study	Technology type	Research Region	Method
1	Adrian et al. (2005)	precision farming	USA	structural equation model
2	Asare and Segarra (2018)	precision farming	USA	probit model
3	Aubert et al. (2012)	precision farming	Canada	partial least squares
4	Barnes et al. (2019)	precision farming	Belgium, Germany, Greece, the Netherlands and the UK	logit model
5	Boyer et al. (2016)	precision farming	USA	probit model
6	Caffaro and Cavallo (2019)	smart farming	Italy	structural equation model
7	D'Antoni et al. (2012)	precision farming	USA	logit model
8	Drewry et al. (2019)	digital farming	USA	descriptive analysis
9	Gallardo et al. (2019)	precision farming	USA	probit model
10	Isgin et al. (2008)	precision farming	USA	logit and poisson models
11	Kutter et al. (2011)	precision farming	Germany	descriptive analysis
12	Lambert et al. (2014)	precision farming	USA	logit model
13	Lambert et al. (2015)	precision farming	USA	logit model
14	Larson et al. (2008)	precision farming	USA	logit model
15	Lencsés et al. (2014)	precision farming	Hungary	ANOVA test
16	Lynne et al. (1995)	Micro-drip irrigation	USA	tobit model
17	Michels et al. (2020)	smart phone in farming	Germany	logit model
18	Mitchell et al. (2018)	precision farming	Canada	descriptive analysis
19	Paustian and Theuvsen (2017)	precision farming	Germany	logit model
20	Pedersen et al. (2004)	precision farming	Denmark	descriptive analysis

21	Pino et al. (2017)	water-saving measures (micro-drip, sprinkling irrigation, plastic sheeting)	Italy	structural equation model
22	Pivoto et al. (2019)	smart farming	Brazil	logit and poisson models
23	Pokhrel et al. (2018)	precision irrigation	USA	poisson model
24	Reichardt and Jürgens (2009)	precision farming	Germany	descriptive analysis
25	Robertson et al. (2012)	precision farming	Australia	logit model
26	Salimi et al. (2020)	automation	Iran	structural equation model
27	Schimmelpfennig and Ebel (2016)	precision farming	USA	probit model
28	Takácsné György et al. (2018)	precision farming	Hungary	descriptive analysis
29	Tamirat et al. (2017)	precision farming	Denmark and Germany	logit model
30	Vecchio et al. (2020)	precision farming	Italy	logit model
31	Walton et al. (2008)	precision farming	USA	probit model
32	Zheng et al. (2018)	unmanned aerial vehicles	China	probit model

Source: own results

2.A.2 Partially standardised coefficients of factors from models with binary outcome



Source: own results

Chapter 3

How much can farmers pay for weeding robots? A Monte Carlo simulation study[8]

Abstract: We investigate the Maximum Acquisition Values (MAVs) of weeding robots and their determinants in both organic and conventional sugar beet farming in Germany. The MAV is defined here as the price of the weeding robot that renders the same net profit as the current weeding methods. For our analysis, a Monte Carlo simulation approach is used, combined with empirical data and data collected from weeding robot companies. The results show that the MAVs of mechanical weeding robots for organic farming are substantially higher than that of spot spraying robots for conventional farming. Technology attributes are more influential than labour market effects in determining the MAVs of weeding robots: In organic farming, technology attributes such as area capacity and weeding efficiency impact the MAVs of mechanical weeding robots the most, while in conventional farming, supervision intensity and the robot's ability to save herbicides are the most influential factors. The wage rate of unskilled labour, relevant for manual weeding, plays a more important role in determining the MAVs than that of skilled labour, relevant for supervision of the robot. This implies that a shortage of seasonal workers and hence increases in the wage of low-skilled labour could be important drivers of the adoption of mechanical weeding robots. Plot characteristics such as plot size and mechanisation level only have limited impacts on the MAVs.

[8]Chapter 3 is currently under review in an international journal in the category of "Agriculture, Multidisciplinary" as Shang, L., Pahmeyer, C., Heckelei, T., Rasch, S., and Storm, H.: How much can farmers pay for weeding robots? A Monte Carlo simulation study. The data and codes used for this chapter can be found in the following Github repository: https://github.com/linmeishang/RobotPaperGit

Keywords: *weeding robot, labour, technology adoption, supervision, investment*

JEL classification: Q12; Q16; Q18

3.1 Introduction

Weed control is a key activity for both organic and conventional farming systems. In organic farming, manual weeding is labour-intensive and increasingly expensive in the European Union due to the shortage of workforce in the agricultural sector (Williams and Horodnic, 2018), which is amplified by the Covid-19 pandemic and the recent war in Ukraine (Bochtis et al., 2020; Dahm, 2022). In conventional farming, chemical weeding methods are effective, but they are usually costly, can create herbicide resistance problems and cause adverse environmental impacts. Thus, the Farm to Fork Strategy of the European Green Deal sets a goal of reducing chemical pesticide use by 50% by 2030 (European Commission, 2022; Montanarella and Panagos, 2021). In addition, farmers face regulatory uncertainties about the future availability of herbicides (see e.g. Stokstad, 2017). Weeding methods that are both cost-effective and environmentally friendly are urgently needed to ensure food security and the sustainability of agriculture in the context of a growing world population (MacLaren et al., 2020).

Autonomous weeding robots have great potential to overcome the challenge of agricultural labour shortage and reduce the negative environmental impacts of agricultural production (Gallardo and Sauer, 2018; Khanna et al., 2022; Lowenberg-DeBoer et al., 2021a). Combining the recent advances in information and communications technology, robotics and artificial intelligence, autonomous weeding robots can distinguish weeds from crops and precisely treat the targeted weeds at the individual plant level (Bawden et al., 2017). Currently, there are many types of weeding robots that are commercialised or in development such as GPS-based mechanical weeding robots (e.g. FarmDroid, 2022) and vision-based mechanical weeding robots (e.g. Dino of Naïo Technologies, 2022), vision-based selective spot spraying robots (e.g. AVO of Ecorobotix, 2022), and vision-based thermal weed control with laser (e.g. LaserWeeder of Carbon Robotics, 2022).

Despite the rapid advancement in the engineering of agricultural robotics, the economic analysis of agricultural robots has lagged due to their limited adoption and data availability from farm trials (Lowenberg-DeBoer et al., 2020; Spykman et al., 2021). In the review of Lowenberg-DeBoer et al. (2020), only 18 studies that include economic analyses of agricultural automation and robotics are identified. However, economic analyses are highly relevant for farmers' adoption decisions, technology providers' machine design (Shockley et al., 2019), and policy-makers' strategies to promote adoption and tackle the uncertainties in the labour market. Therefore, this study contributes in this regard by conducting a cost-based investment analysis of weeding robots.

The aim of this chapter is to investigate the Maximum Acquisition Values (MAV) (Shockley et al., 2019; Sørensen et al., 2005) of weeding robots and their determinants in both organic and conventional sugar beet farming in Germany. Following Shockley et al. (2019) and Sørensen et al. (2005), the MAV of a weeding robot is defined here as the price of the robot that renders the same net profit as the current weeding methods. Specifically, this chapter will (1) evaluate the MAVs of weeding robots in both organic and conventional sugar beet farming in Germany; (2) compare the importance of technology attributes and labour market effects in determining the MAVs of weeding robots; and (3) examine the impact of plot characteristics on the MAVs of weeding robots. Accordingly, we employ a Monte Carlo simulation based on farm planning data extracted from the KTBL[9] (In German: Kuratorium für Technik und Bauwesen in der Landwirtschaft e.V.; In English: the Association for Technology and Structures in Agriculture) database. To define the ranges of the robot characteristics for the Monte Carlo simulation, relevant information about the characteristics of currently available robots was collected through the homepages of technology firms. Additionally, personal interviews with leading weeding robot companies were conducted (in total 7 companies: 6 for mechanical weeding robots, 1 for spot spraying weeding robots). Those companies already offer commercial robots on the market. Interviews were conducted on the DLG (In German: Deutsche Landwirtschaftsgesellschaft; In English: German Agricultural Society) field days (14th-16th June 2022, Mannheim, Germany). During the interviews, the aim was to collect information on the robot characteristics, which is then used to specify the parameter ranges considered in the Monte Carlo simulation. For the sake of simplicity, this study focuses on sugar beets since there are many weeding robots already available that support the cultivation of sugar beets[10].

[9]Homepage of KTBL: http://www.ktbl.de (only in German)

[10]See a list of weeding robots available for sugar beets: https://www.ducksize.com/robots-for-beets

This chapter is organised as follows. Section 3.2 reviews the economic studies of agricultural robots, especially weeding robots, in the existing literature. Section 3.3 introduces the KTBL dataset and our method for calculating the MAVs. In section 3.4, the results are analysed and discussed. The last section concludes the chapter and points out its limitations and the directions for future research.

3.2 Literature review

In this section, existing economic studies of agricultural robots in arable farming are reviewed. Studies about mechanical weeding and spot spraying robots were firstly summarised, then those on whole-farm autonomous machinery. Some studies that only indirectly investigate the economics of agricultural robots but provide some important insights are also reviewed.

One of the earliest economic studies of mechanical weeding robots was conducted by Sørensen et al. (2005). Their intra-row mechanical weeding robot was based on a small autonomous vehicle with vision systems and active tools for weed removal. Their result showed that mechanical weeding robots could save the labour requirement by 85% in organic sugar beet farming and by 60% for organic carrot production in case of 100% weeding efficiency (i.e. the percentage of weed removed). With a 75% weeding efficiency, the labour cost could be reduced by around 50%. They also estimated the MAV of a weeding robot: A farmer could pay up to €110,000 for the weeding robot in case of high weeding intensity and high utilisation level of the robot (300 operation hours per year). With a low weeding intensity and low utilisation level (180 operation hours per year), the MAV was less than €40,000. Pérez-Ruíz et al. (2014) evaluated the labour-saving effect of an intra-row mechanical weeding co-robot on an experimental tomato plot at the University of California. In the cooperation of the co-robot and a human, the human provided visual crop detection capability and manually located the hoes in between row crops, while the co-robot took on the drudgery of repetitive hoe movement. The result showed that using the co-robotic system replaced nearly 60% of hand hoeing labour for intra-row weed control.

Turning to spot spraying robots, Pedersen et al. (2006) compared robotic weeding based on a micro spraying system with a conventional sprayer for sugar beet farming in Denmark. This system could weed 0.4 ha/h, and it was assumed to save herbicide use by 90%. Their economic feasibility assessment showed that robotic weeding was more profitable than conventional systems: The robotic system could reduce operating costs by up to 24%. They also estimated an initial cost of nearly €65,000 for such a weeding robot. Pedersen et al. (2008) extended the study and estimated the costs of a similar robotic weeding system for sugar beet farming in Denmark, the US, the UK and Greece. These countries differ in farm size and labour cost, as well as technical parameters of the robotic weeding system. The results indicated that the robotic weeder had a cost advantage in all study regions except Greece, where the wage rate of unskilled labour was relatively lower than in the other three countries and the total treated area was also smaller.

There are also studies on the economics of autonomous machinery for the whole farming system. Shockley et al. (2019) used whole-farm Mixed-Integer Programming (MIP) considering the entire farming system to compare the net returns of using conventional and autonomous machinery (including tractor, planter, sprayer, and fertiliser applicator), guided by intelligent controls, for corn and soybean production in Kentucky, USA. They investigated the economic feasibility and break-even investment price of intelligent controls (not including the machinery). For an 850 ha grain farm, the break-even investment price ranged from around $26,000 up to $160,000, depending on the degree of input reduction and yield increasing effect. Their sensitivity analysis on farm size showed that without considering input saving or yield increasing effect, farm size only had a limited impact on the break-even investment price. However, farm size impacted the break-even investment price dramatically when input saving and yield-increasing effects were considered. The study is extended by Shockley et al. (2021). They examined the farm-level implications of on-site supervisory regulations and a speed restriction. These regulations reduced the profitability of autonomous machinery, and in some scenarios, autonomous machines were no longer an economically viable alternative to conventional machinery.

Lowenberg-DeBoer et al. (2021b) went beyond the economic analysis of Shockley et al. (2019) showing it is technically possible to use Global Navigation Satellite Systems and drone autopilot software to retrofit conventional farm equipment to autonomous operation. They used data from the Hands Free Hectare (HFH) project on a grain-oilseed farm in the UK to estimate the whole farm profitability of an autonomous cropping system. The study showed that arable crop production with autonomous equipment was economically feasible. Although autonomous farms had no substantial improvement in gross margins, they had notably higher returns to operator labour, indicating autonomous farming is more beneficial for production systems that require more labour and field operations. The study suggests using smaller equipment more intensively can decrease equipment investment costs. This also hints at the potential of small robots in utilising small and irregularly shaped farming plots. Lowenberg-DeBoer et al. (2021a) investigated the impact of supervision time of autonomous equipment and farm size on the costs of wheat production in the UK based on the HFH project. The results showed that for a farm of 66 ha, when a 100% supervision time was required, using autonomous equipment had no cost advantage compared to using conventional farming equipment. When more supervision time was required, smaller farms tended to benefit less from autonomous equipment than bigger farms.

