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Research Paper

A participatory impact assessment of digital agriculture: A Bayesian network-based case study in Germany

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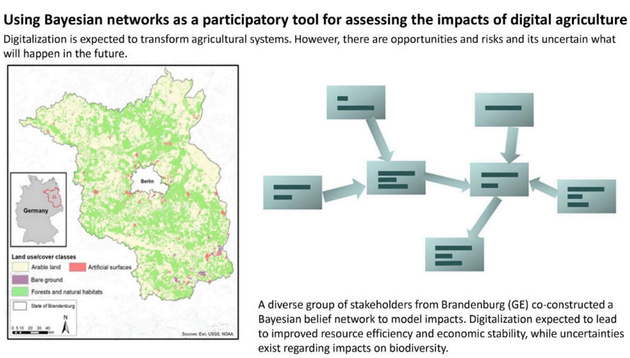
GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: The transition to digital agriculture is likely to lead to systemic changes that will affect production, consumption, governance, and the wider environment of agricultural systems. Nevertheless, the absence of sufficient evidence and ambiguities in perspectives create an ongoing lack of clarity regarding the potential impacts of digital agriculture. Therefore, to discern potential impacts while addressing system complexities, uncertainties, as well as normative aspects associated with this transition, future-oriented and participatory assessments are needed that actively involve diverse knowledge and values of affected stakeholders.
OBJECTIVE: This research aims to explore the impacts and processes of agricultural digitalization according to stakeholders. The objectives are to identify key areas of impact that digital agriculture is likely to influence, identify and explore the causal pathways linking digital agriculture to impacts, and quantitatively examine the uncertainties of stakeholder perceptions associated with these impacts and causal pathways.
METHODS: Through a participatory modelling procedure, diverse stakeholders from the German region of Brandenburg constructed a Bayesian Belief Network (BBN). The BBN facilitated the identification of the main impacts of digital agriculture and allowed for the modelling of uncertainties associated with these impacts.
RESULTS AND CONCLUSIONS: Stakeholders perceived several socioeconomic advantages of digitalization, particularly in terms of bolstering economic stability through improved risk management and enhanced resource use efficiency, validating existing claims in the literature. The perception seems to be influenced by highly

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variable yields and market uncertainties, as well as shortages in labour in the region. On the other hand, there was significant uncertainty among stakeholders concerning landscape diversification and its impact on biodiversity. This uncertainty arises from the potential profitability of cultivating marginal land under heightened digitalization-induced efficiency, posing a risk of diminishing natural habitat and landscape heterogeneity. Local historical trends toward landscape simplification as result of technology-driven efficiency improvements may be a cause for this perception.

SIGNIFICANCE: This study contributes to a growing body of future-oriented research assessing the impacts of digital agriculture through engaging stakeholder knowledge and values. While there is theoretical potential for digitalization to enhance biodiversity, realizing such positive impacts is improbable without improved communication and policy incentives, given the historical trend of efficiency-driven pathways. This study introduces a novel approach to assessing the impacts of agricultural digitalization through the application of a participatory Bayesian belief network.

1. Introduction

Digital agriculture, which is expected to transform agricultural systems in the coming years, is a form of managing and optimizing agricultural production and supply chains using data-driven techniques and precision farming technologies (Ingram et al., 2022; Klerkx et al., 2019). Often referred to as the fourth agricultural revolution (Rose and Chilvers, 2018), this approach represents a significant shift from traditional 'analogue' farming to a system that harnesses real-time and site-specific data, big data analytics, automated decision making and interconnected intelligent systems (Wolfert et al., 2017). Used for tasks such as monitoring, production and communication, key technologies employed in digital agriculture include Unmanned Aerial Vehicles (UAVs), in-situ sensors, satellite images, robotics, digital twins, artificial intelligence, cloud computing, Internet of Things (IoT), decision support software, Variable Rate Technologies (VRT), and GPS guidance systems, among others.

Taken together, the application of digital technologies and processes is expected to increase agricultural efficiency, productivity, and profitability (Shepherd et al., 2020; Basso and Antle, 2020). This is currently the dominant narrative embedded in agricultural policy (MacPherson et al., 2022; Lajoie-O'Malley et al., 2020) as well as a key selling point in media (Barrett and Rose, 2022) and related industries (Clapp and Ruder, 2020). However, limited adoption indicate that farmers may not yet be completely convinced by this proposition (Barnes et al., 2019a; Groher et al., 2020; Kernecker et al., 2020) and that digital agriculture may not deliver on the hype (Thompson et al., 2019; Knierim et al., 2019; Eastwood and Renwick, 2020; McGrath et al., 2023).

With the exception of GPS-assisted tractors and farm management information software, the implementation of more complex digital applications remains limited in European farming (Lowenberg-DeBoer and Erickson, 2019; Balafoutis et al., 2020), and varies significantly by region (Barnes et al., 2019a). Adoption barriers of precision and digital technologies have been attributed to high initial investment costs (Barnes et al., 2019a), lack of operating skills (Klerkx and Rose, 2020), insufficient infrastructure and access to broadband internet in rural areas (Paustian and Theuvsen, 2017; Da Silveira et al., 2023), as well as lack of trust among farmers due to issues of data sovereignty and privacy (Jakku et al., 2019). These barriers do not appear to be insurmountable in the long term as training networks are emerging (in the EU: SFATE - Smart Farm Training for Employment and Digital Innovation Hubs), high-speed internet access is becoming a global reality (e.g. via Starlink), and agri-digital legal frameworks are beginning to take shape (Härtel, 2021). Moreover, new market models that allow farmers to rent or lease agricultural robots means that these technologies are becoming more accessible (Gil et al., 2023), not to mention the substantial growth in recent years of business ventures and investments in digital agriculture should continue to improve the affordability of related technologies in the future (Birner et al., 2021).

If digital agricultural technologies are adopted and how they are instrumentalized depends heavily on the collective and shared perceptions of stakeholders as well as how they perceive their value (Moteiro Moretti et al. 2023), which is subject to dynamic change (Kaplan and Tripsas, 2008). Therefore, to secure technological improvements into current and future socio-economic and environmental contexts, an emphasis has been placed on iterative involvement of stakeholders in decision-making processes (Reed, 2008). This sentiment has been echoed by others who underlined the need for greater societal inclusion and user-centred design in the development and implementation of digital agriculture technologies (Eastwood et al., 2022). Stakeholder inclusion is seen as also necessary at higher levels to set goals and develop indicators to measure progress toward sustainability (Basso and Antle, 2020), as well as reflect on the potentially disruptive impacts of innovative digital technologies (Rose and Chilvers, 2018; Eastwood et al., 2021). Further, involving stakeholders in research will be crucial toward gaining their trust for digital technologies in the future, jointly mitigating adverse impacts and promoting acceptance of digital agriculture solutions (Jakku et al., 2019).

Society is at a crucial turning point in terms of directing digital agriculture toward alignment with principles of social responsibility and sustainability (Lioutas et al., 2021). However, due to the ambiguity in perceptions of different stakeholders (Knierim et al., 2019; Regan, 2019; Monteiro et al., 2023), uncertainty surrounding the impacts of digitalization is pervasive, which means a core challenge is articulating a conceptualization of digital agriculture – including a vision for its future - that is consensual. This requires not only accounting for potential positive and negative impacts of digital agriculture through participation by societal actors but also carefully addressing the uncertainties within those varying perceptions.

To address uncertainties and to ensure that digital agriculture contributes to societal well-being and sustainability, many scholars have embraced the Responsible Research and Innovation approach (RRI) (Eastwood et al., 2019; Rijswijk et al., 2021; Klerkx and Rose, 2020). The RRI approach is guided by four main principles: anticipation, inclusion, reflexivity, and responsiveness (Stilgoe et al., 2013), aiming to inform research design, facilitate anticipation and reflection on both intended and unintended consequences of innovations, and collaboratively design solutions to minimize risks and maximize opportunities. Recently there has been an increase in empirical studies assessing digital agriculture through the lens of the RRI framework. For example, Zscheischler et al. (2022) investigated the perceptions of agricultural digitalization with a group of stakeholders in Germany, illuminating risks related data ownership and power dynamics, as well as the effects of automation on farmers' decision-making capacities. Fleming et al. (2021) employed participatory scenario building to reflect on probable futures of digital agriculture in the Australian context, underlining the importance of improved connectivity and infrastructure as well as training and advisory services to overcome concerns related to equity and distribution of benefits arising from a digital transformation. Examining 21 Living Labs across Europe, Metta et al. (2022) identified several effects of digitalization, pointing out trade-offs between enhancing existing processes (e.g., efficiency gains) and enabling new ones (e.g., site-specific monitoring and control). However, they also noted the potential for rebound effects (e.g., increased material use) and the disruption of traditional practices and organizations (e.g., displacement of workers due to automation). Regan (2019) interviewed key governance actors in Ireland, drawing attention to concerns about public aversion to digital technologies, data ownership and sharing, as well as changing farmer identities and isolation from farming activities via automation. Reichelt and Nettle (2023) demonstrated the importance of implementing procedures based on inclusion and reflexivity to highlight different adoption logics and develop responsible adoption strategies at early stages of development. Other forward-looking empirical studies have focused on the implications of digital agriculture on changing roles in agri-environmental governance at the EU level (Ehlers et al., 2022) as well as comparing media, policy and practitioner narratives in the UK (Barrett and Rose, 2022).

What these studies underline is the importance of utilizing participatory approaches that engage stakeholders' perspectives in anticipating and reflecting on systemic impacts, both positive and negative, of agricultural digitalization (Klerkx and Rose, 2020). However, a research gap exists where the perceptions of stakeholders and associated uncertainties regarding agricultural digitalization have been quantitatively modelled.

In this light, our study asks the following research question: What are the expected impacts of digital agriculture according to stakeholders from an arable farming region characterized by high mechanization and high affinity to digital agriculture? To answer this question, the current study aims to fulfil three main objectives: i) identify the key areas of impact that digital agriculture is likely to influence by 2031; ii) identify and explore the causal pathways linking digital agriculture to impacts; and, iii) examine, quantitatively, the uncertainties of stakeholder perceptions associated with these impacts and causal pathways.