Studies that do not directly investigate the profitability of agricultural robots nevertheless provide some important insights. De Witte (2019) calculated the operating costs of large and small machine combinations for grain harvesting and tillage using mainly farm planning data. The study found small machinery for tillage was 7% cheaper than using large machinery if labour costs were not considered, but small machinery got more expensive than the latter when considering labour costs. For harvesting, using large machinery had an economic advantage no matter if labour costs were included. Thus, it is reasoned that small autonomous machines can become cost-competitive for less capital-intensive processes like tillage and seeding. Interviews with AgTech startups conducted by Rübcke von Veltheim and Heise (2020) reveal the expectation that field crop robots would first be implemented in specialty crops and organic farming as the economic case for conventional farming is not yet strong enough. They also predicted that farms with larger fields would adopt field crop robots sooner than farms with small fields, irrespective of total acreage, due to logistic costs. Rübcke von Veltheim et al. (2022) further investigated the behavioural intention of German farmers with respect to their future adoption of autonomous field robots. It is found that farmers' expected performance and trust in technology had a significant positive impact on their intention to adopt autonomous field robots. They suggested policy-makers should create a stable legal situation for autonomous systems to promote the adoption of field robots. Spykman et al. (2021) investigated farmers' attitudes towards field crop robots in Bavaria, Germany. The study showed larger farms focus more on the economic advantages of robots and prefer large autonomous tractors. In contrast, small-scale or organic farms consider the environmental impacts of robots relatively more important and favour small robots. Organic farming also positively correlates with the intent to invest in field robots. To our knowledge, quantitative economic analyses explaining these attitudinal results do not yet exist.

Based on the literature review above, the following research gaps are identified: (1) no studies have compared the MAVs of weeding robots in organic farming with conventional farming; (2) no studies have compared the importance of different technology attributes, labour market effects, and plot characteristics in determining the MAVs of weeding robots; and (3) no studies have investigated the economic implications of weeding robot for German sugar beet farms. Given that filling these gaps will provide relevant information for business strategies and the design of policy measures, this study aims to investigate the MAVs of weeding robots and their determinants in German sugar beet farming of both conventional and organic farming systems.

3.3 Data and method

This section first describes the KTBL dataset and the baseline scenario with current weeding methods (KTBL, 2020). Then, it introduces the weeding robot scenario. Afterwards, the calculation of MAVs is presented based on the two scenarios.

3.3.1 The KTBL database and the baseline scenario

The KTBL database provides detailed farm planning data for various farm branches such as arable, livestock and horticultural production in Germany. This extensive data source mainly serves as a basis for planning calculations and business assessments on German farms, but it is also regularly used for policy assessments, research and education (Heinrichs et al., 2021). For arable farming, the dataset provides information on crops including yields, revenues, and costs of all working steps (e.g. seeding, weeding, harvesting) in production. For each working step, labour requirements, machinery costs, and the costs of contractor services are provided. It also includes data about different types of costs such as variable costs (variable labour costs and variable machine costs), fixed costs (fixed labour costs and fixed machine costs), and direct costs (e.g. fertiliser and herbicide, etc.).

Note that all data on costs and revenues is provided on a *per ha* basis instead of per farm. Depending on the plot characteristics, costs and revenue per ha differ from plot to plot. The KTBL database differentiates plots by plot size, mechanisation level (indicating the power of the tractor used on the field), farm-plot distance, and yield level. Data on sugar beet production in both organic and conventional farming systems was extracted. For simplicity, we only vary plot size and the mechanisation level and fix other plot characteristics. Plot size is chosen because the average cost of setting up a robot for a field depends on the plot size assuming the robot only needs to be set up once per field. The mechanisation level represents the existing technology, thus determining the profit level of the plot. Other plot characteristics are fixed: The farm-plot distance is fixed at 2 km (the average in Germany), and the yield is fixed at a medium level. In the dataset used for this study, plot size is a discrete variable including {1, 2, 5, 10, 20, 40, 80} ha, and the mechanisation level is also discrete including {45, 67, 83, 102, 120, 200, 230} kW. In total, there are 49 combinations (7 plot sizes × 7 mechanisation levels) of different plot characteristics for organic and conventional farming, respectively.

To present the dataset, the example plot of size of 10 ha and mechanisation level of 102 kW in organic farming is used to illustrate the two tables provided by the dataset: working steps (Table 3.1) and gross margin (Table 3.2). Table 3.1 shows the costs (*per ha*) of each working step. There are multiple weeding steps (i.e. hoeing) from April to June. Normal hoeing is mechanical weeding with a curry-comb carried by a tractor, while hand hoeing stands for manual weeding. The labour costs of these two types of weeding are different. According to the assumption of KTBL, mechanical weeding is done by a skilled permanent farm worker (hired or family labour, calculated as fixed labour cost), while the labour requirement of manual weeding consists of 11% skilled permanent labour (i.e. fixed labour cost) and 89% unskilled seasonal labour (i.e. variable labour cost). The gross margin table (Table 3.2) presents the revenue, direct costs, variable costs, and fixed costs of all the farming steps *per ha*.

In the baseline scenario, farmers use the current weeding methods, i.e. manual weeding and mechanical weeding with a tractor in organic farming, and chemical spraying in conventional farming. From Table 3.2, the net profit (*per ha*) of the baseline scenario (π_1) can be calculated as shown in Equation (3.1):

$$\textit{Net profit} = \textit{Revenue} - \textit{Total direct costs} - \textit{Total variable costs} - \textit{Total fixed costs} \quad (3.1)$$

3.3.2 Robot scenario

The previous section has introduced the working steps and gross margin tables. This section describes the assumptions of the robot scenario and the simulated variables in this scenario.

3.3.2.1 *Assumptions*

(1) Two types of weeding robots

It is assumed in this study that a mechanical weeding robot will be used for organic farming, and a spot spraying robot for conventional farming. The differentiation has been established since labour intensity is a major driver of the costs in organic sugar beet cultivation (see Table 3.1 and Table 3.2), whereas in conventional agriculture the cost of herbicides plays a larger role than labour intensity (KTBL, 2020). The exact technical execution of the weed removal is not crucial in this study as long as no chemicals are used in organic farming and conventional farming still uses herbicides to kill weeds.

(2) Working steps replaced by weeding robots

Based on the tables of working steps from KTBL, it is assumed here that weeding robots go through the fields twice per season in both organic and conventional farming. For organic farming (see Table 3.1), only manual weeding steps (i.e. hand hoeing) are replaced by a mechanical weeding robot (twice per season, in May and June, respectively) because we assume that normal hoeing with a tractor is efficient enough that a robot cannot compete with it. If a robot is not able to remove 100% of the weed, the rest will be done by manual weeding (11% fixed labour cost and 89% variable labour cost, as assumed by KTBL). In conventional farming, weeding is done by a tractor with a sprayer driven by a permanent farm worker (twice per season, in March and May, respectively), thus no unskilled labour is required. We assume that the spot spraying robots are able to kill all weeds in the field, but their ability to save herbicide varies.

(3) Revenue per ha stays the same as in the baseline

It is assumed here that the revenue per ha in the robot scenario is the same as in the baseline for each plot, meaning the quality of crop output and yield stay the same. Since the KTBL data only provides the costs and revenue per ha, the costs and revenue in the robot scenario are also calculated per ha. In this way, the MAV is the price of the robot that renders the same net profit per ha as the current weeding methods. Since the KTBL dataset does not provide information on farm size, this study only focuses on the average profit of each plot and no farm size is assumed. Thus, our analysis is not at the farm level but focuses on the profit of the production activity.

(4) Robots are operated at full capacity

The focus on the plot level comes with the assumption that the weeding robots work at full capacity regardless of farm size. This implies either that the farm has the appropriate size or that the remaining capacity can be rented out at rates reflecting the costs. Assuming that a robot works at full capacity may cause an overestimation of MAVs for small farms that do not manage to rent out excess hours.

(5) Skilled labour for setting up and supervising the robot

It is assumed here that the robot is set up and supervised by skilled labour to ensure safe operations on the field for both organic and conventional farming. Although Shockley et al. (2021) and Lowenberg-DeBoer et al. (2021a) see the required level of supervision time as a regulation, it can also be seen as a technology attribute depending on the levels of autonomy of the robot. For simplicity, this study includes required level of supervision time as a technology attribute (see "supervision intensity" in section 3.3.2.2).

Table 3.1: The costs (per ha) of all working steps of the example plot

Month	Working steps	Time	Depreciation	Interest costs	Other costs	Maintenance	Lubricants	Services
OCT1	Soil sample	0.02	0.08	0.01	0	0.07	0.01	1.2
OCT2	Ploughing with a reversible plough	1.13	16.67	4.85	2.08	20.44	18.99	0
FEB2	Harrowing with spring tine harrow	0.32	6.79	2.03	0.94	5.86	4.62	0
FEB2	Nmin-sampling, 0-30 cm	0.19	0.64	0.06	0.01	0.53	0.05	2
MAR1	Spreading liquid manure, from farm	1.01	17.65	4.33	2.3	14.55	7.34	0
MAR1	Harrowing with seedbed combination	0.28	6.73	2.02	0.9	6.06	4.15	0
MAR2	Precision sowing	0.44	24	6.48	1.1	11.88	2.69	0
APR2	Hoeing, 1. and 2. hoeing	0.49	7.31	1.97	0.69	6.02	3.29	0
MAY1	Hoeing, 1. and 2. hoeing	0.49	7.31	1.97	0.69	6.02	3.29	0
MAY2	Crop appraisals	0.1	0.08	0.02	0.06	0.03	0.14	0
MAY2	Hand hoeing (1. hoeing)	85.43	0.92	0.21	1.33	1.1	2.58	0
MAY2	Hoeing, 3. and 4. hoeing	0.41	6.99	1.89	0.64	5.52	2.91	0
JUN1	Hand hoeing (at row closing)	77.74	0.86	0.19	1.26	1.04	2.35	0
SEP2	Harvesting	1.05	96.66	26.1	5.26	65.14	34.65	0
OCT1	Lime fertilisation	0.01	0.13	0.03	0.01	0.08	0.07	0
OCT1	Lime fertilisation	0.03	1.92	0.44	0.2	0.52	0.42	0
OCT1	Processing stubbles, flat, sloped (30°)	0.48	8.41	2.47	1.35	8.63	4.97	0
	Sum	**169.62 h/ha**	**203.15 €/ha**	**55.07 €/ha**	**18.82 €/ha**	**153.49 €/ha**	**92.52 €/ha**	**3.2 €/ha**

Source: KTBL (2020)

Table 3.2: Revenue and different types of costs (per ha) of the example plot

Gross Margin Category	Detailed Item	Amount	Amount Unit	Price	Price Unit	Total (€/ha)
Revenue	Sugar beet, organic	50	t/ha	105	€/t	5,250
Direct Costs	Seeds, organic	1.23	U/ha	230	€/U	282.9
Direct Costs	Interest (3 month)	91.68	€/ha	0.03	€/€	2.75
Direct Costs	Liquid manure	20	m^3/ha	0	€/m^3	0
Direct Costs	Calcium carbonate	1	t/ha	40.7	€/t	40.7
Direct Costs	Hail insurance	5,250	€/ha	8.21	€/1000 €	43.1
Variable Costs	Variable machine costs	/	/	/	/	246.01
Variable Costs	Variable labour costs	145.04	h/ha	13.25	€/h	1,921.78
Variable Costs	Services	/	/	/	/	3.2
Variable Costs	Interest (3 month)	542.75	€/ha	0.03	€/€	16.28
Fixed Costs	Fixes machine costs	/	/	/	/	277.04
Fixed Costs	Fixed labour costs	24.58	h/ha	21	€/h	516.18

Source: KTBL (2020)

3.3.2.2 *Variables and the accounting system*

To calculate the MAVs of weeding robots, variables of technology attributes and their values need to be defined and chosen, same for the wage rates of skilled and unskilled labour. Definitions and ranges of value are presented in Table 3.3. The actual values used to calculate the MAVs are drawn from these ranges in a Monte Carlo simulation. The ranges of the variables come from various sources: information from technology providers (through internet or personal interviews as described in the section 3.1), KTBL database, and existing literature.

(1) Area capacity

The area capacity of a weeding robot is measured by the amount of area (in ha) it can weed in its useful life. This information is usually difficult to estimate for technology providers. Thus, the area capacity is approximated based on the lifetime and weeding capacity per year of a robot. The total lifetime of a robot is assumed to be 10 years according to Sørensen et al. (2005), Pedersen et al. (2006), and FarmDroid (2022), which is also similar to the average lifetime of hoeing equipment and self-propelled machinery. According to FarmDroid (2022), the mechanical weeding robot FD20 is designed to a farm up to 20 ha per season. When assuming weeding twice per year and 10 years of useful life, the area capacity is 400 ha. According to the personal interviews, three other robot companies also estimated a similar capacity for their robots. Although spot spraying robots should have higher area capacity because of their faster speed, due to the lack of data, we use 400 ha as an average level and set a range between 200 to 600 ha for area capacity for both types of robots. This allows us to compare the MAV of the two types of robots assuming they have the same characteristics.

(2) Setup time per plot

The setup time per plot is defined as the time required for preparing the robot for the actual fieldwork. According to robot companies, the setup of the first time involves settling the GPS station and loading the map, which takes about several hours. But from the second time, each setup per plot only needs from 10 minutes to 2 h depending on the situation. Therefore, the range from 0.16 h to 2 h is chosen for this variable. It is assumed that a robot must only be set up once for a whole plot irrespective of plot size.

(3) Repair and energy costs

Repair and energy costs are difficult to estimate for technology providers because they have not got enough experience yet. Therefore, we use the KTBL data for a standard tractor (all-wheel drive, manual gearbox, 40 km/h, 102 kW) and attached hoeing machine (3m, row width 45-50cm, 6 rows). The combined repair and energy costs for this combination are 28 €/ha. Since the weeding robot can be solar-powered and the maintenance costs might differ among different robots, for the analysis, the range is assumed to be a minimum of half the respective costs (14 €/ha), and a maximum of twice the costs of the standard tractor (56 €/ha).