To these ends, we employ a participatory modelling approach to construct a Bayesian Belief Network (BBN) in collaboration with multiple groups of stakeholders from the German federal state of Brandenburg. As BBN models are widely acknowledged for their ability to integrate knowledge from diverse domains and transparently address uncertainty of causation via probability estimates (Voinov and Bousquet, 2010), they offer a suitable yet novel approach for assessing the complexities and unknowns of agricultural digitalization with stakeholders.

The results of this study illuminate risks and opportunities of digital agriculture by tapping into stakeholder knowledge, thereby contributing to sustainable and societally responsible innovation. In addition, the study contributes methodological insights on how to address uncertainty of stakeholders' perspectives in impact assessment more directly using a BBN. The participatory modelling process and the resulting BBN provided a conduit for constructive discussion and learning between diverse stakeholders, while to the greatest possible extent mitigating overly emotional and less objective debates. Last, the findings reveal patterns of thought of various stakeholder groups regarding digitalization, drawing attention to societal concerns for researchers and policymakers in the region.

2. Background

2.1. Digital agriculture: what is it in practice?

Agricultural digitalization is a growing trend that includes concepts like Precision Farming, Smart Farming, Agriculture 4.0 and Digital Agriculture, which are often used interchangeably (Klerkx et al., 2019). This general domain encompasses a wide range of technologies that can be considered part of the digital toolbox, many of which focus on improving the efficiency of on-farm input use. In crop production, for example, in-situ sensors provide real-time data on soil health and crop conditions, helping farmers make decisions about input (i.e. fertilizers, pesticides and water) optimization (Pedersen and Lind, 2017; Wolfert et al., 2017), while remote sensing technologies like satellites and drones provide similar information over larger areas (Gao et al., 2020). Artificial Intelligence (AI) and machine learning algorithms are used to analyse large datasets, aiding in crop monitoring and yield prediction, which enables strategic planning and resource allocation (Wolfert et al., 2017). Variable Rate Technologies (VRT) utilize data from sensors to adjust inputs based on soil and crop variations, significantly boosting resource efficiency (Finger et al., 2019; Späti et al., 2021). GPS technology enables precise field mapping and vehicle guidance to reduce overlap of planting, spraying, and harvestings thereby minimizing input wastage (Fielke et al., 2019; Godoy et al., 2012).

More recently, although mostly confined to research and development, agricultural digitalization has expanded to include the deployment of AI-assisted robots that work autonomously on activities including weeding, planting and harvesting. It has been proposed that such field robots could work in fleets, offering scalability and efficiency previously unattainable with traditional labour (Sparrow and Howard, 2021; Spykman et al., 2021; Lowenberg-DeBoer et al., 2020). Utilizing data gathered from various sources, computer software like Farm Management Information Systems (FMIS), integrate data analytics and modelling techniques to manage agricultural enterprises and provide farmers with comprehensive decision support on complex tasks, such as crop management, irrigation scheduling, fertilizer application, and risk assessment (Tummers et al., 2019; Melzer et al., 2023). These devices are connected through the internet, also known as the Internet of Things (IoT), allowing them to gather and communicate data among themselves, thereby streamlining operations and enhancing productivity. Technologies such as blockchain and Radio-Frequency Identification (RFID), combined with IoT devices, enable real-time tracking of products, providing detailed information on product origin, handling, and quality throughout the supply chain (Kamilaris et al., 2017).

Last, and no less important, mobile phone apps have become ubiquitous, providing farmers with information on aspects such as crop protection, crop selection, weather forecasts, market prices and entry points, e-learning, communication with other farmers and consumers, as well as promoting citizen science (Daum et al., 2018; Dehnen-Schmutz et al., 2016).

2.2. Digital agriculture: systemic impacts

Beyond efficiency and productivity objectives, digital agriculture offers additional benefits, such as helping to meet increasing food demands, supporting rural livelihoods, and achieving sustainability goals (Wolfert et al., 2017; Finger et al., 2019; MacPherson et al., 2022; Garske et al., 2021). For example, more efficient use of inputs such as pesticides and fertilizers will help to reduce runoff and pollution in the environment (Balafoutis et al., 2017; Finger, 2023; Balasundram et al., 2023). Digital tools can also support the redesign of agricultural fields and landscapes by promoting smaller-scale structures, diversification, and the integration of agroecological principles, which enhance ecosystem service supply (Finger, 2023; Donat et al., 2022; Mouratiadou et al., 2023).

From a larger, agri-food system perspective, digital technologies can enhance information exchange among suppliers, producers, consumers, and governments within agri-food value chains (Poppe et al., 2013). Increased traceability has significant benefits for monitoring food safety, reducing food waste, ensuring regulatory compliance and capturing additional value for farmers (Yu et al., 2022; Weersink et al., 2018; Finger, 2023), while at the same time engaging consumers more deeply with their food and how it is produced (Regan, 2019), thereby empowering them in their food choices (Voglhuber-Slavinsky et al., 2023). The effectiveness of agri-environmental governance also stands to benefit from digital agriculture and big-data to craft targeted, site-specific environmental policies (Ehlers et al., 2021).

On the other hand, digital agriculture may have significant implications for socio-economic structures. An increased reliance on digital tools may distance farmers from the hands-on aspects of their work, contributing to “de-skilling”, where traditional knowledge is lost or replaced, while simultaneously leading to a sense of isolation of farmers from their fields and animals (Rotz et al., 2019b; Carolan, 2020; Rose et al., 2021). Although digitalization can simplify certain tasks, alleviating both physical and mental strain, the financial burden of acquiring such technologies, along with the learning curve required to operate them, may introduce additional stress (McGrath et al., 2023). Concerns have also been raised that digital agriculture could also lead to a form of digital Taylorism, potentially reducing worker autonomy and turning their tasks into highly monitored, repetitive work processes, which may undermine job satisfaction and working conditions (Prause, 2021).

Another major issue involves the governance and management of data. For example, the control of farm-generated data by large agricultural and tech corporations can create power imbalances, leaving farmers at a disadvantage, as they often receive little to no value from sharing their data (Lioutas et al., 2021). Additionally, the lack of interoperability or compatibility between products from different ag-tech companies can “lock in” farmers to specific technologies, deepening their dependency on these corporations and intensifying existing power asymmetries (McGrath et al., 2023). Moreover, it is possible that the economic benefits of precision and digital technologies will accrue primarily to large-scale arable farma that are able afford these technologies (Kutter et al., 2011), leaving smallholder farms behind and potentially creating a digital divide (Hackfort, 2021; van der Burg et al., 2019).

3. Methods and materials

3.1. Participatory modelling with Bayesian Belief Networks (BBN)

Modelling with stakeholders, or participatory modelling, is a problem-solving approach that improves system understanding and decision-making by synthesizing stakeholder knowledge and values in a coherent manner. More specifically, participatory modelling has been defined as ‘a purposeful learning process for action that engages the implicit and explicit knowledge of stakeholders to create formalized and shared representations of reality ’(Voinov et al., 2018). These shared representations of reality provide descriptions of the problem at hand by defining the impacts and potential solutions (Voinov and Bousquet, 2010). Participatory modelling integrates stakeholder insights with model-based methods, where stakeholders contribute their qualitative knowledge to frame issues, identify relevant themes and indicators, and guide the development of assessment models. These models translate stakeholder input into quantitative and semi-quantitative outcomes. Analytical tools for participatory modelling include system dynamics modelling, fuzzy-cognitive mapping, agent-based modelling, and BBNs (Voinov and Bousquet, 2010). The literature outlines the strengths and weaknesses of these tools (Gray, 2016) and provides guidance on selecting the appropriate one (Voinov et al., 2018). This study employs a BBN approach to engage stakeholders in a participatory modelling process. We chose to use a BBN approach over other participatory modelling methods for its ability to easily and transparently integrate diverse knowledge streams and explicitly handle uncertainty in knowledge via probability estimates, which is useful in the context of assessing the complexity of impacts of digital agriculture through a multi-stakeholder approach.

BBNs are graphical representations of real-world systems that rely on probabilities to model relationships and dependencies (Kjaerulff and Madsen, 2013). They are visually represented as Directed Acyclic Graphs (DAGs), which consist of three main elements: (1) nodes representing variables of the system under investigation; (2) directed arrows indicating causal dependencies between nodes; and (3) probability distributions expressed in Conditional Probability Tables (CPTs). These CPTs describe the probability distribution of a node given the states of its parent nodes, quantifying the statistical dependence between variables. While BBNs are often used to model causal relationships, they can also represent associations or dependencies without implying causation. BBNs enable the propagation of information throughout the network through techniques like Bayesian inference. This allows for the calculation of updated probabilities for variables based on observed evidence, making BBNs valuable tools for modelling, reasoning, and conducting probabilistic inference in complex systems. They can be developed using empirical data from models, direct observations, expert knowledge, or a combination of these (Marcot, 2012). As such, BBNs are practical in situations where empirical data is lacking and for integrating data of different quality (Uusitalo, 2007). In respect to the latter, integrating knowledge across domains assists with understanding complex management problems in a more comprehensive way (Cain, 2001). Additionally, established BBNs can be updated when new information becomes available, allowing for iterative scenarios analyses, which is useful for adaptive management approaches (Uusitalo, 2007). The structure of a DAG prevents cycles and feedback loops, ensuring conditional independence among unrelated nodes and unidirectional probability inference. This design is important to avoid infinite regress and recursive causation scenarios during probability calculations. Although feedback loops are an inherent property of dynamic systems, including agri-ecological and social systems, the static systems representation contained within the DAG of BBN helps to reduce system complexity and facilitate identification as well as analysis of causal interactions.

There are many examples in the literature of participatory BBNs being applied to support agricultural management, especially in the European context. Henriksen et al. (2007) used a BBN to explore complexity and uncertainties when assessing the impacts of pesticide management actions on agricultural economics and groundwater and drinking water quality on the national Danish scale. Along with stakeholders, Carmona et al. (2011) worked on developing a decision support system combining an agro-economic model and object-oriented BBN to study different management options for groundwater management in Spain, focusing on the trade-offs between agriculture and the environment. Duspohl and Doll (2016) used a participatory BBN approach to identify implementable strategies for promoting renewable electricity generation in a German county. In a pre-Alpine region in Switzerland, Celio and Gret-Regamey (2016) applied a BBN approach for land-use modelling to understand the influence of farmers on land-use change in a spatially explicit manner. Salliou et al. (2017) used a BBN with stakeholders in Southwest France to model ambiguity in perceptions of different stakeholders in the context of biological pest control in apple orchard cultivation.

The diversity of applications in which participatory BBNs have been employed speaks to their overall usefulness as a participatory modelling approach for engaging implicit and explicit knowledge (as well as uncertainty in this knowledge) of stakeholders. Recognizing the uncertainty surrounding the impacts of digitalization, including lack of hard data and the need to reconcile and integrate multiple (often conflicting) perspectives, we find the participatory BBN approach an intriguing method for addressing these issues. However, no studies have - to our knowledge - used BBNs in the context of modelling the impacts of agricultural digitalization till now.

3.2. Selecting system variables and indicators with stakeholders

The selection of system variables and respective indicators is a crucial step in assessing sustainability since it affects what is measured, how it is measured, and what conclusions can be drawn from the findings (Pope et al., 2004). Here, stakeholder involvement is seen as a key criteria for conducting impact assessment and developing indicators that are relevant, meaningful, and reflective of the local context (Binder et al., 2010; Latruffe et al., 2016). In our study, we involved stakeholders in identifying system variables and respective indicators through the creation of a causal network (i.e. in the form of a BBN) following the commonly used DPSIR approach (more on this in Section 2.4.1) (Niemeijer and de Groot, 2008; König et al., 2013). By engaging stakeholders in this process, their knowledge and perspectives are incorporated, ensuring that the chosen system variables and indicators capture the diverse aspects of sustainability that are important to the region under study (Reed, 2008). This leads to a better understanding of the interconnectedness between indicators and the complex relationships within the system (Chopin et al., 2021).

3.3. Case study: Brandenburg, Germany

The federal German state of Brandenburg covers 29,640 km^2, of which 45 % of the land area is dedicated to agricultural production (Amt für Statistik Berlin-Brandenburg, 2016) (Fig. 1). Within the utilized agricultural area, 77 % comprises of cropland and 23 % of permanent grassland (Troegel and Schulz, 2016). The agricultural landscape is characterized by homogenization and intensified production, which have had detrimental effects on biodiversity, soil and water quality (Thomson et al., 2019). This environmental degradation is despite existing economic incentives from the EU's Common Agricultural Policy (CAP) for sustainable land management practices (Wolff et al., 2021).

The main crops grown in Brandenburg are wheat, maize, rye, and barley (Gutzler et al., 2015; Amt für Statistik Berlin-Brandenburg, 2021). Agricultural enterprises are relatively large, having an average farm size of 242 ha, or four times the German average (Gutzler et al., 2015; Troegel and Schulz, 2016). These enterprises tend to be highly mechanized and make intensive use of fertilizers and agrochemicals (Gutzler et al., 2015).

Regarding natural conditions, the region is characterized by comparably low-quality soils, from which almost two-thirds are sandy and sandy-loamy (Wolff et al., 2021). Rainfall is also low, being on average less than 600 mm/year with the likelihood to decrease even further in the future. For a more detailed description of Brandenburg's agricultural landscape, Wolff et al. (2021) provided an analysis of landscape metrics indicating agricultural landscape structure, diversity and management using plot-based agricultural data.

3.4. Digital agriculture: state of adoption in the EU, Germany and Brandenburg

There is not much evidence available about the level of adoption of digital agriculture across Europe, and most of the research is country-specific (Barnes et al., 2019a), showing that there are significant regional variations in adoption. In a survey of farmers from 7 EU countries ($n = 287$), Kernecker et al. (2020) found that adopters of smart farming technologies mostly used GPS-supported tractors, with higher levels of adoption correlating with increased farm size and arable cropping systems compared to livestock or mixed cropping systems. However, it should be noted that in their study they used a purposive sample, targeting adopters and non-adopters, so the rates of adoption

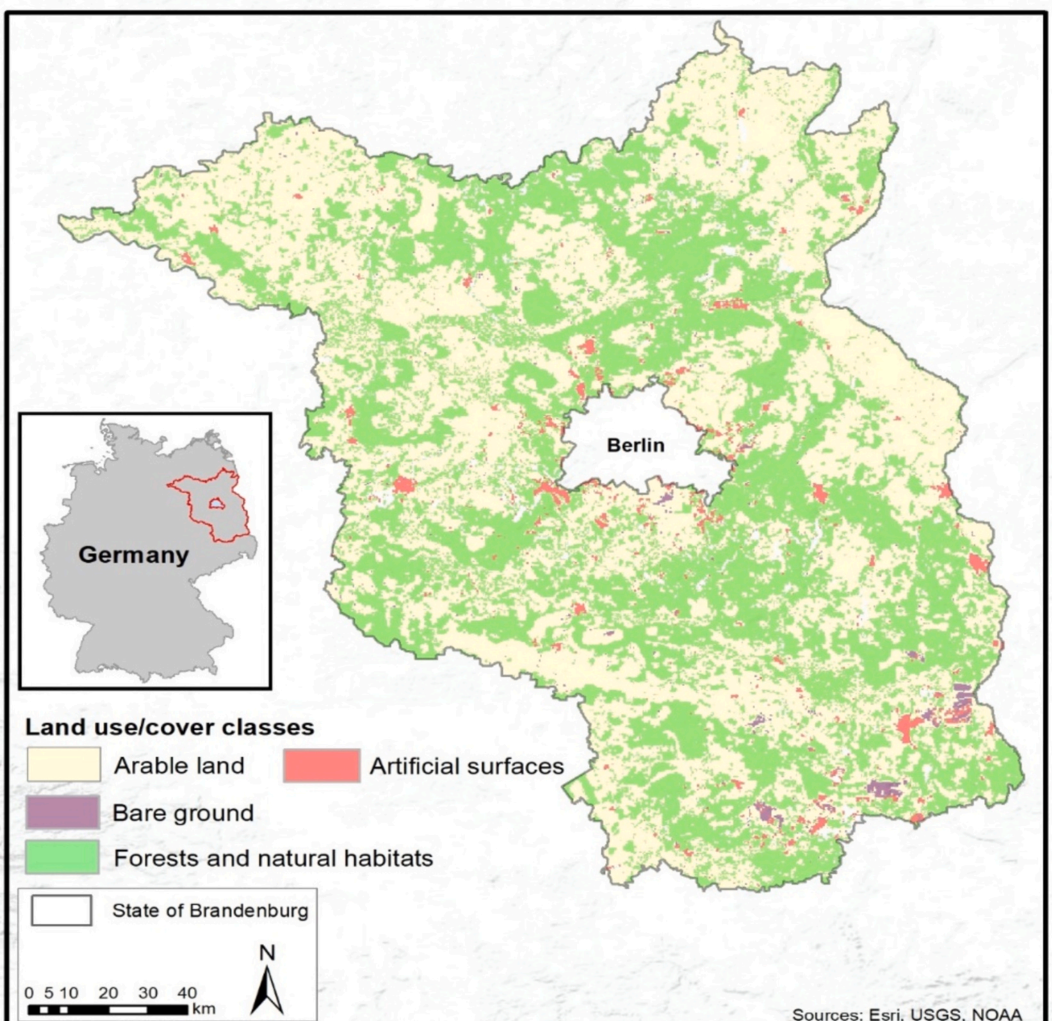

Fig. 1. Map depicting the location and major land use classes of the German Federal State of Brandenburg, the case study region (European Environment Agency, 2019).

across the EU are probably lower.

In Germany, higher levels of adoption also correlate with larger farms, which points to future growth in adoption rates due to the continuing structural change in the rural sector (Paustian and Theuvsen, 2017). In a survey of 500 farmers from arable cropping and livestock systems, Rohleder et al. (2020) found that 8 out of 10 farmers make use of digital technologies in Germany. From that study, 45 % of respondents reported using GPS-supported machinery and 40 % used smartphone apps and farm management software. Site-specific application technologies for pesticides and fertilizers were used by 32 % of respondents, while robotics and drones were adopted by 12 % and 11 %, respectively. The necessary infrastructure in Germany for a wide adoption, such as broad network connectivity and speed, is still lacking, although it is probably a question of time until German rural areas are fully connected (Bernhardt et al., 2021).

As Brandenburg is characterized by large farm sizes and high levels of mechanization, the adoption of digital technologies in this region is likely. No data is available, however, on the current state of adoption among farmers in Brandenburg, although there is ongoing discussion about the future of digitalization, especially considering the unlocked possibilities coming with the expansion of the 5G mobile network (Land Brandenburg, 2019). The state government has its own digital strategy and claims that it wants to expand Brandenburg's leading role in digital agriculture and forestry, as well as the digitalization of companies and value chains (Landesregierung Brandenburg, 2021). There is also ongoing research projects specifically focused on agricultural digitalization considering the regional context (Bloch and Bellingrath-Kimura, 2020).

Our research is a component of the BMBF-funded DAKIS (Digital Agricultural Knowledge and Information Systems) research project, which is – among other things - developing a Decision Support System (DSS) to allow farmers and advisors to incorporate ecosystem services and biodiversity in farm-level agri-economic planning (Mouratiadou et al., 2023). The DAKIS DSS executes models and simulations that are supplied with high resolution real-time, site-specific data from in-situ measurements and remote sensing. Based on these models, the project is also anticipating the integration of field robots within its DSS infrastructure. Taken as a whole, DAKIS is a state-of-the-art example of how digital agriculture technologies can be theoretically applied to promote the provision of multiple agricultural ecosystem services. Most of the project's activities are located within the German Federal State of Brandenburg. Therefore, Brandenburg was chosen as the case study area.

The current study does not focus exclusively on the technologies utilized in the DAKIS project but takes a broader view on digitalization and related technologies, defining it as the utilization of data-driven techniques and precision technologies to inform, optimize and partially automate decision-making processes and activities throughout agricultural production and supply chains (Ingram et al., 2022; Klerkx et al., 2019; Walter et al., 2017). While acknowledging the significance of digital technologies in animal husbandry and horticulture production, the focus of our analysis remains on their application within large-scale arable farming.