(4) Weeding efficiency

The weeding efficiency of the two types of weeding robots is defined differently. For a mechanical weeding robot, weeding efficiency measures the percentage of weeds that can be autonomously removed by the robot, whereas for a spot spraying robot, it measures the quantity of herbicide that can be saved (compared with the baseline). According to the information collected from robot companies, the efficiency of a mechanical weeding robot ranges from 70% to 99%, which is similar to Bawden et al. (2017) and Kunz et al. (2015). The spot spraying robot can save up to 95% herbicide depending on the weed density (see e.g. Ecorobotix, 2022). The spot spray technology See & Spray of John Deere (2021) can reduce herbicide use by 77% on average. Thus, a minimal weeding efficiency of 50% and a maximum weeding efficiency of 100% are assumed for both types of robots.

(5) Supervision intensity

Supervision intensity is defined here as a fraction of the field time, which is same as the level of supervision time in Lowenberg-DeBoer et al. (2021a) and Shockley et al. (2021). This study assumes a field time (i.e. weeding time) of 3.2 h/ha for a mechanical weeding robot based on the information collected from the internet (FarmDroid, 2022; Farmers Weekly, 2021; Naïo Technologies, 2022) and through personal interviews with robot companies. Spot spraying robots are usually faster, for example, the AVO of Ecorobotix needs 1.6 h/ha (Ecorobotix, 2022). Due to the limited number of observations for spot spraying robots, and for the sake of comparability, this study also uses 3.2 h/ha as the field time for spot spraying robots in this study. As the requirement regarding supervision intensity is uncertain, we use a range from 0 to 100% for this variable.

(6) Wage rate of unskilled labour

Of relevance is the wage rate of seasonal labour hired to remove weeds for organic farming. This variable is assumed to be irrelevant in conventional farming as weeds are not removed manually in this production system. The wage rate of unskilled labour in the KTBL database is assumed as a minimum (13.25 €/h), and the maximum is set to 21 €/h, which is the wage rate of the permanent farm worker according to KTBL (2020). Wage rates include employer contributions to social security.

(7) Wage rate of skilled labour

We consider the wage rate of the skilled labour hired to set up and supervise the robot. The minimum is assumed to be the same as the wage rate of a permanent farm worker in KTBL database (21 €/h), and the maximum is assumed to be twice as much as the minimum (42 €/h). Wage rates include employer contributions to social security.

Table 3.3: Definitions and ranges of variables in the Monte Carlo simulation

Variable	Definition	Range	Unit
Area capacity	The amount of area the robot can weed in its useful life	200-600	ha
Setup time per plot	Time required to set up the robot per plot	0.16-2	h/plot
Repair and energy costs	Repair and energy costs of the robot for weeding one ha	14-56	€/ha
Weeding efficiency	Percentage of weeds removed by the robot (organic farming);	50%-100%	/
	Percentage of herbicide saved by the robot (conventional farming)		
Supervision intensity	Percentage of field time required to supervise the robot	0-100%	/
Wage rate of unskilled labour	Wage rate of seasonal labour	13.25-21	€/h
Wage rate of skilled labour	Wage rate of the personal who sets up and supervises the robot	21-42	€/h

Note: All variables will be drawn from uniform distribution.

3.3.2.3 *Costs in the robot scenario*

The costs of working steps that are not replaced by the robot will stay the same as for the baseline. Depending on the farming system and the weeding efficiency of the robot, weeding steps might be partially or completely replaced by the robot. For organic farming, if the weeding efficiency is below 100%, the manual weeding steps can only be partially replaced because the rest of the weeds that are overlooked by the robot must be removed by humans (both fixed and variable labour costs are involved). This causes additional labour and machine costs. The additional costs are fractions of the original costs of baseline depending on the weeding efficiency. For conventional farming, it is assumed that weeding steps are completely replaced by the weeding robots, which means the robot can always achieve the required weeding efficiency. The weeding efficiency only determines how much herbicide, thus the direct costs, can be saved by the spot spraying robot.

In both organic and conventional sugar beet farming, there are weeding steps in the baseline that will be replaced by robotic weeding in our simulation. Following the structure of Table 3.1, the costs of one robotic weeding step per ha are shown below.

(1) Time (h/ha): It is the labour requirement of robotic weeding per ha. In this study, it is the sum of the setup time and supervision time per ha as shown in Equation (3.2), where field time per ha is fixed at 3.2 h/ha as shown above. Since both setup and supervision are assumed to be conducted by skilled labour paid on an hourly basis, these costs will be counted as variable labour costs.

$$Time = \frac{Setup\ time\ per\ plot}{Plot\ size} + Supervision\ intensity \times Field\ time\ per\ ha \tag{3.2}$$

(2) Depreciation (€/ha): The depreciation cost per ha is the MAV of the robot divided by the area capacity since we assume that the robot depreciates linearly during its useful life. The MAV will be an unknown variable that must be solved in our simulation.

$$Depreciation = \frac{MAV}{Area\ capacity} \tag{3.3}$$

(3) Interest costs and other costs (€/ha): They are assumed to be fractions of the depreciation (similar to what KTBL assumes) due to the limited data.

$$\textit{Interest costs} = \textit{Depreciation} \times 0.3 \tag{3.4}$$

$$\textit{Other costs} = \textit{Depreciation} \times 0.1 \tag{3.5}$$

(4) Maintenance and lubricants (€/ha): These two items are merged into "Repair and energy costs".

$$\textit{Maintenance} + \textit{Lubricants} = \textit{Repair and energy costs} \tag{3.6}$$

(5) Services (€/ha): No costs of services are calculated because the costs of hiring skilled labour to set up and supervise the robot are counted as variable labour costs.

After the weeding steps are replaced (partially or completely) by robotic weeding, the net profit of a robot scenario can be calculated. The following costs are the total costs of one ha, including the costs of robotic weeding, the costs of other steps that stay the same as in the baseline, and possibly the costs of additional manual weeding caused by an imperfect weeding efficiency.

$$\begin{aligned}&\textit{Variable machine costs}\\&= \textit{Sum of maintenance} + \textit{Sum of lubricants}\end{aligned} \tag{3.7}$$

$$\begin{aligned}&\textit{Fixed machine costs}\\&= \textit{Sum of depreciation} + \textit{Sum of interest costs} + \textit{Sum of other costs}\end{aligned} \tag{3.8}$$

Variable labour costs

$$= \textit{Skilled labour time} \times \textit{Wage rate of skilled labour} + \textit{Unskilled labour time} \times \textit{Wage rate of unskilled labour} \tag{3.9}$$

Fixed labour costs

$$= \textit{Fixed labour time} \times \textit{Wage rate of fixed labour} \tag{3.10}$$

At the end, the net profit per ha of the robot scenario (π_2) can also be calculated using Equation (3.1).

Figure 3.1 illustrates the accounting system and how each variable influences the net profit of using robotic weeding. The types of costs that will change in the robot scenario are marked in dotted boxes, under which the variables that influence them are noted.

3.3.3 Data generation and calculation of MAVs

In this study, the MAV of a weeding robot is the maximum price of a robot that renders the same net profit (per ha) as using the current weeding methods. Figure 3.2 depicts the data generation process and the derivation of MAV of one random draw.

The data generation process of organic farming and conventional farming are separated. Here, the process for organic farming is described as an example. First, a Monte Carlo simulation draws a random combination of all variables that matter in organic farming (7 variables here, 6 variables for conventional farming). Then, for each combination of plot size and mechanisation level *i* (49 combinations for organic farming and conventional farming each), the net profits per ha of baseline and robot scenario are calculated given the randomly drawn values: The net profit per ha of baseline (π_{i1}) is calculated given the new wage rate of the unskilled labour (this step is unnecessary for conventional farming because unskilled labour is not used there). The net profit per ha of the robot scenario (π_{i2}) is a function of technology attributes, wage rates of skilled and unskilled labour, and an unknown MAV. The "fsolver" of the "SciPy" library (Virtanen et al., 2020) will

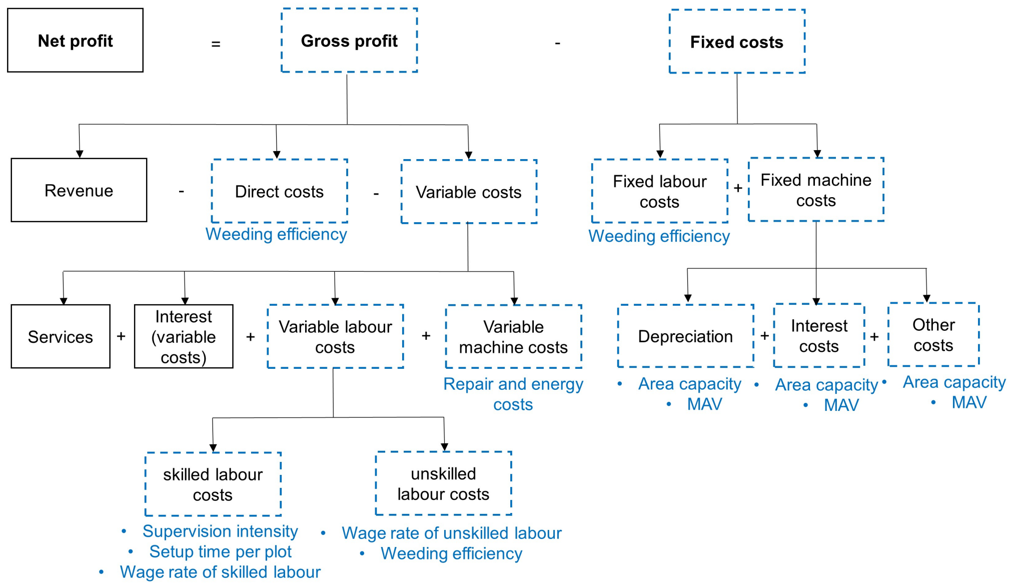


Figure 3.1: Accounting system and how each variable influences the net profit per ha

Source: based on KTBL (2020)

Note: MAV is not drawn from the Monte Carlo simulation but will be derived from the system.

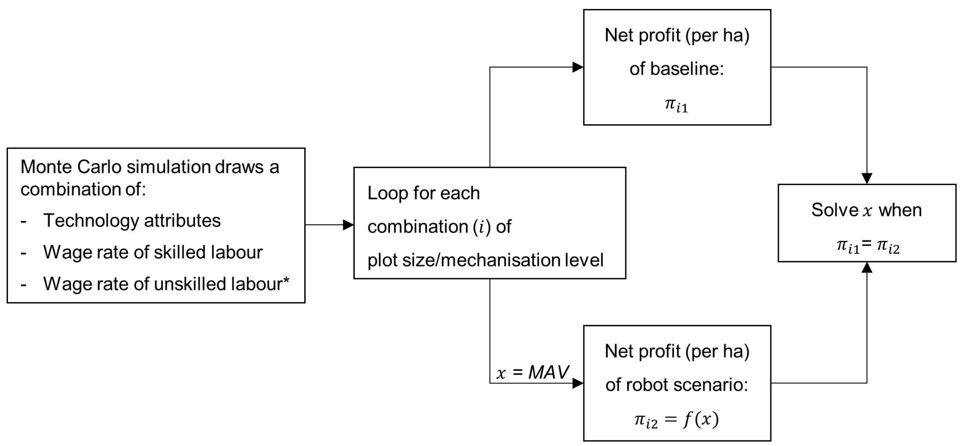


Figure 3.2: Data generation and the calculation of the MAV of one random draw

Source: authors' own figure

Note: * only for organic farming.

find the MAV that equalises net profits (i.e. $\pi_{i1} = \pi_{i2}$) and implicitly determines the MAV.

The same process is iteratively implemented. A large number of draws are needed to obtain a relatively well-represented sample in the multi-dimensional parameter space. In this way, a large dataset consisting of the MAVs and the variables is generated. For organic farming, 32,000 data points were drawn for each combination of plot size and mechanisation level. In the end, 1,568,000 possible data points for all organic farms (32,000 × 49) are generated. For conventional farming, 12,000 draws for each combination are generated, resulting in 588,000 data points.

3.4 Results and discussion

3.4.1 Range of MAVs in two farming systems

Figure 3.3 shows the distributions of the MAVs in organic and conventional sugar beet farming systems in Germany. First, it shows that the MAVs in the organic farming system are distinctly higher than in conventional farming. The MAVs of mechanical weeding robots in organic farming range from €62,564 to €694,073 with a mean of €279,884. In contrast, the MAVs of spot spraying robots in conventional farming have a maximum of €63,364 and a mean of €10,362. Around 21% of the data points have negative MAVs in conventional farming, which means under certain conditions compensation to farmers for using the robot is required to keep the same profitability as in the baseline.

Second, from the distributions of the MAVs of weeding robots in the two farming systems, the MAVs in organic farming are more sensitive to the changes in the randomly drawn variables compared to conventional farming, although the ranges and distributions of the random variables for the two types of robots are the same. This implies that chemical spraying robots in conventional farming must have better technology performances (e.g. higher area capacity, higher weeding efficiency, less repair and energy costs, etc.) to increase the MAVs.

The implication of our result is consistent with the findings by Rübcke von Veltheim and Heise (2020) and Spykman et al. (2021). The higher MAVs of weeding robots in organic farming show that organic farms (especially for high-value crops) can pay much more for weeding robots to obtain the current profit level, thus having a stronger economic incentive to adopt autonomous weeding robots than conventional farms. Besides, the availability of weeding robots (and generally agricultural robots) might change the conversion consideration of conventional farms, for whom the high labour requirement has been an obstacle to convert to organic farming (Olabisi et al., 2015).