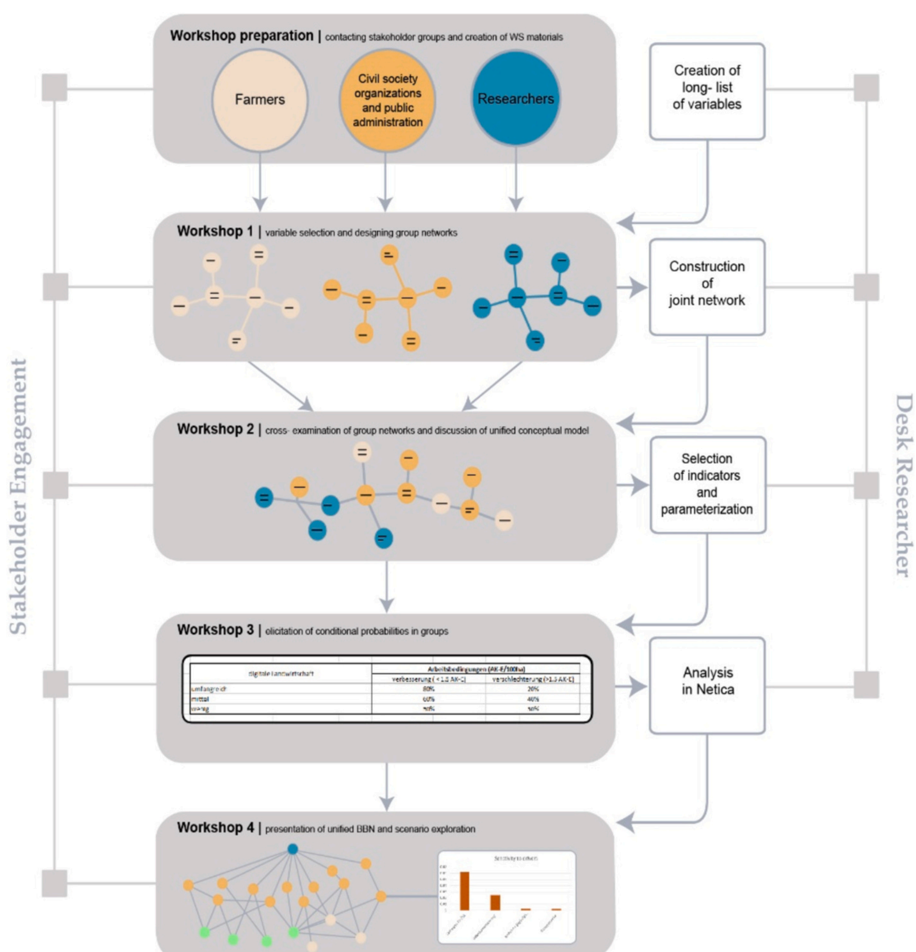

Fig. 2. Overview of methodological workflow of the participatory modelling process to construct the BBN.

3.5. Stakeholder workshops

In this study, a participatory modelling approach employing a BBN was used to identify and assess the potential impacts of agricultural digitalization in the future (i.e. by 2031) in Brandenburg, Germany. We designed our protocol based partially on those developed by Cain (2001) and Bromley et al. (2005) through engaging a group of stakeholders in a series of workshops and iterative consultation to co-construct a BBN. The following subsections describe the methodological approach used to construct our Bayesian network. For a graphical overview of the methodology, see Fig. 2.

During three online workshops (each about 3 h long), stakeholders were led through a stepwise process to co-construct a BBN. The main tasks of the workshops were to select relevant system variables,arrange them into a graphical network, and elicit conditional probability estimates (e.g. quantification). A final workshop was held to discuss the resulting BBN with the participants. The workshops were spread out over a six-month period in 2021–2022 and conducted online to comply with the COVID-19 regulations at that time. Workshop materials were prepared on the collaborative whiteboard software MURAL (https://mural.co/) as well as with MS Excel. Data obtained from the workshops were later entered into Netica (Netica V5.18, 2015), a Bayesian network modelling software package, for analysis.

For our case study area, we identified four stakeholder groups of interest, namely: farmers, researchers, civil society organizations and public administration. We considered these groups because farmers offer firsthand insights into the tangible effects of digital technologies on their livelihoods, while researchers can provide technical expertise and guidance on innovations. Civil society organizations ensure alignment with societal values and public administration contributes perspectives on regulation and policy-shaping. The public administration and civil society organization can both be seen as expressing the broad viewpoint of the public, thus we felt that they could be combined into one group, which we named the 'civil society group' for the purpose of this study. Based on this grouping, we non-randomly identified potential participants using personal contacts and Google search. We sought out participants that were familiar with regional agricultural conditions in Brandenburg. Within each group, we aimed to incorporate individuals with diverse backgrounds and experiences to leverage a wide range of expertise. While it would have been preferable for participants to have prior knowledge of digital agriculture, we did not reach out to participants based on their existing familiarity with the subject. However, we contacted farmers engaged in large-scale arable crop farming, as they are representative of local farming practices as well as more inclined to utilize mechanization and possess familiarity with precision agriculture and digital technologies compared to those involved in small-scale farming.

Due to the high time requirements for developing the BBN and to consider the shorter attention span of online workshops compared to face-to-face workshops, it was necessary to divide the participatory modelling exercise across multiple days. It was therefore requested that participants be able to attend all workshops. This was deemed important to provide continuity of perspectives and ensure a cohesive and comprehensive modelling process. Considering this, a smaller group of workshop participants was more feasible in terms of achieving continuous participation as well as more desirable for the in-depth discussions required for the study.

In total, fourteen stakeholders participated in the workshops: three were farmers, four were researchers, and seven were representatives from various local civil society organizations and administrative authorities. Eleven participants attended the first workshop, ten attended the second workshop and nine attended the third workshop. In cases where a participant was not able to attend a subsequent workshop, they were requested to send a substitute participant to attend the workshop in their stead. In the end, the participants in the farmer and researcher groups showed continuous attendance (except for one researcher who could not attend the last workshop), whereas the participants from the civil society group showed fluctuating attendance between the first and second workshops. For an overview of participants and their backgrounds as well as their attendance in the workshops, please see Supplementary Material I.

3.5.1. Workshop 1: variable selection and construction of conceptual models

The aim of the first workshop was to collect insights into how different stakeholder groups perceive the impact of digitization on agricultural systems by guiding them in the selection of relevant system variables and the creation of conceptual models (Fig. 3). The first workshop was initiated with a brief overview of digital agriculture, including associated technologies and potential applications aimed at improving resource use efficiency as discussed within the literature as well as promoting landscape diversification within the context of the DAKIS DSS. Additionally, the research objectives were outlined, followed by a short round of discussion for clarifications. Following this, the researchers', farmers', and civil society group acted in parallel to develop their own conceptual model, as recommended by Cain (2001), through in-depth discussions and intra-group consensus-building. Before network construction, it was necessary for each group to identify and select the system variables (e.g. relevant agricultural system components such sustainability targets, digital agricultural technologies, affected ecosystem and social conditions, and drivers) to be included in their models. Therefore, each group first systemically selected variables from a list of pre-selected variables. The pre-selected list of variables was compiled from objectives outlined in policy strategy documents, including the EU F2F Strategy (European Commission, 2020), the German National Sustainability Strategy (Deutsche Bundesregierung, 2018), and the 2035 national Arable Farming Strategy (BMEL, 2019), as well as indicators from agricultural sustainability assessment frameworks and models, including SAFA (FAO, 2013), RISE (Grenz et al., 2012), KSNL (Breitschuh, 2008), MODAM (Zander and Kächele, 1999), and ViSA (Shaaban, 2022). Additionally, relevant scientific literature (Wolfert et al., 2017; Walter et al., 2017; Finger et al., 2019) was used to derive variables specific to agricultural digitalization and precision agriculture. Each of the above-mentioned sources was thoroughly reviewed by the authors before being entered into the pre-selected list of variables. During this workshop, participants were given the option of 'writing-in' new, additional variables they felt were missing from the pre-selected list (see Supplementary Material I for an overview of the pre-selected list of variables used in the workshop).

The list of pre-selected variables were categorized according to the DPSIR framework as a means to structure the variable selection and model construction processes (Tscherning et al., 2012; Bosch and Gabrielson, 2003; Niemeijer and de Groot, 2008). Consisting of Drivers (D), Pressures (P), States (S), Impact (I), and Response (R), the DPSIR framework analytical tool highlights cause-effect relationships in nature-human interactions (Bosch and Gabrielson, 2003). In our study,

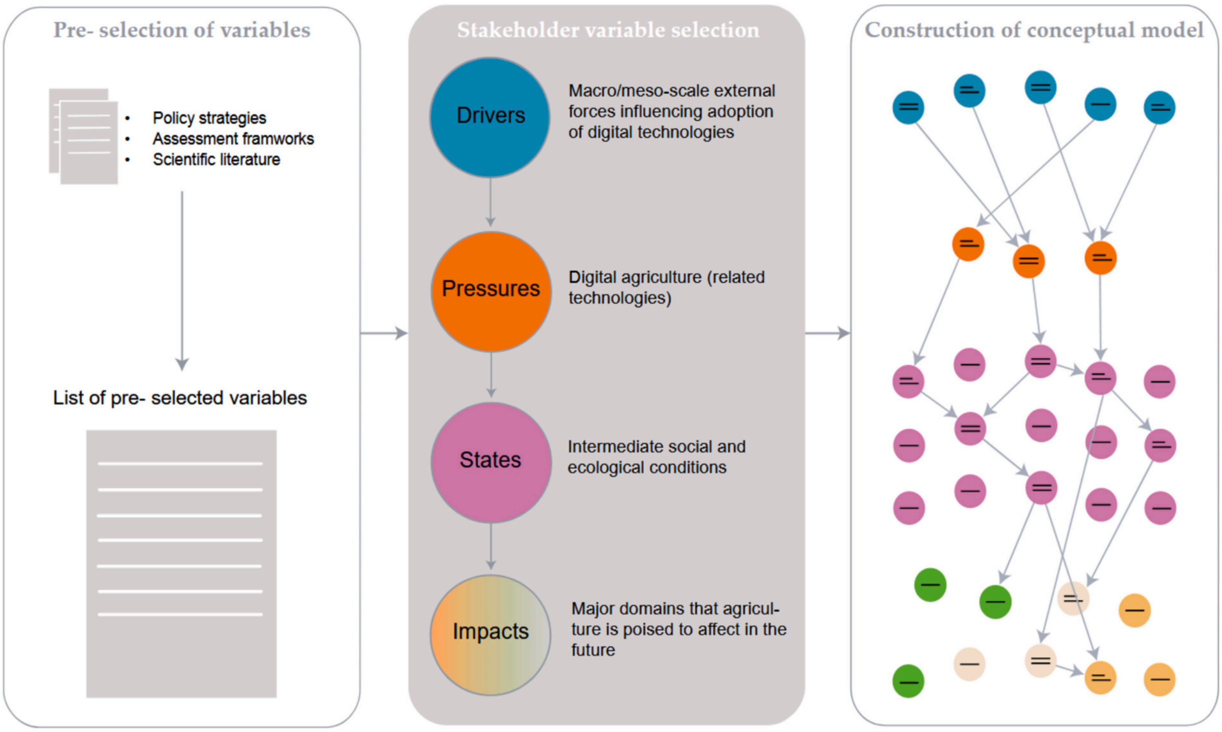

Fig. 3. Variable selection and construction of conceptual models using the DPSIR framework.

the Drivers category represented macro- and meso-scale external factors (e.g. subsidies, producer prices, costs of digital technologies) influencing the adoption of agricultural digitalization. The Pressures category was used to represent digital agricultural management as an intervention. The States category represented intermediary social and ecological conditions (e.g. ecosystem connectivity, wages, health hazards) that lead to Impacts. The Impacts category represented major domains of influence that agriculture is expected to have in the future (e.g. biodiversity, food security, regional identity). The Response category represents actions taken by society to affect impacts by influencing other elements, including Drivers, Pressures and States within the system. These actions commonly involve policy measures related to compensation, prevention and adaptation. To facilitate a focused analysis of the impacts arising from digital agriculture and streamline the assessment process, the study deliberately excluded responses from consideration.