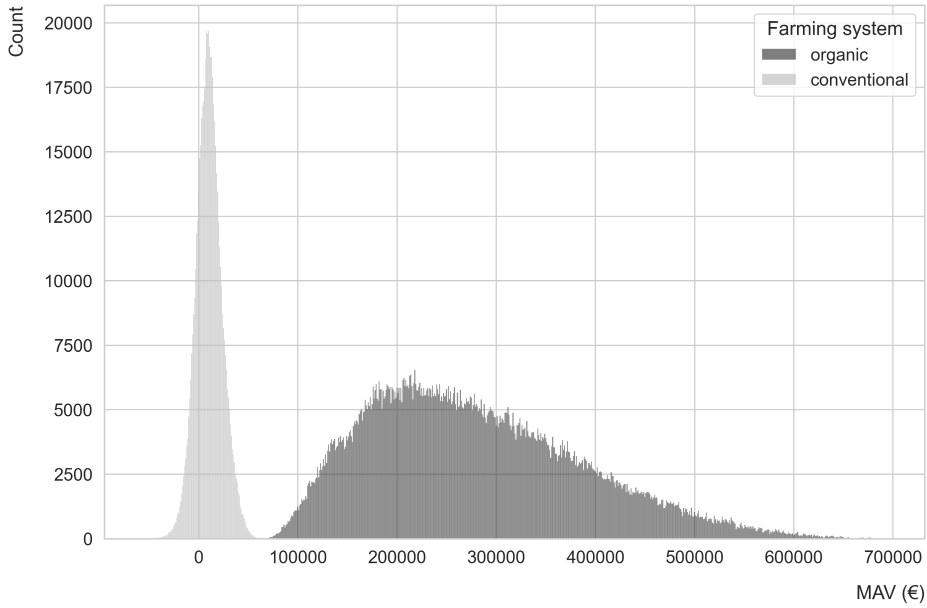


Figure 3.3: Histograms of the MAVs of weeding robots in organic and conventional sugar beet farming systems

Source: simulation results

Note: Organic farming system contains 1,568,000 data points, and conventional farming contains 588,000 data points.

3.4.2 Importance of different factors

To compare the importance of different factors, Table 3.4 is constructed to show how the average MAV changes across each quarter of the simulated range of each factor (averaging across the outcome for all simulations, i.e. averaging across the other variables). For example, for the variable "area capacity" (ranging from 200 to 600 ha), the range is split into four quarters to calculate the average MAV of all data points.

€175,650 is the average MAV of those data points whose area capacity is between 200 ha and 300 ha in organic sugar beet farming. Besides, for each variable, Table 3.4 also presents the change of MAV from Q1 to Q4 (ΔMAV), which measures the importance of the variable in determining the MAV of a weeding robot considering the assumed scale of the variable.

According to this measure, the most important factor in determining the MAVs of weeding robots in organic farming is the area capacity of a weeding robot. When the area capacity increases from a low level (Q1: 200-300 ha) to a high level (Q4: 500-600 ha), the average MAV increases by €208,741. Weeding efficiency (i.e. the percentage of weeds removed by the mechanical weeding robot in organic farming) is the second most important factor. A robot that can remove 87.5%-100% (Q4) of the weeds can attract farmers to pay €150,118 more than a robot with an efficiency between 50%-62.5% (Q1). In terms of labour market effects, the wage rate of unskilled labour has a larger impact than the wage rate of skilled labour on the MAV of a weeding robot in organic farming: The ΔMAV of the wage of unskilled labour is €87,345, but €-9,345 for the wage rate of skilled labour. This is because changes in the wage rate of unskilled labour influence the production cost much greater than the wage rate change in skilled labour. This finding implies that increasingly more expensive seasonal labour could be one important driver for adopting mechanical weeding robots in organic farming. Supervision intensity is the fourth most important factor among the seven factors in influencing the MAV of a weeding robot. When the supervision intensity increases from Q1 (0%-25%) to Q4 (75%-100%), the MAV of a mechanical weeding robot would drop by €21,111. The impacts of repair and energy costs and setup time per plot are less influential compared to other factors.

In conventional sugar beet farming, the most influential factor is supervision intensity. As can be seen, when supervision intensity increases from Q1 (0%-25%) to Q4 (75%-100%), the MAV of a spot spraying robot would drop by €21,934. Both Shockley et al. (2021) and Lowenberg-DeBoer et al. (2021a) found that high supervision intensity can lead to a negative profit level in conventional farming. When only looking at the data points with negative MAVs, the average supervision intensity is 77% (not shown in the table). This result corresponds with the study of Lowenberg-DeBoer et al. (2021a). They found that for a 66 ha farm, using autonomous equipment had no cost advantage anymore when 100% supervision was required. In our simulation, the second most important factor is weeding efficiency (i.e. the percentage of herbicide saved by the spraying robot in conventional farming). Farmers can pay €17,285 more for a spraying robot that can save herbicide by 87.5%-100% (Q4) than a robot that is only able to save 50%-62.5% (Q1) of the herbicide use. Repair and energy costs and the wage rate of skilled labour are of similar importance in determining the MAV. In conventional farming, the area capacity of a weeding robot is much less influential than in organic farming because the economic benefit per ha of using a weeding robot is less than that in organic farming. However, when considering the environmental impact of applying less herbicide, with policy incentives, conventional farmers might be willing to switch to robotic weeding methods.

In both farming systems, setup time per plot plays the least important role in determining the MAV of a weeding robot because the setup cost is only a minor part of the production costs. In general, a longer setup time per plot will decrease the MAV of a weeding robot. However, the differences in MAVs seem to be quite small, in some cases (e.g. in organic farming from Q3 to Q4) even smaller than the sampling noise.

When comparing the impact of technology attributes and labour market effects, it can be seen that the first two most important factors in organic farming are area capacity and weeding efficiency, implying that the advancement of technology will change the MAVs of weeding robots more than the changes in the labour market. And in conventional farming, the most important factors are supervision intensity and weeding efficiency. Thus, in the two farming systems, the results show that the most impact factors are both technology attributes, and labour market effect - within the chosen ranges - is weaker than the impact of technology attributes in determining the MAVs of weeding robots.

3.4.3 Impact of plot characteristics

Figure 3.4 (a) and Figure 3.4 (b) show the average MAV of each plot size and mechanisation level in organic sugar beet farming across all simulation data points. When the plot size increases from 1 ha to 10 ha, the average MAV increases by €9,451, which is only 3.4% of the mean MAV (€279,884) of a weeding robot in organic farming. From 10 ha to 80 ha, there is only a minor increase in MAV. Regarding the mechanisation level, the MAV of a robot that operates on a plot with a mechanisation level of 67 kW is €3,712 higher than that of a plot with a mechanisation level 45 kW. But the average

MAV of farms with a mechanisation level beyond 67 kW does not change. It is because KTBL assumes that beyond 67 kW, the production costs (specifically machine costs and labour costs) do not change for organic farming even though the mechanisation level increases.

Figure 3.4 (c) and Figure 3.4 (d) show the average MAV of each plot size and mechanisation level in conventional sugar beet farming. When the plot size increases from 1 ha to 10 ha, the average MAV increases by €7,468, which is 72% of the mean MAV (€10,362) of a weeding robot in conventional farming. From 10 ha to 80 ha, the average MAV goes up only slightly. It can be observed that the impact of plot size in conventional farming is bigger than that in organic farming. This indicates that a sprayer can work more efficiently on larger fields due to less turning time compared to smaller fields. However, in organic farming, the time requirement of manual weeding (per ha) stays relatively stable as the plot size increases. In terms of mechanisation level, the average MAV is the highest when the mechanisation level is 67 kW. From 67 kW to 120 kW, the average MAV decreases because the average spraying cost goes down as the mechanisation level increases. However, with a mechanisation level of 120 kW, KTBL assumes there is another person driving a water tank when spraying. We will not dig into the assumptions of KTBL but focuses on the overall implication of the results of the two farming systems: When the mechanisation level is above 40 kW, a higher mechanisation level reduces the MAVs of spot spraying robots but has no influence on the MAVs of mechanical weeding robots based on the assumptions of KTBL data.

Comparing the changes in MAVs caused by plot characteristics with the ΔMAVs (Q4 - Q1) caused by technology attributes and labour market effects, it can be seen that plot characteristics have only limited importance in determining MAVs of weeding robots in both farming systems.

Table 3.4: Average MAV (€) of each quarter and the change of MAV (€) from Q1 to Q4

Organic sugar beet farming (Mechanical weeding robots)	**Average MAV (Q1)**	**Average MAV (Q2)**	**Average MAV (Q3)**	**Average MAV (Q4)**	**ΔMAV (Q4-Q1)**
Area capacity (200-600 ha)	175,650	245,224	314,760	384,391	208,741
Setup time per plot (0.16-2 h/plot)	281,580	280,301	278,674	278,956	-2,624
Repair and energy costs (14-56 €/ha)	284,029	280,537	278,316	276,700	-7,330
Weeding efficiency (50%-100%)	204,185	255,289	307,269	354,303	150,118
Supervision intensity (0-100%)	290,236	283,126	277,182	269,125	-21,111
Wage rate of skilled labour (21-42 €/h)	285,200	281,143	277,383	275,855	-9,345
Wage rate of unskilled labour (13.25-21 €/h)	234,391	266,080	296,884	321,736	87,345
Conventional sugar beet farming (Spot spraying robots)	**Average MAV (Q1)**	**Average MAV (Q2)**	**Average MAV (Q3)**	**Average MAV (Q4)**	**ΔMAV (Q4-Q1)**
Area capacity (200-600 ha)	6,473	9,324	11,476	14,107	7,634
Setup time per plot (0.16-2 h/plot)	11,984	10,716	9,953	8,830	-3,154
Repair energy costs (14-56 €/ha)	15,228	11,922	8,975	5,244	-9,984
Weeding efficiency (50%-100%)	1,950	7,430	13,067	19,235	17,285
Supervision intensity (0-100%)	21,170	13,913	6,637	-764	-21,934
Wage rate of skilled labour (21-42 €/h)	14,436	11,833	8,987	6,153	-8,283

Source: simulation results

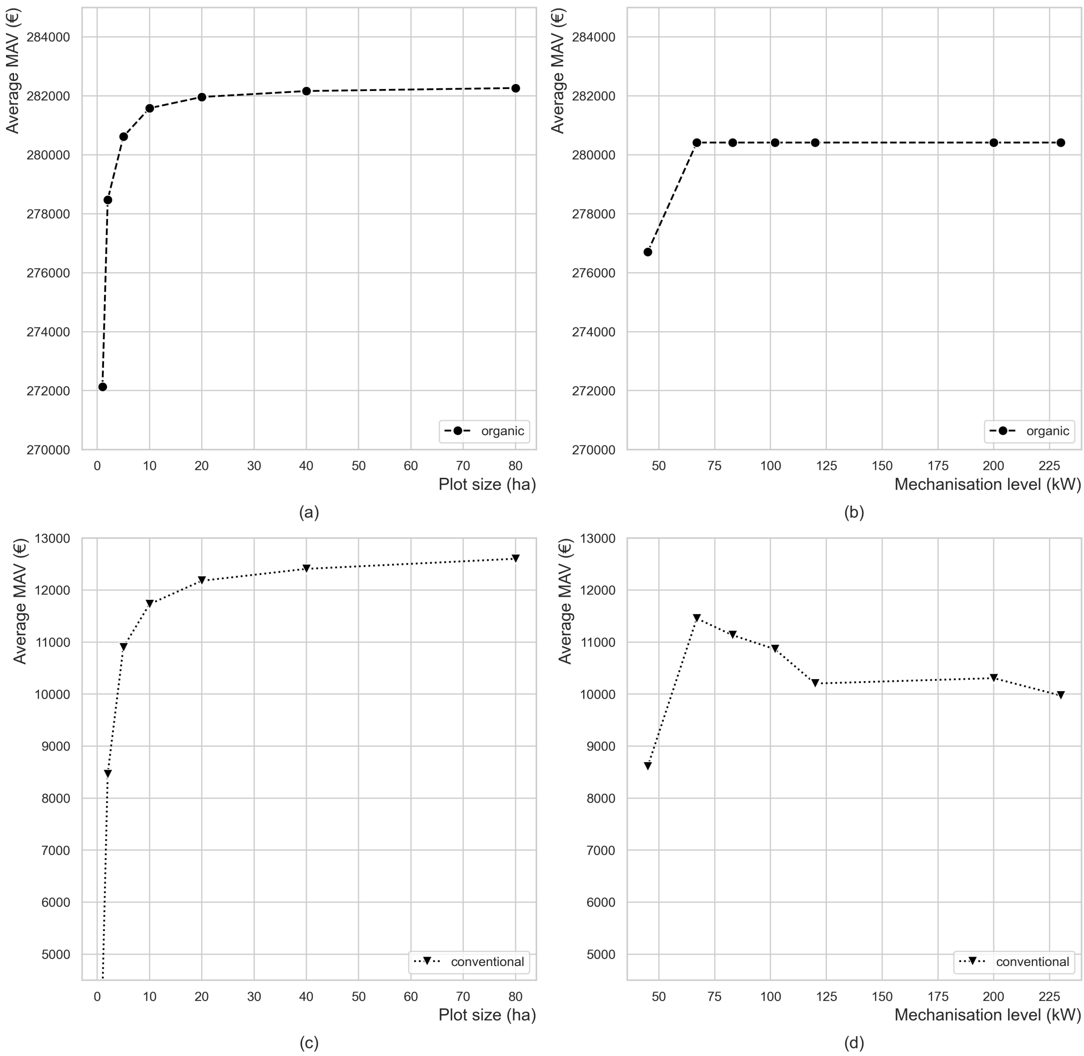


Figure 3.4: Average MAVs of weeding robots of each plot size and mechanisation level in both farming systems

Source: simulation results

3.5 Conclusion

This chapter investigates the MAVs of weeding robots and the importance of factors from different categories (including technology attributes, labour market effects, and plot characteristics) in determining MAVs of weeding robots in German sugar beet farming. It uses a Monte Carlo simulation approach combined with empirical data of KTBL and assumptions about different robotic characteristics based on the information collected from weeding robot companies. The MAV is defined as the break-even investment price that renders the same net profit level as using the current weeding methods.

Under the assumption that mechanical weeding robots replace manual weeding in organic farming, and spot spraying robots replace untargeted herbicide spraying in conventional farming, and considering plausible ranges for the robot characteristics, the results show that the MAVs of mechanical weeding robots in organic farming range from €62,564 to €694,073 with a mean of €279,884. In contrast, the MAVs of spot spraying robots in conventional farming have a maximum of €63,364 and a mean of €10,362. The huge difference in MAVs between organic and conventional farming systems indicates that the economic benefit of mechanical weeding robots for organic farming surpasses that of spot spraying robots for conventional farming, and organic farms are able to pay considerably more for a weeding robot than conventional farms to maintain the current net profit level. Therefore, the adoption and diffusion of weeding robots might also start among organic farms, which is consistent with the findings from previous qualitative studies. Another implication is that the availability of weeding robots (and generally agricultural robots) might change the conversion decision of conventional farms, for whom the high labour requirement could be an obstacle so far.

This chapter also quantifies and compares the importance of factors in determining the MAVs of weeding robots from different categories. Firstly, technology attributes are more influential than labour market effects in determining the MAVs of weeding robots. For organic farming, the area capacity of a robot impacts its MAV the most, followed by weeding efficiency (the percentage of weeds that can be removed by the mechanical weeding robot). For conventional farming, supervision intensity is the most influential factor, and weeding efficiency (the percentage of herbicides that can be saved by the spot spraying robot) is the second. Secondly, the wage rate of unskilled labour has a larger impact than the wage rate of skilled labour on the MAV of a weeding robot in organic farming because of the high share of unskilled labour costs in the total production costs. The implication is that the shortage in seasonal labour could be one important driver for adopting mechanical weeding robots in organic farming. Thirdly, supervision intensity is the most influential factor in determining the MAVs of spot spraying robots. Our results indicate that high supervision costs in robotic weeding can cause economic infeasibility in conventional farming. In addition, we find that plot characteristics have limited importance in determining the MAVs of weeding robots, compared to technology attributes and labour market effects.

To the best of our knowledge, this study innovates by comparing the importance of factors from different categories (technology attributes, labour market effects, and plot characteristics) in determining the MAVs of weeding robots in both organic and conventional farming systems. Our approach allows us to experiment with different performances of weeding robots and changes in the labour market. One of the limitations of this study is that the robot scenario does not consider the changes in crop yield and quality, the alternative use of the farm labour after adopting weeding robots, and the environmental impacts at both farm and regional levels due to the lack of data. Future research can make use of data collected by large-scale on-farm precision experimentations (Bullock et al., 2019) with input use decisions and precision and autonomous farming equipment to capture not only the economic but also environmental impacts.

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Chapter 4

Surrogate modelling of detailed farm-level models using state-of-the-art neural networks[11]

Abstract: Technological change co-determines agri-environmental performance and farm structural transformation. Meaningful impact assessment of related policies requires farm-level models to be rich in technology details and environmental indicators, integrated with agent-based models capturing dynamic farm interaction. However, such integration faces considerable computational challenges affecting model development, debugging and application. Surrogate modelling using machine learning techniques may enable such integration for simulations with broad regional coverage. We develop surrogates of the farm model FarmDyn using state-of-the-art neural networks. All tested neural networks achieve a high fit but differ substantially in inference time. We develop evaluation metrics allowing practitioners to assess trade-offs among model fit, inference time and data requirements. The Multilayer Perceptron shows almost equal performance in all criteria but saves strongly on inference time compared to a Bi-directional Long Short Term Memory.

Keywords: *deep neural networks, surrogate model, farm modelling, agent-based model, upscaling*

[11]Chapter 4 is currently under review in an international journal in the category of "Agricultural Economics & Policy" as Shang, L., Wang, J., Schäfer, D., Heckelei, T., Gall, J., Appel, F., and Storm, H.: Surrogate modeling of detailed farm-level models using state-of-the-art neural networks. The data and codes used for this chapter can be found in the following Github repository: https://github.com/linmeishang/SurrogateNN

JEL classification: C45; C63; Q12; Q18

4.1 Introduction

Modelling the impacts of agri-environmental policies increasingly requires accounting for detailed farm-level decision-making, heterogeneous local conditions, and interaction among farmers. Policies that are relatively homogenous across regions (such as tariffs and export subsidies at the EU level or decoupled income support) are continuously substituted or complemented with more targeted farm-level policies, e.g. the newly introduced eco-schemes or collective agri-environmental payments that require coordination and participation of local communities (Kuhfuss et al., 2016; Šumrada et al., 2022). Detailed farm-level models (Richardson et al., 2014; Weersink et al., 2002), usually implemented as optimisation models, are capable of representing individual decision-making with a rich representation of input choices, investments, and environmental indicators. However, those farm-level models usually do not account for interaction among farmers, market feedback, or environmental feedback on larger scales (Heckelei, 2013; Shang et al., 2021). Here, Agent-based Models (ABMs) (Gilbert, 2007) step in to model endogenous market feedback and to capture the dynamic interaction of heterogeneous farms (Kremmydas et al., 2018; Müller et al., 2020; Rasch et al., 2017). However, computational demands limit the complexity of the employed farm decision-making model within an ABM or the number of agents and hence the regional coverage of those models (Bradhurst et al., 2016; Murray-Rust et al., 2014; Sun et al., 2016). Integrating detailed farm-level models as individual decision-making models into ABMs - while still covering a larger region - is desirable for policy analysis but usually comes with high computational costs. This chapter addresses this issue by training and evaluating computationally efficient surrogates that can be integrated into ABMs in place of the original farm models without any relevant losses in accuracy and details of model outcomes.

We demonstrate the training and evaluation of surrogate models of the farm-level model FarmDyn (Britz et al., 2016), which could be integrated into an ABM like Agricultural Policy Simulator (AgriPoliS) (Appel and Balmann, 2019; Happe et al., 2006). FarmDyn simulates farm production and investment decisions under changes in prices of inputs/outputs, technology, and policy instruments for different farming branches in Germany and beyond (Britz et al., 2021). The linkage of biophysical parameters to highly detailed farming activities enables users to assess both economic and environmental policies with a wide range of social, economic, and environmental indicators at the farm level. FarmDyn has been applied to assess the impact of the German fertilisation regulation (Kuhn et al., 2020), the impact of changes in water levels of peat soils on farm income (Poppe et al., 2021), and the impact of European fertiliser laws on legume production (Heinrichs et al., 2021). The profit-maximising solution of a farm is solved by Mixed-Integer Programming (MIP), which is time-consuming when many variables and constraints of different types are involved (Seidel and Britz, 2019). AgriPoliS is a spatial and dynamic ABM that explicitly models farmers' interaction on the land market. It has been used to study the impact on agricultural structural change of different policies, e.g. decoupling direct payment (Happe et al., 2008) and Germany's biogas policy (Appel et al., 2016). In AgriPoliS, farmers maximise the household income/profit, which is also solved by MIP. Compared to FarmDyn, the MIP in AgriPoliS is simpler because it models less detailed technology choices and faces fewer constraints (e.g. environmental constraints). If we directly integrate the MIP of FarmDyn into AgriPoliS to combine the strengths of both, it will be computationally demanding and quickly prohibitive as the spatial coverage expands (Bradhurst et al., 2016; Huber et al., 2022; Sun et al., 2016). However, combining the advantages of both types of models becomes increasingly necessary for agri-environmental policy analysis (Huber et al., 2018).

Surrogate models, also known as metamodels or emulators, may solve this problem (Jiang et al., 2020; Ratto et al., 2012). They approximate computationally costly simulation models by mapping the relationship between inputs and outputs while being much cheaper to run. The availability of highly flexible machine learning tools such as Neural Networks (NNs) (Goodfellow et al., 2016) offers the opportunity to build surrogates of complex and computationally demanding simulation models (Razavi, 2021; Storm et al., 2020). In this way, a surrogate model functions as a bridge between detailed farm-level models and large-scale ABMs to efficiently utilise the advantages of both types of models. Surrogate modelling has been applied in various fields, such as water resource modelling (Razavi et al., 2012), engineering (Jiang et al., 2020), and weather forecasting (Chen et al., 2020). However, the application of surrogate modelling using NNs in agricultural economics is relatively rare compared to other fields. Audsley et al. (2008) use a classical type of NN, Multilayer Perceptron (MLP), to replace a crop model and predict crop yields, which are further used in an economic model. Nguyen et al. (2019) also employ a MLP as a surrogate of a biogeochemical model to predict crop yields and soil organic carbon. The predictions of the MLP are used to compute the objective and constraint functions for farm-level optimisation. Nevertheless, to the best of our knowledge, surrogate modelling using state-of-the-art architectures of NNs is unexplored in agricultural economics. This chapter aims to develop surrogate models for FarmDyn as a first step such that it can be integrated into ABMs like AgriPoliS.

We aim to make four main contributions. First, we show it is possible to build well-fitted surrogates of detailed farm-level models using NNs. Second, we systematically compare the performances of different state-of-the-art architectures of NNs. Third, we develop a set of evaluation metrics to assess the quality of surrogate models. Here, we go beyond criteria such as R^2 or Mean Squared Error (MSE) and develop generic metrics that can also be applied to evaluate other surrogate models. They help judge if the trained surrogate provides the required accuracy for the intended purposes. It is essential because different architectures of NNs deviate substantially in inference time (i.e. the time to make one prediction) with only minor differences in R^2 or MSE. Thus, more detailed and practically relevant evaluation metrics are required to judge if those differences in R^2 or MSE are of practical importance and justify the increased inference time. Fourth, we investigate the performance of surrogate models given different sample sizes to provide practical guidance for modellers. While it is possible to increase the sample size by running the underlying model deliberately, it is often computationally expensive. Hence, for practical purposes, it is crucial to determine how much data is required for different architectures of NNs to achieve the desired performance on the defined evaluation metrics.

This chapter is organised as follows. Section 4.2 reviews existing surrogate models to identify the common architectures of NNs currently used in the literature. Section 4.3 introduces the overall research design. In section 4.4, we analyse the results and assess the performance of NNs given different sample sizes. Section 4.5 concludes and points out directions for future research.

4.2 NNs as surrogate models in the literature

Surrogate models in the literature are based on a large variety of model types, including polynomial regression (Hussain et al., 2002), radial basis functions (Amouzgar and Strömberg, 2017), kriging (Kleijnen, 2009), Gaussian processes (Picheny, 2015), support vector machines (Xiang et al., 2017), genetic programming (Fallah-Mehdipour et al., 2013), Bayesian networks (Gruber et al., 2013), and NNs (Sun and Wang, 2019). Throughout this study, we focus on NNs as they bring new promise to build cost-effective surrogate models (Chen et al., 2021). This section introduces basic concepts of NNs and identifies the common architectures of NNs used as surrogates in the literature.

4.2.1 Basic concepts of NNs

NNs are mathematical models that try to mimic the biological nervous systems. They are capable of representing highly non-linear relationships and are well-placed to deal with high dimensions in the input and the output space. Figure 4.1 (a) depicts the most commonly used architecture of NN: MLP. It consists of an input layer, an output layer, and at least one hidden layer between the two. Each layer contains a certain number of neurons. Like a biological neuron, an artificial neuron processes the information from the inputs in the previous layer and transfers the signal to the next neuron, as shown in Figure 4.1 (b). An artificial neuron performs two steps of computation. First, a weighted sum of all inputs is computed as shown in Equation (4.1):

$$z = \sum_{i=1}^{m} w_i x_i + b, \tag{4.1}$$

where w_i is the weight of the input neuron x_i, b is the bias, m is the number of input neurons, and z is the weighted sum.

Second, the weighted sum will be transferred by an activation function ($f(z)$). Typically, activation functions are non-linear. For example, the Rectified Linear Unit (ReLU) returns the value that is equal to the input if it is positive, and it returns zero otherwise[12].

[12]See Goodfellow et al. (2016) for further details.

Weights and biases are called "parameters" of a NN. Training a NN like MLP is to find the optimal parameters to minimise the loss function, i.e. a function that measures the difference between the predicted outputs and the true outputs (e.g. the MSE loss). This process is usually done iteratively through backpropagation algorithms that compute the gradient of the loss function with respect to the weights and biases (Rumelhart et al., 1986). The gradients are then used by an optimisation algorithm, i.e. an optimiser, to update the parameters. Training the NN with all the training data for one cycle is called one "epoch". Usually, NNs are trained for multiple epochs. Within one epoch, the training dataset can be divided into mini-batches, which will be passed through to the NN at one time. The number of data points that a mini-batch contains is called the "mini-batch size".

While parameters can be estimated by algorithms from the training data, "hyperparameters" cannot be estimated from the data and are usually set manually by the modeller before training. NNs have various hyperparameters (like the number of layers and neurons). They may interact with each other in non-linear ways. Hyperparameter tuning is a procedure of finding the optimal hyperparameters of a NN (or other machine learning models). We will introduce this in detail in section 4.3.