Given the complexity of interactions in agricultural systems, it was necessary to narrow down the range of variables considered for developing the BBN to a manageable number. Considering this and in order to stay within the time limits of the workshops, we imposed constraints on the number of variables each group was allowed to select. The focus of the study was on identifying Impacts (differentiated with 9 variables) of digital agricultural management (Pressure, differentiated with 3 variables). However, we recognize there may be a multitude of intermediate processes that connect digital agriculture management with impacts. Therefore, we decided to allow for a higher limit on the maximum number of States, or intermediate variables, that could be included in the model (20 variables). Lastly, we allowed for 5 variables to differentiate the Drivers. The decision on the number of variables stem from earlier experiences with participatory assessment workshops (König et al., 2013; Hermanns et al., 2017; Hamidov et al., 2022). To provide a familiar means to the workshop participants for conceptualizing system components, the variables in the Impact and State categories were divided according to environmental, economic and social dimensions. To promote a fair and balanced approach to selecting Impacts, we instructed the participants to choose three Impact variables from each of the three dimensions of sustainability, with the aim of ensuring that each dimension is given equal consideration in the modelling process.

After completing the variable selection process, the groups were instructed to arrange their variables into network diagrams using arrows to indicate causal relationships between the variables. With the help of a moderator, the group participants were encouraged to draw as many connecting arrows as needed, while explaining the reason behind these connections as they were made. The conceptual models of each stakeholder group can be seen in the Supplementary Material III.

3.5.2. Desk analysis: construction of a unified conceptual model

After the first workshop, the three individual conceptual models of the stakeholder groups were merged into a unified conceptual model. To limit model size and complexity, only variables that were common to two or more of the three stakeholder group models were included in the unified conceptual model. All connecting arrows between these common variables as found in the individual conceptual models were included in the first elaboration of the unified conceptual model.

3.5.3. Workshop 2: discussions of individual group models and joint conceptual model

In the second workshop, similarities and differences between the individual stakeholder conceptual models were highlighted and mixed-

Table 1
Different levels of digitalization as used in the BBN for Digital agriculture variable.

Degrees of digitalization	
Intensive	Sensors and automated decisions (AI-based) are fully integrated at every stage of production. Drones and small autonomous robots are widespread. Farmers are contractually integrated into larger systems/associations, and management is carried out at a higher level with AI support. Precise use of inputs and environmental impacts are monitored in real time.
Moderate	Mixture of large, manually operated machines and small autonomous robots. Precision farming is used to reduce environmental impacts. Some sensors and robots are used to monitor plant and animal health and soil moisture. Farmers use apps and other decision support systems to follow real-time developments.
Limited (BAU)	Only certain parts of the cultivation process are digitized and most of the processes remain analogue, performed by humans and large machines (e.g. tractors with GPS-RTK). Digital technology is only used to support analogue processes. This scenario represents business as usual.

group discussions were held to allow for in-depth exchanges on viewpoints between groups. After that, the participants were divided back into their respective stakeholder groups, where they were presented the unified conceptual model. The participants were then requested to review the model for logical consistency, such as clarifying the reasoning behind connections, while identifying superfluous and missing connections. Their feedback was then later incorporated into the second elaboration of the unified conceptual model (Supplementary Material III).

During this workshop, participants were also introduced to the Digital agriculture variable (i.e. Pressure) and the specific digital agricultural technologies encompassing it, as selected by the groups in the first workshop. This was done to establish an initial conceptual basis between the participants to help define digital agriculture. Since the focus of this study was on the broader implications of digital agriculture rather than on any specific digital technology, we simplified the modelling process by grouping these technologies under a single variable. This variable was assigned different degrees (i.e. scenarios) of digitalization: intensive, moderate, and limited (corresponding to business-as-usual) (Table 1). The delineations for these distinct scenarios were partially drawn from the work of Dönitz et al. (2020) and were employed to provide comprehensive descriptions and a common understanding of digital agriculture among participants.

3.5.4. Desk analysis: indicator selection for unified conceptual model

Following the second workshop, the system variables of the unified conceptual model were assigned indicators. This was done for two reasons: first, to transfer the qualitative conceptual model into a quantitative one and, second, to become more precise about the variables and their interactions for the next workshop. Through a review of the literature, policy documents and expert consultations, a set of Brandenburg-specific indicators for the variables in the unified conceptual model was produced. This set of indicators was then sent via email to the workshop participants for their feedback. After receiving and incorporating their feedback, the authors assigned discrete values to each indicator in order to reasonably describe a condition the variable could possess in the case study region. This was also done through literature analysis. Additional information and sources of the indicators used in the BBN is available in Supplementary Material II.

3.5.5. Workshop 3: quantifying probabilities

In the third workshop, probability estimates were elicited from the stakeholder groups for quantifying the conditional probability distributions of the variables in the network. For each group, a set of blank CPT formulas were provided where they were requested to input percentage probabilities that aligned with their expertise and knowledge. Due to time limitations, it was not feasible for each group to derive estimates for all CPTs. Instead, the groups were assigned a limited number of CPTs to complete. Certain CPTs were completed by all three groups, specifically focusing on variables and connections that were shared among their conceptual models. Estimates from CPTs that were common to each group were summed and averaged as input for the final model.

3.5.6. Desk analysis: analysis of workshop results in Netica

The elicited network structure and CPTs obtained from the workshops were then entered into Netica (Netica V5.18, 2015). We then ran scenario analyses on the final BBN using different degrees of digitalization to observe marginal changes in probabilities of nodes, allowing us to identify areas of certainty and uncertainty in the model.

3.5.7. Workshop 4: presentation of results and reflection on process

In the fourth and final workshop, the participants were presented the final BBN and a short demonstration was conducted using Netica. An open discussion was held where the participants were given the chance to express their views on the BBN and the overall modelling process.

4. Results

Using the procedure outlined above, each stakeholder group developed a conceptual model to determine crucial agricultural system components affected by digitalization as well as the relationships that lead to these effects. The commonalities between the various conceptual models were then used to construct a unified BBN (Fig. 4), portraying the three stakeholder groups' shared understanding of the impacts of agricultural digitalization. The unified Bayesian network included a total of 28 variables, consisting of 1 Pressure variable (i.e., digital agriculture), 4 Driver variables, 14 State variables and 9 Impact variables. The network contained a total of 44 causal relationships (i.e., conditional dependencies) between variables and 272 unique probability values quantifying these relationships.

Table 2 presents the connections identified in the BBN, along with descriptions of each (the numbers in Fig. 4 correspond to the connections listed in this table). Table 3 provides a comprehensive overview of the characteristics of variables within the Impact category, including indicators, corresponding values, and probability estimates for different scenarios of agricultural digitalization. Table 4 presents the same respective details for variables within the State category, while Table 5 lists the Drivers and their corresponding indicators and values.

In the following, key findings based on the analysis of the unified BBN related to Impacts, States, Pressures and Drivers are outlined. For the Impacts and States categories, we describe a scenario with an intensive degree of digitalization as compared with a limited degree of digitalization (i.e., business as usual). To assess the level of certainty regarding the effects of digitalization for each variable, we adopted a categorization technique. This involved categorizing the variable range of probabilities, derived from the percentage point difference between intensive and limited degrees of digitalization, which spanned from 0 % to 56 %, taking all variables into account. The resulting categorization scheme consisted of three equally partitioned levels: low certainty (0–18 %), medium certainty (19–38 %), and high certainty (39–56 %).

Table 2
Connections within the BBN and their descriptions under an intensive degree of digitalization.

Nr.	Connection	Description	Nr.	Connection	Description
1	Legal framework to Digital agriculture	Clear agri-digital laws promote innovation and technology use while safeguarding the rights of farmers and the environment	12	Digital agriculture to Working conditions	Automation reduces labour units per hectare, easing workload on farmers
2	Data harmonization to Digital agriculture	Standardizes data exchange and integration across digital devices and databases facilitates the use of digital tools in agriculture	13	Digital agriculture to Risk management (predictability)	Use of decision support tools and big-data analytics improves on-farm risk management strategies
3	Payments for ecosystem services to Digital agriculture	Subsidies that support provision of ecosystem services incentivize farmers to adopt digital practices that enhance ecosystem services	14	Risk management (predictability) to Product (crop) diversification	Improved risk management reduces operational uncertainties of crop diversification and associated market risks
4	Producer prices to Digital agriculture	Higher producer prices improve farm revenue, allowing farmers to invest in digital equipment and machinery	15	Product (crop) diversification to Regional self-sufficiency	The diversity of crops grown regionally improves the ability of the region to produce enough nutritious food to meet the dietary needs of the local population
5	Digital agriculture to Field size	The use of autonomous machines allows reduction of field sizes and fine-scale operations with no drawback on labour costs	16	Product (crop) diversification to Economic stability (variability in revenue)	The diversity of crops grown reduces variability in revenue and improves economic stability through spreading production and market risks across different crops
6	Digital agriculture to Nutrient (nitrogen) balance	Site-specific fertilizer technology optimizes and reduces the amount of nitrogen applied to fields	17	Product (crop) diversification to Regional value chains	The diversity of crops grown regionally increases the number of products that flow into regional value chains
7	Digital agriculture to Energy consumption (diesel)	The substitution of electric-powered robots for tractors reduces diesel consumption	18	Working conditions (Labour unit /100 ha) to Attractiveness for farm successors	Improved working conditions and reduced workload improve the appeal of farming as a profession and the likelihood of attracting farm successors
8	Digital agriculture to Field (water holding) capacity	The use of lightweight field robots reduces soil compaction and improves water holding capacity of soils	19	Ammonia emissions to Social acceptance of agriculture	Ammonia emissions, associated with strong odours, may affect societal acceptance of agriculture (no CPT)
9	Digital agriculture to Plant diversity (Shannon-Index)	Site-specific management technologies improve diversity of crops within fields or per unit area	20	Field (water holding) capacity to Soil quality (humus content)	Improved water holding capacity may affect soil quality in terms of promoting microbial activity and humus accumulation (no CPT)
10	Digital agriculture to Ecologically valuable agriculture (organic farming)	Digital tools may support organic farming practices	21	Nutrient (nitrogen) balance to Resource efficiency (kg CO2-eq/ product)	Reduction of nitrogen inputs increases resource use efficiency by decreasing embedded CO2-eq per product produced
11	Digital agriculture to Ammonia emissions	Site-specific fertilization technology reduces the amount of ammonia emissions	22	Nutrient (nitrogen) balance to Water quality (N concentration of wells)	Reduced nitrogen inputs improve water quality by decreasing runoff and infiltration of nitrates into ground water

Nr.	Connection	Description	Nr.	Connection	Description
23	Field size to Biodiversity (farmland birds)	Smaller field sizes may affect the diversity of cropping systems over a larger area thereby improving habitat conditions for farmland birds	34	Soil quality (humus content) to Productivity (grain yields in t/ ha)	Soil quality and humus content may affect the growth of crops and potential yields (no CPT)
24	Field size to Landscape diversity (landscape elements)	Field sizes may affect the amount of field edges and space available for linear landscape elements	35	Attractiveness for farm successors to Social appreciation for agriculture	Farm successors and the perception that farming is a viable career may affect social appreciation of agriculture (no CPT)
25	Landscape diversity (landscape elements) to Biodiversity (farmland birds)	Edge habitats provided by landscape elements may affects biodiversity and farmland bird abundance	36	Productivity (grain yields in t/ ha) to Social appreciation for agriculture	Productivity and yields may affect the perception and appreciation of society for agriculture (no CPT)
26	Landscape diversity (landscape elements) to Water quality (N concentration of wells)	Landscape elements act as buffer zones that reduce runoff of nitrates into water bodies	37	Productivity (grain yields in t/ ha) to Attractiveness for farm successors	Higher productivity and yields have a positive influence on the perception of farming as a viable career for farm successors
27	Landscape diversity (landscape elements) to Plant diversity (Shannon-Index)	Landscape elements may provide edge habitats for a diversity of plant species	38	Attractiveness for farm successors to Regional value chains	New farmer successors are more likely to innovate and improve marketing for products for local value chains
28	Plant diversity (Shannon-Index) to Biodiversity (farmland birds)	In-field plant species diversity and longer crop rotations may affect food sources for farmland birds	39	Risk management (predictability) to Variability of yield	Improved risk management and predictability of environmental events improves management and variability of yield
29	Plant diversity (Shannon-Index) to Soil quality (humus content)	In-field plant species diversity and longer crop rotations affect soil quality and humus content	40	Variability of yield to Productivity	Variability of yield may affect total productivity and yields (no CPT)
30	Ecologically valuable agriculture (organic farming) to Soil quality (humus content)	Organic farming practices may affect microbial activity and humus accumulation (no CPT)	41	Variability of yield to Economic stability (variability in revenue)	Reduced variability in yields mitigates variability of revenue, thereby improving economic stability
31	Ecologically valuable agriculture (organic farming) to Food quality	Organic farming practices may affect nutrient content and safety of food	42	Productivity (grain yields in t/ ha) to Economic stability (variability in revenue)	Higher yields increase incomes thereby buffering impacts of variability in revenue
32	Ecologically valuable agriculture (organic farming) to Social appreciation for agriculture	Organic farming may affect the societal reputation of farming as a profession (no CPT)	43	Energy consumption (diesel) to Resource efficiency (kg CO2-eq/ product)	Energy consumption and the amount of diesel used in operations contributes to the embedded CO2-eq per product produced

(*continued on next page*)

Table 2 (*continued*)

Nr.	Connection	Description	Nr.	Connection	Description
33	Soil quality (humus content) to Variability of yield	Stable soil quality and humus content improves nutrient availability for plant growth and reduces variability of yield	44	Soil quality (humus content) to Attractiveness for farm successors	Good soil quality and humus content improve economic viability of farming and appeal for farm successors

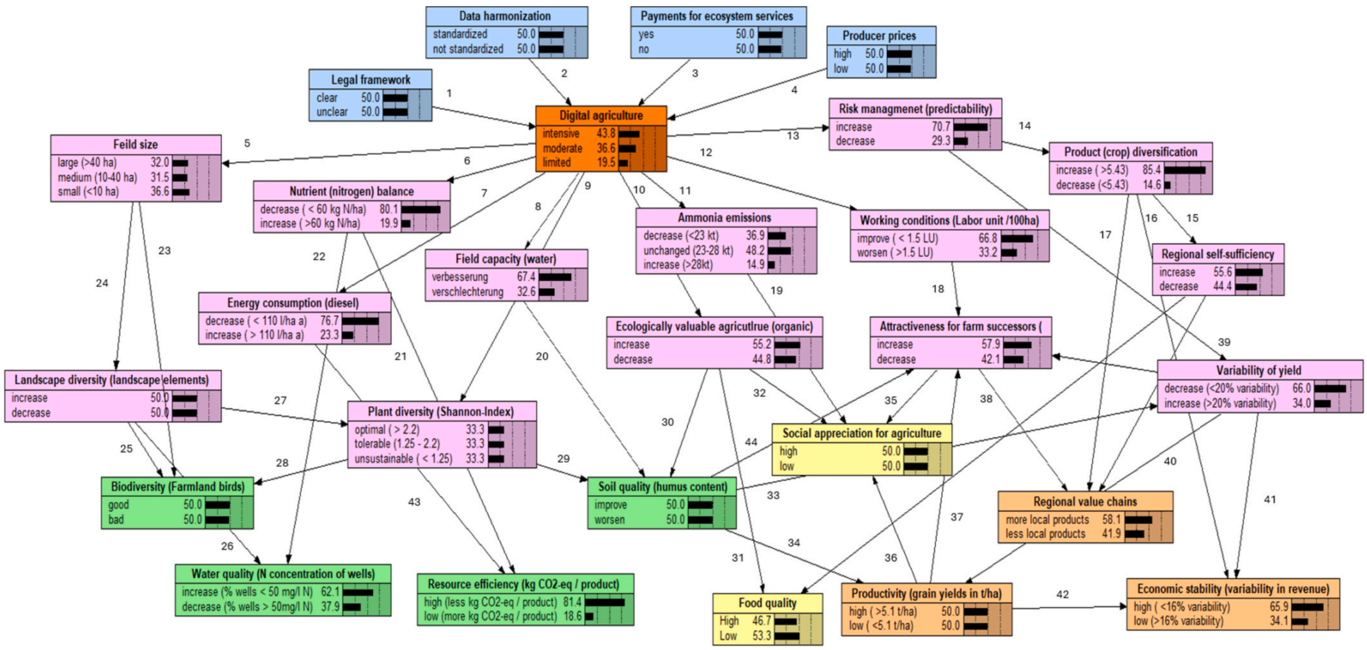

Fig. 4. The unified Bayesian belief network (BBN) in Netica. Blue variables = Drivers; orange variable = Pressure; pink variables = States; Green/Yellow/light Orange = environmental/social/economic impacts. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

4.1. Impacts

A total of nine Impact variables and respective indicators were included in the unified BBN, representing the key impact areas that digital agriculture in Brandenburg is likely to influence in the future (Table 2). According to the stakeholders in our study, digitalization is perceived to have a positive impact on *Resource use efficiency* (with medium certainty), specifically in terms of reducing the carbon footprint per product. This is primarily attributed to two main factors: decreased energy consumption of diesel fuel and reduced usage of synthetic fertilizers, both of which contribute to greenhouse gas emissions (e.g., regarding the usage of fertilizers, the indirect emission associated with their production is emphasized). *Economic stability*, or variability in revenue from crop production, is expected to be positively impacted by

Table 3
Impact variables, corresponding indicators, values and probabilities under different degrees of digitalization.

Impacts			Degree of digitalization			
Variable	Indicator	Value	Limited (BAU)	Moderate	Intensive	Level of certainty
Biodiversity	Farmland bird occurrence	Good	50,2 %	50,2 %	50,2 %	Low
		Bad	49,8 %	49,80 %	49,8 %	Low
Economic stability	Variability in revenue from crop production (€/ha UAA)	Good (<16 % variability)	47,2 %	70,0 %	75,2 %	Medium
		Bad (>16 % variability)	52,8 %	30,0 %	24,8 %	Medium
Food quality	Not defined	High	41,2 %	44,6 %	50,9 %	Low
		Low	58,8 %	55,4 %	49,1 %	Low
Productivity	Yield in t/ha (only grains)	High (> 5.1 t/ha)		N/A		
		Low (< 5.1 t/ha)				
Regional value chain	Share of agricultural products that are marketed locally/regionally	More local products	50,9 %	58,4 %	61,0 %	Low
		Less local products	49,1 %	41,6 %	39,0 %	Low
Resource efficiency	kg CO_2-eq/product	High (less kg CO2-eq/ product)	60,0 %	78,8 %	93,2 %	Medium
		Low (more kg CO2-eq/ product)	40,0 %	21,2 %	6,8 %	Medium
Social appreciation of the agricultural sector	Not defined	High		N/A		
		Low				
Soil quality	Humus content	Good		N/A		
		Bad				
Water quality	Share (in %) of wells with a nitrate concentration of 50 mg/l	Increase (% wells <50 mg/l N)	43,9 %	59,4 %	72,3 %	Medium
		Decrease (% wells >50 mg/l N)	56,1 %	40,6 %	27,7 %	Medium

digitalization (with medium certainty), primarily through increased product diversification and decreased variability of yields, two factors that are strongly influenced by improved risk management. *Water quality*, specifically the nitrate concentrations in water wells, is expected to improve (with medium certainty) through the reduction of total nitrogen fertilizer inputs as a result of site-specific fertilizer application. Digitalization was perceived to have a marginal positive effect on *Food quality and security* (with low certainty) through improved regional self-sufficiency. The impacts of digital agriculture on *Biodiversity*, particularly farmland bird abundance, and *Regional value chains*, measured by the share of agricultural products marketed locally, are unclear. Regrettably, due to time limitations in the workshops, it was not possible to obtain the CPTs for the Impact variables on *Societal appreciation for the agricultural sector*, *Soil quality*, and *Productivity*.