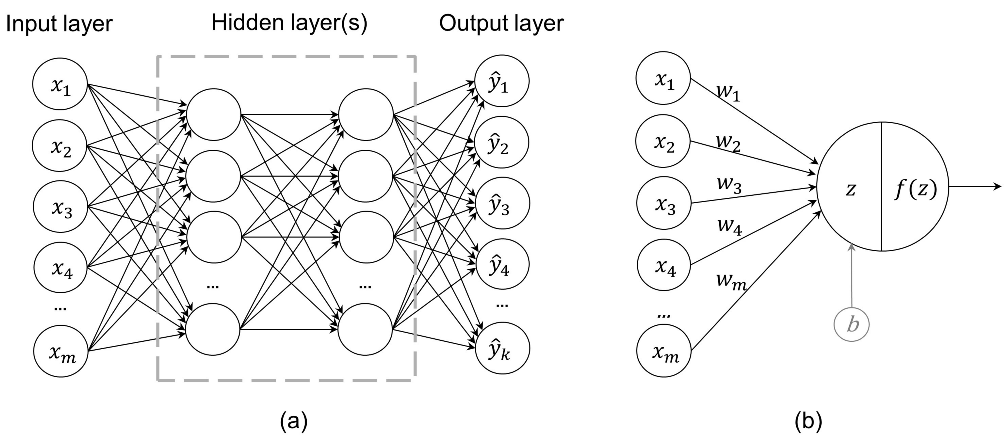

Figure 4.1: The architecture of a MLP (a) and an artificial neuron (b)

Source: based on Goodfellow et al. (2016)

Note: x_i is the value of an input neuron, $\hat{y}_i$ is the prediction of an output neuron, w_i is the weight of a neuron, b is the bias, z is the output of the weighted sum, and $f(z)$ represents the activation function.

4.2.2 Different architectures of NNs used in surrogate modelling

MLPs have been widely used as surrogates in diverse disciplines (Roman et al., 2020). It has been proven that a MLP of one hidden layer (i.e. a shallow NN) with an adequate number of neurons can be trained to approximate any measurable function to any desired degree of accuracy (Hornik et al., 1989). As a result, studies using shallow MLPs are common in surrogate modelling. For example, Carnevale et al. (2012) use a one-hidden-layer MLP to learn the relationship between emissions and air quality indices. In the review of Razavi et al. (2012) about surrogate models in water resource modelling, 13 out of 14 papers used shallow NNs. However, deep NNs (i.e. with more than one hidden layer) might require fewer neurons to capture a similar level of complexity and thus are also applied as surrogates. For instance, Liong et al. (2001) use a NN with three hidden layers to mimic a hydrological model.

The second common type of NNs used as surrogate models is Convolutional Neural Networks (CNNs) (LeCun et al., 1990), originally designed for image data. CNNs build connections across neurons in the same layer by hooking neurons and their neighbours together through convolution kernels. Neurons of CNNs do not have to be connected to all the neurons of the next layer (Davies, 2018), and the position of an input neuron matters. CNNs are also promising in handling time-series data (Fawaz et al., 2019). Although deeper CNNs might be able to capture more complex relationships, classical CNNs do not perform well as they grow deeper due to the problem of vanishing gradient (i.e. the gradients of the loss function approach zero, making NNs hard to train) (Bengio et al., 1994). To overcome this issue, Residual Networks (ResNets) (He et al., 2016) allow skip connections to enable the training of deeper networks. Weber et al. (2020) find ResNets perform better than classical CNNs in surrogate modelling for climate forecasts.

The third common type of NNs used is Recurrent Neural Networks (RNNs) (Elman, 1990; Rumelhart et al., 1986; Werbos, 1988), designed for sequence prediction tasks, such as speech recognition (Graves et al., 2013) and time series modelling (Hsu, 2013). RNNs use their internal state (memory) to process variable-length sequences of inputs by returning the output of one neuron as input to another neuron of the next time step. However, as the length of inputs increases, long-term dependencies can hardly be learnt by classical RNNs (Marhon et al., 2013). Long Short-Term Memory (LSTM) (Hochreiter and Schmidhuber, 1997) is a special RNN, capable of learning long-term dependencies. Rahmani et al. (2021) have developed LSTMs as surrogates of a process-based model to predict stream water temperature. LSTMs have been used to predict crop yields (e.g. Sun et al., 2019; Tian et al., 2021), but to our knowledge, they are not yet applied as surrogates of agricultural models. The BiLSTM (Bidirectional Long Short-term Memory) (Graves et al., 2005) is an extension of LSTM. It learns the sequence and the reversed sequence of the inputs. Alibabaei et al. (2021) use a BiLSTM to model evapotranspiration and soil water content in irrigation scheduling. RNNs are also helpful for non-sequential data. For example, Chopra et al. (2017) train a RNN with non-sequential data to predict whether a patient would be readmitted to the hospital.

Although MLPs have been applied as surrogates by Audsley et al. (2008) and Nguyen et al. (2019) (see section 4.1), and LSTMs have been used to predict crop yields as mentioned above, using NNs of different architectures as surrogates is unexplored in agricultural models. Besides, no NN applications to approximate economic farm models are known to us. Given these research gaps, this study will employ the four state-of-the-art architectures of NNs including MLP, ResNet, LSTM, and BiLSTM to develop surrogate models of the detailed farm-level model FarmDyn.

4.3 Method and data

Our research design is shown in Figure 4.2. First, from the underlying farm model FarmDyn, we generate the data that will be used for training NNs. This involves defining the inputs/outputs of the farm model, generating data, and some data preparation steps. Second, for each of the four NN architectures, we define three different implementations that vary in depth (i.e. the number of layers). This results in 12 variants of depth, for which we perform optimisation for the remaining hyperparameters. The loss function used to train NNs is the MSE loss. It should be noted that minimising MSE is by construction equivalent to maximising R^2 (see Equation (4.2)). We then select one best model in terms of R^2 from each variant of depth (in total 12 best models) and compare their inference time. Third, from each NN architecture, we select the best model with the most promising hyperparameters and inspect model performance in greater detail. Specifically, we examine model performance across varying sample sizes by considering a set of evaluation metrics. The details of these three steps are described below.

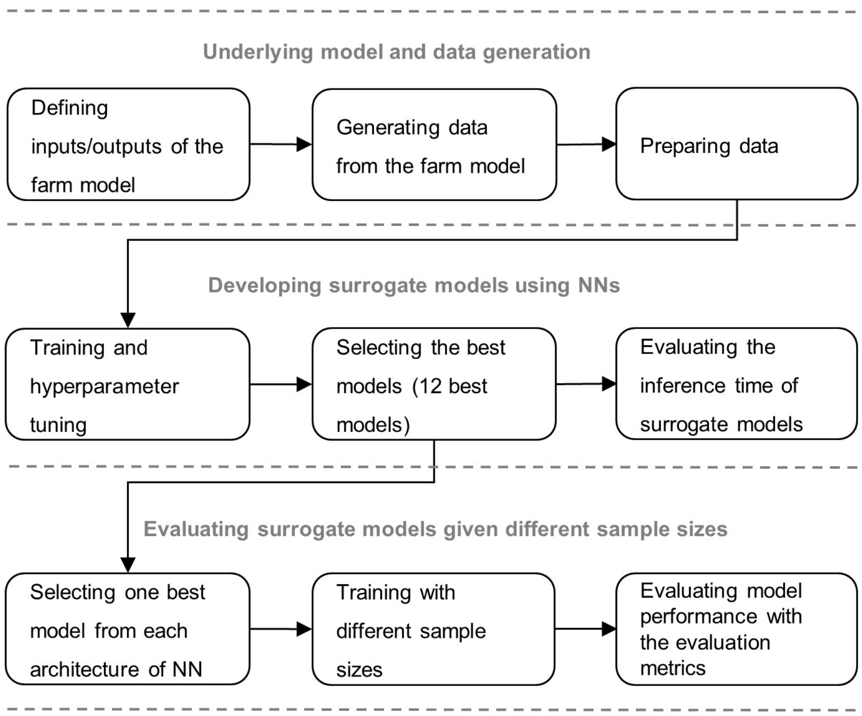

Figure 4.2: The overall research design of this chapter

Source: own illustration

4.3.1 The underlying model and data generation

4.3.1.1 *Define inputs/outputs of the farm model*

To build a surrogate model of FarmDyn, it is necessary to define the model interface clearly. This means we need to define what input variables we pass to the model and what output variables we aim to obtain. In our case, the surrogate model takes the same inputs and produces the same outputs as the underlying model FarmDyn. Therefore, defining the inputs/outputs of FarmDyn will technically define the inputs/outputs of the surrogate model. FarmDyn models a wide range of farm branches, such as arable, dairy, beef cattle, pig fattening, and biogas. This study focuses on approximating the behaviour of arable farming. Table 4.1 summarises the inputs and outputs of arable farms in FarmDyn. They include variables about crops, farming inputs, machinery, farm endowment, environmental indicators, and farm accounting. Crops included in the model are winter wheat, winter barley, winter rapeseed, summer cereal, maize, and sugar beet. The farming inputs include diesel, fertiliser (urea-ammonium nitrate, phosphorus, and potassium), seed, lime, herbicide, fungicide, insecticide, growth control, water, and hail insurance. In total, there are 77 inputs and 248 outputs. There are many constant parameters in FarmDyn, but we exclude them here since the surrogate model should be able to learn the underlying constant parameters that reflect the relationship between inputs and outputs.

Table 4.1: Summary of inputs and outputs of arable farms in FarmDyn

	Inputs (unit)	Outputs (unit)
Crops	• selling price of crops (€/t)	• production level (ha) • production quantity (t) • sale quantity (t) • crop revenues (€) • amount of fertiliser used (kg/ha) • output quantity of crop residues (t) • revenue from crop residues (€)
Farming inputs	• price (€/L, €/kg, €/t, €/ha)	• used amount (L, kg, t, ha) • cost (€)
Machinery	• price (€)	• applied area (ha) • fixed cost (€) • variable cost (€)
Farm endowment	• farm size (ha)	• amount of idle land (ha) • shadow price of land (€/ha) • distribution of labour to each month (hours) • distribution of labour to on-farm and off-farm work opportunities (hours)

Environmental indicators	• nitrogen needed from mineral fertiliser per ha (kg/ha) • phosphate need from mineral fertiliser per ha (kg/ha)	• average nitrogen/phosphate input (kg/ha) • average nitrogen/phosphate surplus (kg/ha) • nitrogen leaching on the farm (kg) • phosphorus loss on the farm (kg) • emissions on the farm (e.g. phosphorus, nitrous oxide) (kg) • global warming potential as CO_2 equivalent (kg) • particulate matter formation potential (kg) • terrestrial acidification potential (kg) • freshwater eutrophication potential (kg) • marine water eutrophication potential (kg)
Farm accounting	/	• variable costs of crops, fertilisers, phytosanitary, machinery (€) • total crop revenue (€) • off-farm income (€) • sum of investments (€) • profit (€) • cash flows (€) • withdraw (€) • depreciation (€) • total premium (€) • income (€)
Number of variables	**77**	**248**

Source: based on FarmDyn (Britz et al., 2016)

4.3.1.2 *Data generation and preparation*

The initial farm data is generated from FarmDyn by Latin Hypercube Sampling (LHS) (McKay et al., 1979). LHS independently stratifies each input dimension into N equal intervals, where N is the number of data points. For a given dimension, it generates one data point in each interval and randomly combines this with the selected interval of the other dimensions. LHS provides outcomes from a uniform distribution of the data within the design space (Tyan and Lee, 2019). The optimal sample size to train a surrogate model depends on the complexity of the problem and the computational budget available. Since NNs need large datasets for problems with high dimensionality, we generated as many data points as possible given our time budget. With 10,000 model outcomes (i.e. observations) each time, the data generation process ran 17 times and produced 163,480 data points (taking about 45 hours) because FarmDyn did not successfully solve for some input draws due to implausible input combinations. The whole dataset is then randomly split into two subsets including the training set (90%) and the test set (10%), each having 147,132 and 16,348 observations, respectively. The training set is used to train the model, and a test set is solely used to assess the model. During the training process, 10% of the training set is used as a validation set to monitor the models' performance on unseen data to avoid overfitting, meaning the network learns too much information that is specific to the training data and does not generalise for other datasets. The validation set is also used to implement "early stopping" given a stopping criterion, e.g. when the loss function stops decreasing after a certain number of epochs. The difference between the validation set and the test set is that the test set is used to assess the final performance of a trained model, but the validation set is a part of the training set that is used during training to monitor the performance of the model. Normalisation of data is recommended since it usually leads to faster convergence (Huang et al., 2020). For the training set, we normalised both input and output data between 0 and 1 with the "MinMaxScalar" of the python package "scikit-learn" (Pedregosa et al., 2011). The test set is then normalised by the scalar of the training set because the unseen data must fit into the trained scale of the NN.

4.3.2 Developing surrogate models using NNs

4.3.2.1 *Training and hyperparameter tuning*

Developing surrogate models using NNs means obtaining well-fitted NNs that can approximate the underlying model. As mentioned above, while the training process that optimises parameters of a NN is automatically done by computer algorithms, hyperparameters are usually set by modellers manually before training. Types and numbers of hyperparameters differ among different types of NNs. Here, we focus on the main hyperparameters.

The number of hidden layers (i.e. the depth) is a determinant for NNs' ability to capture complex relationships. Although deep networks might perform better than shallow networks, increasing the depth does not always improve the performance (He et al., 2016). To compare the performance of NNs of different depths, we train three variants of depth for each architecture of NN: For MLP, LSTM and BiLSTM, we train models with one, two, and three hidden layers, respectively; for ResNet, we train models with 18, 34, and 50 layers since these are proposed by the original paper of He et al. (2016). Our ResNets are one-dimensional CNNs due to the characteristics of our input data. The hyperparameter tuning for the 12 variants was done according to the following steps (Table 4.2).