4.2. States

The unified BBN encompasses fourteen state variables and their corresponding indicators, effectively capturing the intermediate processes that link digital agriculture to its impacts (Table 3). The analysis highlights the considerable positive influence of digitalization on *Risk management* (with high certainty), specifically through enhanced risk predictability, facilitated by data-driven decision support tools and AI. This improvement in risk management is expected to have positive impacts on *Product diversification*, measured by the average number of crops per farm, and the mitigation of *Variability of yield* for a typical crop rotation in Brandenburg (with medium certainty). Furthermore, the BBN shows that *Nutrient balance* will improve (with medium certainty) by optimizing the application of synthetic nitrogen fertilizers through data-driven, site-specific approaches. Moreover, by substituting diesel-powered machinery with electric-powered field robots, digital agriculture is likely to decrease *Energy (diesel) consumption* (with medium certainty). A shift toward automation will also contribute to improved *Working conditions* for farmers (with medium certainty), allowing them to work larger areas of land in less time, positively impacting the *Attractiveness of farming as a profession for successors* (with low certainty). Additionally, the utilization of lightweight field robots instead of heavy machinery is expected to mitigate soil compaction, resulting in an increase in *Field (water holding) capacity* (with medium certainty). Digitalization and site-specific fertilization were anticipated to have only a minor effect on reducing *Ammonia emissions* (with low certainty). There was only a slight inclination toward smaller *Field sizes* (with low certainty) through the adoption of autonomous crop machines. The impact of digitalization on variables such as *Regional self-sufficiency*, *Ecologically valuable agriculture*, *Plant diversity*, and *Structural diversity of landscapes* remained uncertain.

4.3. Pressures

To conceptualize digital agriculture and establish common ground between participants on the diverse array of technologies falling under its purview, a discussion was held where eight specific technologies were identified between the three stakeholder groups: AI, DSS, VRT, in-situ sensors, GPS, satellites, yield maps, and robotics. As it would have been impractical to include all selected technologies in the BBN, these technologies were subsequently bundled together under a single pressure variable named *Digital agriculture* in the unified BBN. For modelling purposes, the digital agriculture variable was differentiated by varying conditions (i.e. degrees) of digital integration (see Table 1).

Table 4
State variables, corresponding indicators, values and probabilities under different degrees of digitalization.

Impacts			Degree of digitalization			
Variable	Indicator	Value	Limited (BAU)	Moderate	Intensive	Level of certainty
Ammonia emissions	NH_3 emissions (in kt) from the agricultural sector	Decrease (< 23,7 kt)	27,8 %	32,8 %	44,4 %	Low
		Unchanged (23–28 kt)	51,1 %	51,1 %	44,4 %	Low
		Increase (> 28 kt)	21,1 %	16,1 %	11,2 %	Low
Attractiveness for farm successors	Share (%) of farm managers under 55 years old	Increase	47,5 %	56,6 %	63,5 %	Low
		Decrease	52,5 %	43,4 %	36,5 %	Low
Ecologically valuable agriculture	Share (%) of organic farms in the total agricultural area	Increase	46,7 %	50,0 %	63,3 %	Low
		Decrease	53,3 %	50,0 %	36,7 %	Low
Energy consumption	Average diesel consumption in L/ha-a	Decrease (< 110 L/ha-a)	53,3 %	73,3 %	90,0 %	Medium
		Increase (> 110 L/ha-a)	46,7 %	26,7 %	10,0 %	Medium
Field capacity (water)	% Vol. of water available to plants in the root area up to 100 cm	Increase	46,7 %	63,3 %	80,0 %	Medium
		Decrease	53,3 %	36,7 %	20,0 %	Medium
Field size	Average field size in hectares	Large (> 40 ha)	58,3 %	48,7 %	43,8 %	Low
		Medium (10–40 ha)	23,1 %	25,6 %	25,7 %	Low
		Small (< 10 ha)	18,6 %	25,7 %	30,5 %	Low
Nutrient balance	Nitrogen balance	Decrease (< 60 kg N/ha)	56,7 %	76,7 %	93,3 %	Medium
		Increase (> 60 kg N/ha)	43,3 %	23,3 %	6,7 %	Medium
Plant diversity	Shannon index (HS)	Optimal (>2.2)	37,5 %	37,5 %	37,5 %	Low
		Tolerable (1.25–2.2)	31,2 %	31,2 %	31,2 %	Low
		Unsustainable (<1.25)	31,2 %	31,2 %	31,2 %	Low
Product diversification	Average number of crops per farm	Increase (> 5.43)	65,0 %	85,0 %	93,3 %	Medium
		Decrease (< 5.43)	35,0 %	15,0 %	6,7 %	Medium
Regional self-sufficiency	Percentage of food produced and consumed in a region	Increase	49,5 %	56,0 %	58,0 %	Low
		Decrease	50,5 %	44,0 %	42,0 %	Low
Risk management	Risk predictability	Increase	30,0 %	73,3 %	86,7 %	High
		Decrease	70,0 %	26,7 %	13,3 %	High
Landscape diversity	Share (%) of the area of landscape elements in the total agricultural area	Increase	50,0 %	50,0 %	50,0 %	Low
		Decrease	50,0 %	50,0 %	50,0 %	Low
Working conditions for farmers	Labor Unit per hectare	Decrease (< 1.5)	50,0 %	60,0 %	80,0 %	Medium
		Increase (> 1.5)	50,0 %	40,0 %	20,0 %	Medium
Variability of yield	Coefficient of variation for typical crop rotation	Decrease (< 20 %)	39,5 %	67,6 %	76,4 %	Medium
		Increase (> 20 %)	60,5 %	32,4 %	23,6 %	Medium

Table 5
Selected Drivers, indicators and values of agricultural digitalization.

Drivers		
Variable	Indicator	Value
Data harmonization	Standardized data	Standardized Not standardized
Legal framework	Agri-digital law	Clear, supportive Unclear, unsupportive
Payments for ecosystem services	Subsidies	Yes No
Producer prices	Producer price index	High Medium Low

4.4. Drivers

The Drivers category includes several key variables that influence the adoption and implementation of digital agriculture (Table 4). Based on agreement between the stakeholder groups, four drivers were included in the unified BBN. One important driver of agricultural digitalization is *Data harmonization*, which involves the standardized exchange and integration of data across digital devices and databases. Another driver is the *Legal framework* surrounding digital agriculture. For example, clear agri-digital laws balance innovation and technology use while protecting the rights of farmers, the public, and, by extension, the environment. In contrast, unclear laws can have the opposite effect, leading to negative societal and environmental impacts. *Payments for ecosystem services* also play a role in driving the adoption of digital agriculture: subsidies that support technology-assisted agricultural measures can incentivize farmers to adopt these practices and support ecosystem service provision. Lastly, *Producer prices*, measured by the producer price index, impacts the revenue and cost situation in agriculture¸ thereby affecting a farms ability to invest in new equipment and machinery.

5. Discussion

Our study highlights the potential impacts of digital agriculture as perceived by key stakeholder groups from a region characterized by highly mechanized arable systems. The findings on the perceived benefits align closely with prior studies, suggesting that resource efficiency and economic stability will benefit from digitalization (Barrett and Rose, 2022; Regan, 2019; Metta et al., 2022). These advantages are attributed to precision farming technologies and improved risk management, respectively. However, our study raise new questions about the risks of digitalization on biodiversity-related factors, where the impacts on landscape diversification are acknowledged but remain unclear to stakeholders.

Our study contributes to the growing body of empirical research embracing a Responsible Research and Innovation (RRI) approach by engaging stakeholders in the process of co-creating a BBN to anticipate various impacts of digitalization. It builds on prior studies assessing the risks and opportunities of digitalization by utilizing a quantitative approach to address uncertainty and ambiguity and by encouraging in-depth dialogue to collectively explore diverse perceptions and values, as well as future options (Regan, 2019; Fleming et al., 2021; Zscheischler et al., 2022). In this context, the acknowledgment of differing perceptions, knowledge uncertainties and values, as well as their integration into a collectively agreed-upon model, speaks to the value of employing our method to enhance reflexivity in RRI-driven impact assessment.

In the remainder of this section, we present and discuss key findings on the impact of digitalization on resource use, risk mitigation, and biodiversity. Additionally, we reflect on the novelty of our approach, as well as the strengths and limitations of using BBNs for participatory modelling.

5.1. Digitalization and resource savings

The stakeholders in our study perceived that digital agriculture will lead to a more efficient use of resources, such as fuel, fertilizer, and labour, which is consistent with the majority of research and asserted benefits on the topic (Basso and Antle, 2020; Finger et al., 2019; Balafoutis et al., 2017; Schimmelpfennig, 2016). It is not unexpected that stakeholders held this opinion given that some farmers in the area, including those involved in our study, have experience using precision farming technologies such as GPS guidance and yield mapping. Precision farming technologies, such as variable rate spraying, have been accessible in the market for quite some time, though their adoption remains low (Nowak, 2021). More importantly, stakeholders also pointed out the value of these technologies in relation to addressing broader environmental and political challenges the region's agriculture sector is currently facing. For instance, the group of farmers brought up a concern regarding the use of nitrogen fertilizers and expressed that the agriculture industry is under constant political pressure to decrease N-fertilizer inputs, as mandated by the EU Nitrates Directive 91/676/EEC. To address this issue, the group of farmers suggested that digitization could minimize nitrogen fertilizer usage by enhancing the efficiency of site-specific fertilizer application as well as play a role in ensuring regulatory compliance through more accurate and automated record keeping.