Step 1: Number of neurons in a hidden layer/Number of filters in the 2nd stage

For each variant of depth of MLP, LSTM, and BiLSTM, we must tune the number of neurons in each hidden layer since it is an important hyperparameter determining the performance of NNs. A small number of neurons could lead to underfitting, meaning the network is not complex enough to capture underlying relationships in the data. A high number could cause overfitting. We experiment with the number of neurons of {32, 64, 128, 256, 512, 1024, 2048} in each hidden layer.

For the three variants of ResNets, we tune the number of filters in the 2nd stage. The commonly used ResNets have five stages of convolutional process. The number of filters in the 2nd stage will automatically determine the number of filters in the following stages (He et al., 2016). The training process of ResNets estimates the weights of all filters. We explore the space of {16, 32, 64, 128, 256, 512} for this hyperparameter.

Step 2: Learning rate

The learning rate determines the speed of the algorithm to head to the next solution in the parameter search space. A small learning rate takes a long time for the network to converge, and a large learning rate might cause the network not to converge. We explore the space of {0.0001, 0.0003, 0.001, 0.003, 0.01} for learning rate for all models.

Step 3: Mini-batch size

Mini-batch size determines how often the loss function is computed in one epoch and thus influences the updates of parameters. We experiment with a mini-batch size of {16, 32, 64, 128} for all models.

Step 4: Optimiser

Optimisers determine how the parameters of a network are changed to reduce the loss function. We experiment with {Adam (adaptive moment estimation), Adamax (a variant of Adam based on the infinity norm), RMSprop (root mean square propagation), SGD (stochastic gradient descent)}[13] .

Since we only tune one hyperparameter at each step, the rest of the hyperparameters should be set with default values in order to start training. The last column of Table 4.2 indicates the default setting of other hyperparameters at each step besides the tuned hyperparameter. As can be seen, we do not tune the activation function. For MLP and ResNet, we use the ReLU activation function; for LSTM and BiLSTM, we use the tanh activation function (i.e. hyperbolic tangent function) to enable faster training on GPU (Graphics Processing Unit). Early stopping is used to determine when the training process should be stopped. The maximum number of epochs is set to 200, but the training process will be terminated when the validation error stops decreasing after 15 epochs. The performance of a NN is recorded after each epoch, and the model with the lowest MSE on the validation set will be saved as the trained model. All NNs are built and trained using the "Keras" library (Chollet, 2015). To run the experiments, we use a 11 GB GPU (NVIDIA GeForce RTX 2080 Ti).

[13] See the Github repository of the "Keras" library (Chollet, 2015).

4.3.2.2 *Selecting the best models and evaluating the inference time*

After hyperparameter tuning, we select the 12 best models (three variants of depth from each architecture) according to the R^2 on the test set. Then, we examine the inference time, defined as the time to make one prediction (i.e. one forward run of the NN), of the selected models. Inference time determines the efficiency of the surrogate model in future applications. To make a fair comparison between the trained NNs and FarmDyn, we record the simulation time of FarmDyn and the inference time of NNs on the same machine (with Intel Xeon CPU E5-2699 V4, 2.20GHz). The same experiment is repeated five times, and the average inference time per data point of each NN is calculated to avoid fluctuations in computing time.

Table 4.2: Steps and search spaces of hyperparameter tuning of different NNs

Steps	**Tuned hyperparameter at this step**	**MLP** with hidden layer(s) of {1, 2, 3}	**LSTM** with hidden layer(s) of {1, 2, 3}	**BiLSTM** with hidden layer(s) of {1, 2, 3}	**ResNet** with layer(s) of {18, 34, 50}	**The default setting of other hyperparameters at this step**
Step 1	Number of neurons in each hidden layer	{32, 64, 128, 256, 512, 1024, 2048}			/	learning rate = 0.001 mini-batch size = 32 optimiser = Adam activation function = ReLU (for MLP and ResNet), tanh (for LSTM and BiLSTM) epochs = 200 (early stopping)
	Number of filters in the 2nd stage	/			{16, 32, 64, 128, 256, 512}	
Step 2	Learning rate	{0.0001, 0.0003, 0.001, 0.003, 0.01} for all NNs				mini-batch size = 32 optimiser = Adam activation function = ReLU (for MLP and ResNet), tanh (for LSTM and BiLSTM) epochs = 200 (early stopping)
Step 3	Mini-batch size	{16, 32, 64, 128} for all NNs				optimiser = Adam activation function = ReLU (for MLP and ResNet), tanh (for LSTM and BiLSTM) epochs = 200 (early stopping)
Step 4	Optimiser	{Adam, Adamax, RMSprop, SGD} for all NNs				activation function = ReLU (for MLP and ResNet), tanh (for LSTM and BiLSTM) epochs = 200 (early stopping)

4.3.3 Evaluating surrogate models

4.3.3.1 *Motivation to evaluate surrogate models besides R^2*

The training process described above uses the entire training set we have generated. However, from a practical perspective, there are two aspects we must consider when developing and applying the surrogate model: (1) Generating data from highly detailed farm-level models could be time-consuming. Although increasing the sample size is always possible, it is time-consuming and computationally expensive for modellers. From a practitioner's perspective, a natural question is how to determine when to stop generating data. For this, we need to assess how additional data can affect model performance, and we need to determine when the surrogate model has obtained an accuracy that is sufficient for the envisioned application. The latter is usually difficult to assess based on the R^2 measure; (2) Different model architectures might differ substantially in inference time, with MLPs being much faster than the other architectures and possibly only minor differences in model performance in terms of R^2. Thus, we need additional evaluation metrics that are more targeted to the application of the surrogate model to judge if those differences in model performance are relevant from a practical perspective and justify a longer inference time.

Therefore, we first develop evaluation metrics besides R^2 (see section 4.3.3.2) that are relevant for the application of the surrogate model. Secondly, we perform a simulation exercise (see section 4.3.3.3) where we evaluate the performance of the four different architectures when trained with varying sample sizes. These simulations allow us to assess if similar performance could be achieved with a smaller sample or if we can expect performance increases from additional data. Additionally, it allows us to inspect how the alternative model evaluation criteria (besides R^2) behave when varying sample sizes. This helps us decide which sample size is required to achieve acceptable performance from an application point of view.

4.3.3.2 *Evaluation metrics*

(1) Goodness of fit

Like many other studies (see Roman et al., 2020), we use R^2 to measure the overall goodness of fit of a surrogate model on the test set. R^2 measures the proportion of the total variation in an output variable explained by the model. For an output variable y, the R^2 in terms of this output is calculated with Equation (4.2).

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}, \tag{4.2}$$

where y_i is the true value of the output y of the observation i, $\hat{y}_i$ is the predicted value of the output y of the observation i, and $\bar{y}$ is the mean of the true values of the output y.

The R^2 typically ranges from 0 to 1. However, when a model's performance is worse than simply predicting the mean of the output for all observations, it becomes negative. Since we only select models that have a positive R^2, it ranges from 0 to 1 in this study. We calculate the average R^2 across all outputs with Equation (4.3).

$$R^2 = \frac{1}{K}\sum R^2_{y_k}, \tag{4.3}$$

where K is the number of outputs (K = 248 in this study).

(2) Consistency of bivariate relationships

From an application perspective, it is crucial to assess whether some fundamental relationships between an input and an output or between two outputs are learnt by the surrogate model. This is particularly important for applications where the results of scenarios strongly depend on the relationship between certain variables. For example, when simulating scenarios about nitrogen fertilisation and its environmental impact, modellers would want to check if the surrogate model can correctly capture the relationship between fertilisation decision and the environmental outcomes. Here, we consider if the relationship between the amount of nitrogen applied and the amount of nitrogen leaching on a farm is learnt by the surrogate model. In FarmDyn, for a specific crop of a certain yield level, the relationship between the two variables is linear. However, it becomes non-linear at the farm level depending on the crop rotation decisions. To capture the non-linear relationship between two variables, we use the Maximum Information Coefficient (MIC) (Reshef et al., 2011, see Appendix 4.A), a non-parametric method that has been widely applied (Cao et al., 2021). MIC ranges from 0 to 1. The higher the MIC is, the stronger the relationship between the two variables. We use the python package "minepy" (Albanese et al., 2013) to calculate the

MICs. Then, we calculate the Absolute Percentage Error (APE) between the true and predicted MICs between the two variables with Equation (4.4).

$$APE_{relationship} = |MIC_{true} - MIC_{pred}| \,/\, MIC_{true}, \tag{4.4}$$

where MIC_{true} is the MIC between the amount of nitrogen applied and nitrogen leaching on a farm calculated from the true data, and MIC_{pred} is calculated from the predicted data.

(3) Accuracy in capturing corner solutions

Another important aspect for the application of surrogate models is if the surrogate model is capable of capturing corner solutions. These are special solutions to an optimisation problem in which the quantity of one of the arguments in the objective function is zero (Debertin, 2012). In arable farming, examples of corner solutions are an available technology that is not chosen or a particular crop that is not produced. A previous study has shown that corner solutions are usually challenging for surrogate models to capture (Seidel and Britz, 2019). The ability of the model to capture corner solutions is difficult to assess from R^2. When R^2 is low, it would be interesting to see if the surrogate model is able to capture corner solutions, i.e. if it at least gets the farmers' choices correct without considering the level. This dimension becomes particularly relevant if farmers' choices are the focus of the analysis in applying surrogate models, e.g. when simulating farmers' technology adoption decisions.

For example, we measure NNs' ability to capture corner solutions of farmers' crop choices. For a crop c, we first transform its true and predicted production levels for each observation into binary: 0 (if not produced[14]) and 1 (if produced). Then, we count the number of farms whose decisions are correctly predicted. The accuracy in capturing corner solutions of crop c is calculated with Equation (4.5).

$$A_c = \frac{1}{N}\, a_c, \tag{4.5}$$

[14] In practice, this threshold is < 0.01 because NNs usually do not predict a strict "0" but rather a very small number like 0.000001.

where a_c is the number of observations whose decision on crop c is correctly predicted, and N is the number of observations in the test set.

The average accuracy in capturing corner solutions across all crops is calculated with Equation (4.6).

$$Accuracy_{corner} = \frac{1}{C} \sum A_c, \tag{4.6}$$

where C is the number of crop types (C = 6 in this study).

(4) Accuracy in holding constraints

Individual farm optimisation models simulate farmers' choices to maximise an output subject to a set of constraints (e.g. land/labour endowment). When employing a surrogate model of such an individual farm model, it is crucial that those constraints hold. For example, the sum of the planted areas of all farm crops cannot exceed the farm size if renting land is impossible. From an economic modelling point of view, a smaller violation of these constraints by the surrogate model is often more problematic than a larger deviation from the underlying model behaviour within the feasible solution space (e.g. some underutilisation of a resource). R^2 does not capture this, as they do not distinguish between feasible and infeasible solution space given by the constraints of the underlying model. Therefore, a dedicated measure of how well the prediction of the surrogate model obeys the constraints is warranted.

As an example, we measure NNs' accuracy in holding constraints of farm size with Equation (4.7).

$$Accuracy_{constraint} = \frac{1}{N}\, a_{constraint}, \tag{4.7}$$

where $a_{constraint}$ is the number of observations whose constraints of farm size are not violated, and N is the number of observations in the test set.

Table 4.3: Summary of the evaluation metrics

Criterion	Example Measurement	Notation	Range
Goodness of fit	Average R^2 across all outputs	R^2	(0, 1)

Table 4.3: Summary of the evaluation metrics

Consistency of bivariate relationships	APE between true and predicted MICs between the amount of nitrogen applied and nitrogen leaching on a farm	$APE_{relationship}$	(0, $+\infty$)
Accuracy of capturing corner solutions	Accuracy in capturing corner solutions of crop choices	$Accuracy_{corner}$	(0, 1)
Accuracy in holding constraints	Accuracy in holding the constraint of farm size	$Accuracy_{constraint}$	(0, 1)

4.3.3.3 *Training with different sample sizes*

To investigate the impact of sample size on the performance of the surrogate model, we choose the best model with the most promising hyperparameters from each NN architecture and train them with varying sample sizes. We split the original training set (section 4.3.1.2) into sizes of {1000, 5000, 10000, 50000, 100000, 147132[15]}. The test set is the same as before, containing 16,348 samples, but it is normalised according to the scale of each training set. To avoid fluctuations, we average the performances of five models trained with the same data using different random seeds for each architecture of NN and for each sample size.

4.4 Results and discussion

4.4.1 The best models and their inference time

We select the 12 best models in total (three variants of depth from each architecture) in terms of R^2 on the test set. Table 4.4 shows the architecture of the selected NNs. As can be seen, BiLSTM3 (BiLSTM with three hidden layers) has the highest R^2 of 0.99, while ResNet18 has the lowest R^2 of 0.93. This shows NNs can capture the variance in the data very well. In terms of R^2, we observe that BiLSTMs and LSTMs perform better than MLPs and ResNets. RNNs, although designed for sequential data, can also adapt to non-sequential data.

[15]This is the maximum amount of observations in the original training set.

As shown in Figure 4.3, the inference time of different NNs differs substantially. MLPs are the fastest in predicting, while LSTMs and BiLSTMs are much slower, reflecting the larger number of parameters than MLPs (see Table 4.4). FarmDyn takes 0.96s to generate one data point on average. In comparison, the MLP3 (MLP with three hidden layers) (R^2 = 0.95) needs 0.000026s to predict one data point being 38,400 times faster than FarmDyn, and the BiLSTM3 (R^2 = 0.99) takes 0.021s being 45 times faster. Whether this speed is satisfying depends on the time budget of future applications.

Table 4.4: The architectures of the 12 selected models based on R^2 on the test set

	Number of hidden layers	Number of neurons in each hidden layer	Number of filters in the 2nd stage	Learning rate	Mini-batch size	Optimiser	Number of parameters	R^2
MLP1	1	128	/	0.001	32	RMSprop	41,976	0.94
MLP2	2	64, 512	/	0.0003	32	Adam	165,496	0.96
MLP3	3	128, 32, 256	/	0.0003	32	Adam	86,296	0.95
ResNet18	18	/	32	0.001	128	Adam	1,119,960	0.93
ResNet34	34	/	8	0.0003	32	Adam	171,648	0.94
ResNet50	50	/	16	0.001	64	Adam	1,666,648	0.94
LSTM1	1	256	/	0.001	32	Adam	327,928	0.97
LSTM2	2	128, 64	/	0.001	32	Adam	132,088	0.97
LSTM3	3	32, 128, 1024	/	0.001	32	Adam	5,063,672	0.98
BiLSTM1	1	2048	/	0.001	32	Adamax	34,603,256	0.98
BiLSTM2	2	32, 256	/	0.001	32	Adamax	793,336	0.98
BiLSTM3	3	32, 128, 512	/	0.001	32	Adamax	3,610,360	0.99

Source: training results

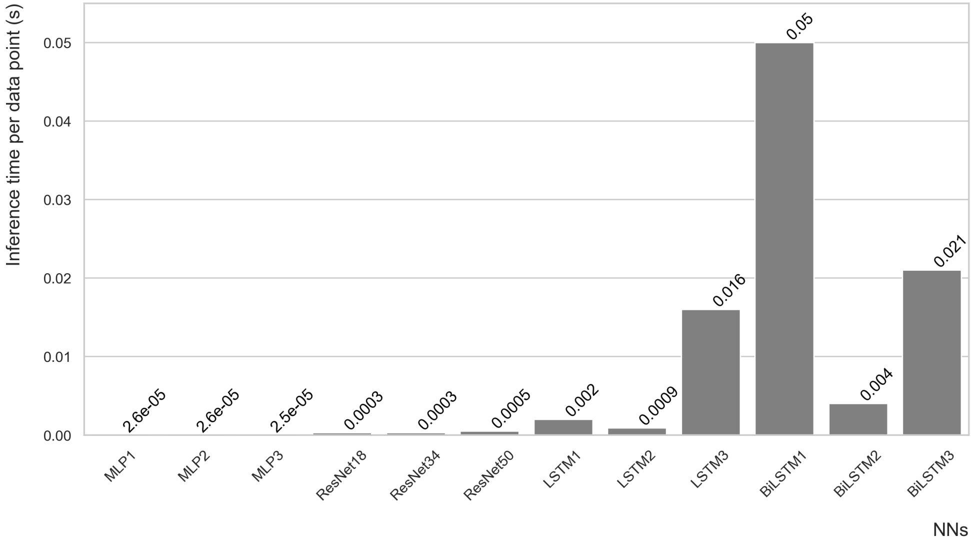

Figure 4.3: Inference time per data point of each NN

Source: simulation results

4.4.2 Model performance and impact of sample size

According to Table 4.4, we select the four best model specifications in terms of R^2 to experiment with different sample sizes as described in section 4.3.3.3. They are MLP with 2 hidden layers (MLP2), ResNet with 50 layers (ResNet50), LSTM with 3 hidden layers (LSTM3), and BiLSTM with 3 hidden layers (BiLSTM3). In the following, we refer to them as MLP, ResNet, LSTM, and BiLSTM without repeating the number of layers.

4.4.2.1 *Goodness of fit*

Figure 4.4 (a) shows the change of R^2 of the selected NNs with varying sample sizes. With a training set of 1,000 observations, BiLSTM and MLP can achieve an average R^2 of 0.8, while LSTM can only achieve around 0.55. For ResNet, 1,000 observations for training are insufficient to converge because the R^2 of ResNet trained with this sample size is negative (not shown in the figure[16]) . As the sample size increases from 1,000 to 5,000, we see a steep increase in R^2 for all four types of models. With a sample size of

[16]Because of the poor performance, the evaluations of ResNet with 1,000 observations are not shown in the following figures, either.

50,000, BiLSTM and MLP can already achieve a R^2 of around 0.95. Interestingly, with a sample size of 100,000, all models except for LSTM achieve the performance level where additional observations hardly increase the performance anymore.

4.4.2.2 *Consistency of bivariate relationships*

Figure 4.4 (b) shows the measure for the ability to capture the relationship between the amount of nitrogen applied and nitrogen leaching on a farm ($APE_{relationship}$). As we can see, MLP and BiLSTM can achieve an APE below 2% given 5,000 data points for training, while LSTM can only reach the lowest APE with 100,000 observations. We also observe that for all architectures of NNs excluding LSTM, 50,000 observations are sufficient (APE < 1%) to learn the relationship between nitrogen applied and nitrogen leaching on a farm.

4.4.2.3 *Accuracy in capturing corner solutions*

Figure 4.4 (c) shows the accuracy in capturing corner solutions of crop choices ($Accuracy_{corner}$) of each NN architecture given different sample sizes. With a sample size of 10,000, BiLSTM can achieve accuracy near to 100% in capturing the corner solutions of crop choices. Once the sample size exceeds 50,000, the accuracy does not increase much for most models except for LSTM. We can also see that MLP is as good as BiLSTM in capturing corner solutions at and beyond 50,000 data points.

4.4.2.4 *Accuracy in holding constraints*

Figure 4.4 (d) shows the accuracy of NNs in holding constraints of farm size ($Accuracy_{constraint}$). With a smaller sample size (less than 20,000), MLP outperforms BiLSTM with an accuracy of 0.98, but BiLSTM dominates once the sample size reaches 50,000. Furthermore, the accuracy of BiLSTM in holding the constraints is very close to 100%, given a sample size of 50,000. After this point, adding more data points does not improve the performance of BiLSTM.

Figure 4.4 (e) shows the total score of each NN, which is calculated by simple addition and subtraction of all criteria (*Total score* = R^2 - $APE_{relationship}$ + $Accuracy_{corner}$ + $Accuracy_{constraint}$) because they all turned out to be in the range of 0 and 1 in this study. As can be seen, increasing the sample size from 1,000 to 50,000 significantly improves the performance of all types of models. Once the sample size reaches 100,000, adding more observations to the training process does not necessarily improve the performance of surrogate models. Thus, in our case, a sample size between 50,000 to 100,000 should be sufficient to develop surrogate models that perform well concerning all our evaluation metrics. In terms of model preferability, BiLSTM almost always dominates over other types of NNs given different sample sizes but has a close competitor - MLP. Considering the inference time of the trained model, MLP may be the go-to model in many surrogate model applications that require a large number of model runs.

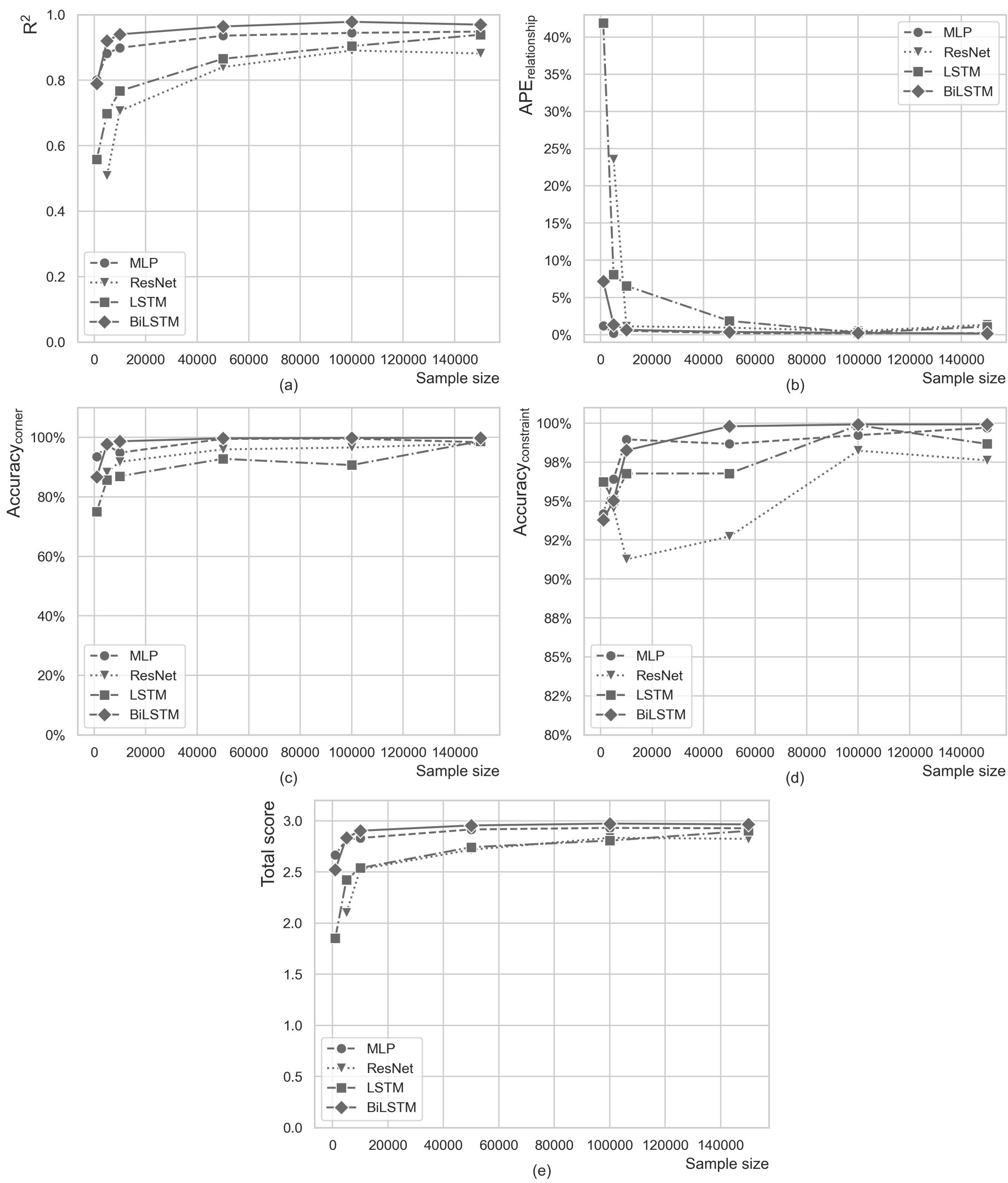

Figure 4.4: Performance of different architectures of NNs given different sample sizes

Source: simulation results

4.5 Conclusion

This chapter investigates the performance of NNs of different architectures in approximating the behaviour of a detailed farm-level model FarmDyn. We compare the performances of four architectures of NNs (MLP, ResNet, LSTM, and BiLSTM), considering 12 different implementations in terms of model depth. The trained NNs are supposed to accurately map the relationship between 77 input variables and 248 output variables of the farm model. The high goodness of fit of the selected surrogate models shows that NNs can explain most of the variation in the output variables. The BiLSTM with three hidden layers achieves an average R^2 of 0.99 across all output variables, while the lowest average R^2 is 0.93 by ResNet with 18 layers. BiLSTM and LSTM achieve better performance than other types of NNs, although they are originally designed to handle sequential data. In terms of inference time, all trained NNs are much faster than FarmDyn. MLPs are about 30,000 times faster, and the best performing BiLSTM regarding R^2 is still 45 times faster.

We also provide generic evaluation metrics to assess the performance of surrogate models, which can offer future modellers additional help in selecting surrogate models in applied modelling. The evaluation metrics consist of four dimensions: (1) Goodness of fit; (2) Consistency of bivariate relationships; (3) Accuracy in capturing corner solutions; and (4) Accuracy in holding constraints. They are calculated for different sizes of samples used for training to understand the effort needed in data generation. In our specific case, increasing the sample size from 1,000 to 50,000 significantly improves the performance of all types of models. Once the sample size reaches 100,000, adding more data points for training does not improve the performance of the surrogate models in any relevant way as defined by the evaluation metrics. MLP performs the second best in general, and its performance on other criteria is close to the best model - BiLSTM. Since it has a strong advantage on inference time, MLP might be the prime choice for many cases with strong computational demands.

Our research shows NNs are efficient in approximating detailed farm-level models. Thus, they can offer upscaling possibilities of ABMs with detailed farm-level model outcomes. Specifically, the integrated modelling system can be used to enable comprehensive analyses of agri-environmental policies that are targeted at the individual farm level. It will be worth exploring whether the slight deviation (like 1%) of the surrogate model at the farm level can cause crucial divergence at the regional level, where heterogeneous farms interact with each other in both the short and long run. Furthermore, updating and debugging the integrated modelling system could be challenging since three different models (i.e. farm model, surrogate model, and ABM) that are potentially operated by different teams are involved.

Finally, future research may move towards more systematic development and integrated application of surrogate models going beyond their stand-alone methodological assessment. An interesting alternative avenue in training surrogate models might be the use of Generative Adversarial Networks (GANs) (Goodfellow et al., 2020). They could learn the criteria for making the outcomes from the original and surrogate model indistinguishable in a data-driven way or could allow us to derive more natural stopping criteria for data generation. The rapid development of machine learning will likely further improve the performance of surrogate models and make the training of NNs a more standard approach.

4.6 References

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4.A Appendix

Maximum Information Coefficient (MIC) (Reshef et al., 2011)

For two variables x and y, the MIC is calculated with Equation (4.A.1).

$$MIC_{x,y} = max\{I(x,y)/log_2 min\{n_x,n_y\}\} \tag{4.A.1}$$

where $I(x,y)$ is the mutual information (Cover and Thomas, 2006) between *x* and *y*;

$log_2 min\{n_x,n_y\}$ is the minimum joint entropy (Cover and Thomas, 2006) between *x* and *y*;

n_x and n_y are the number of bins of *x* and *y*.

Citations in the appendix

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