Given persistent labour shortages of farm workers (permanent and seasonal) in the case study region (Prause, 2021), our group of stakeholders had a favourable impression of the potential labour-saving aspects as well as improved working conditions that digitalization could entail. For instance, it was mentioned by the workshop participants that automation would reduce the amount of a farmer's working hours, which would improve attractiveness of the farming profession and, thereby, attract permanent workers and farm successors. It was also mentioned that a higher degree of automation (e.g. self-driving tractors) would make work easier, reducing the level of skill needed for performing certain tasks and thereby attracting capable workers. These results are largely in line with findings and positive views on the impacts of digitalization on labour availability of many other stakeholder-based studies (McGrath et al., 2023), but contradict arguments made concerning the negative impacts of 'de-skilling' and displacement of workers due to digitalization (Carolan, 2020; Rotz et al., 2019a; Zscheischler et al., 2022; Prause, 2021). However, it should be highlighted that the majority of studies pointing toward labour displacement frequently focus on seasonal labourers and, more specifically, horticulture systems that rely heavily on low-skilled, manual labour. The difference in viewpoints here relates to the fact that large-scale arable farming (mainly grains, maize, rape seed) is the predominant mode of production in our case study region, which necessitates a certain level of expertise and training to operate relatively complex farm machinery such as tractors and harvesters. Of course, for farmers to operate more advanced machinery in the future, such as robots, they will also be required to learn new (digital) skill sets (Prause, 2021). The same holds true for farm advisors who will also need to be upskilled to use new and more complex digital tools (Fielke et al., 2019; Fleming et al., 2021). In this case, we should expect that the quality of work would change for farmers, as they would take on new roles in managing their enterprises, which likely to impact job satisfaction (Rose and Chilvers, 2018; McGrath et al., 2023).

It is important here to note that the current study's focus on large-scale arable farming, along with its longstanding prevalence in Brandenburg, may help explain why concerns about a digital divide between large and small farms, as noted in other studies (Bronson, 2019; Regan, 2019; Hackfort, 2021), were not raised during the workshops. This indicates that when examining the implications of digitalization on labour, a differentiated assessment of local labour markets, potential alternatives and pertinent farming operations is required (Martin et al., 2022).

Although the stakeholders in our study generally had a positive viewpoint on the labour-saving potential of digitalization, the adoption of digital agriculture could also result in a 'technology treadmill', where the need to scale up operations to stay competitive arises because technological advancements often lead to increased productivity, driving down prices and forcing farmers to expand their operations, thereby increasing their workload (Cochrane, 1958; McGrath et al., 2023). Additionally, the financial investments required to adopt costly digital technologies could result in capital lock-in, where farmers are financially bound to pay off debts, compelling them to work more.

In light of rising oil prices and mounting public pressure to halt climate change, digitalization may be advantageous (Pearson et al., 2022). Participants in our case study believed that digital agriculture, e.g. electrification, field robots and precise fertilizer application, would result in fuel savings (diesel) and lower carbon emissions per product. However, as it was not taken up in the BBN, it is important to note that a highly digitalized agriculture at scale and the energy required to power data centres (e.g. cloud computing, data storage, data analysis), drones, robots, sensor networks and electric tractors require significant amounts of energy, which, depending on the source, may not result in a substantial overall reduction of carbon emissions (Leroux, 2020). Similarly, indirect rebound effects from digitalization should also be considered (Lange et al., 2020). However, while evaluating the carbon footprint of digital agriculture, it is also important to take into consideration the fact that the manufacture and disposal of electronic equipment also entail carbon and other emissions (Singh and Ogunseitan, 2022). A clearer understanding of whether digital agriculture would ultimately result in lower carbon emissions from farming activities could be obtained through Life Cycle Assessment (LCA)., To date, there appears to be a dearth of LCA studies applied to digital agriculture technologies and digital agricultural systems.

While there appears to be an absence of research focusing on how digital agriculture could affect soil water retention, there is evidence that tractor-induced soil compaction reduces water infiltration (Keller et al., 2019). This concern was raised by the stakeholders in our study. It was proposed that lighter-weight autonomous machinery could replace heavy, manually operated tractors, thus decreasing soil compaction (i.e. soil bulk density) and improving infiltration and soil water-holding capacity. Although time constraints prevented us from deriving probability estimates for the soil quality variable, it is key to emphasize the importance of soil water holding capacity for soil quality, particularly for farmers in our case study region, as decreasing precipitation and increasing severity of droughts continues to be a major issue affecting plant health and productivity (Reyer et al., 2012; Wolff et al., 2021). This suggests that digitalization could have important implications for soil health and climate change adaptation in the future, meriting further scientific exploration.

5.2. *Supporting economic robustness through mitigating risks*

Stakeholders acknowledged the potential of digital agriculture to contribute to regional economic stability by mitigating major sources of uncertainty associated with environmental and market risks. Data-driven decision-making has the capacity to improve risk management and foster economic resilience during phases of climate and market instability (McFadden et al., 2022; Wolfert et al., 2017). Specifically, in terms of weather risks, the utilization of agri-climatic databases in conjunction with big data analytics (AI-based) can assist farms in adapting to climate change and identifying hazards related to weather extremes, thereby enhancing production stability at specific sites (Martinez-Feria and Basso, 2020). Considering the impact of increased weather extremes on production (Webber et al., 2020) and the resulting (in-) stability of crop yields in the region (Macholdt et al., 2021; Döring and Reckling, 2018), it is logical for the stakeholders in our workshop to have recognized the potential of leveraging digital technologies to address such risks.

Similarly, a farmer's willingness to diversify his or her production systems may also be constrained by production risks. In this regard, digital agriculture could improve risk management related to crop diversification (Hernández-Ochoa et al., 2022). The participants agreed that better decision support could reduce production risks associated with introducing new crops as well as provide better market analytics on consumer demand for new products. In turn, crop diversification could improve economic stability (von Czettritz et al., 2023) and ecosystem functionality (Tamburini et al., 2020). However, due to region-specific policies in Germany subsidizing the production of certain types of energy crops, more diverse crop portfolios do not necessarily translate into a higher stability of income for farmers (Weigel et al., 2018). This means that regions characterized by larger farms specializing in energy crop production may not benefit from increased crop diversification. Considering this and given the relatively large farm sizes and high levels of energy crop production in Brandenburg, digitalization to facilitate crop diversification may have limited impact on reducing economic risks and promoting regional economic stability. On the other hand, as pointed out by the stakeholders in our study, higher crop diversity within a region can promote regional value chains and regional self-sufficiency (Vicente-Vicente et al., 2021). However, both factors are strongly dependent on regional consumption habits and preferences (Zasada et al., 2019), a driving factor not explicitly included in the BBN.

Even though not mentioned by the stakeholder in our study, it is important to acknowledge that increased data availability and analytical capabilities could contribute to greater market volatility. For example, when commodity traders and speculators leverage weather and farm data to make yield predictions, it can lead to rapid adjustments in futures markets and crop prices. This heightened sensitivity of market prices to data-driven forecasts can cause significant fluctuations in producer prices, which may ultimately harm farmers and their ability to plan production and profit in good years of harvest. It is also worth noting that the substantial costs associated with investing in new machinery and digital technologies can pose a significant risk to enterprises if the return on investment is not realized (Duncan et al., 2021).

5.3. *Uncertainties concerning the impacts of digitalization on landscape diversification*

There was uncertainty regarding how digitalization will affect the structural diversity of landscapes. On the one hand, the stakeholders in our study perceived that digital agriculture, specifically autonomous crop machines, could lead to smaller average field sizes and the ability to operate on finer scales. On the other hand, it was not clear whether smaller field sizes would result in an increase or decrease of landscape elements and structures, since automation might open what was once considered unproductive, marginal land to more intensive agronomic management, thereby reducing the amount of land available for semi-natural habitats. Similar results based on stakeholder perceptions were shown in other studies (Zscheischler et al., 2022). However, digitalization might boost productivity per unit of land, reducing the amount of land required to generate the same quantity of output, freeing up — or at least maintaining — land for natural features that support habitat quality (Daum, 2021).

Historical context may help shed light on the source of this ambiguity. For example, in the past, technological innovation, specifically mechanization, have resulted in ever-larger field and farm sizes, monocultures and a notable reduction of landscape diversity in the case study region DBD, (2001). If digitalization is seen as a continuation of this historical tendency toward increasing mechanization and economies of scale, then it is reasonable to believe that productivity- and efficiency-driven digitalization could lead to more of the same (Lajoie-O'Malley et al., 2020). However, recent political and societal developments indicate movement in the opposite direction. As pointed out by the stakeholders in our case study, policymakers and consumers today are becoming more aware of the detrimental consequences that conventional, large-scale agriculture has on the environment, and as a result, they are placing more pressure on farmers to operate sustainably and to 'think' on smaller scales. Moreover, there appears to be a growing trend among farmers in the region to embrace funding from the EU's Common Agricultural Policy by incorporating greening measures. The success of such measures till now has been limited and varies according to region (Gocht et al., 2017). Ehlers et al. (2021) suggested that digitalization may significantly lower costs related to monitoring such agri-environmental schemes in the future and may lead to new forms of results-based payments tailored to local conditions. In this respect, digitalization could be an important tool for promoting biodiversity-related societal objectives under the appropriate political guidance and legal framework (MacPherson et al., 2022; Garske et al., 2021). Additionally, building on practical research in this field could facilitate the implementation of more effective greening measures in the future (Mouratiadou et al., 2023).

Ambiguity surrounding the impacts on biodiversity and landscape diversification may also reflect the stakeholders' opinion in our study that digital agriculture would not have an overall effect. Given the consensus among stakeholders in our study that there is connection between field size, landscape elements and biodiversity, a deeper examination of the BBN by the participants and perhaps more focused analysis on this relationship is warranted. In this regard, gaining more stakeholder knowledge on the implication of agricultural digitalization on biodiversity would complement other research currently working on this topic (Grahmann et al., 2024).

The impacts on biodiversity resulting from digitalization may manifest over longer time periods than that used for modelling in the current study (i.e. 10 years), which could partly account for the ambiguity of stakeholder perspectives in our study surrounding this topic. In other words, while rapid digitalization is a plausible scenario, its effects on biodiversity through, for example, changes in landscape elements, may not be immediately observable due to time lags (Fahrig et al., 2011). Overall, the findings suggest that the impacts of digitalization on biodiversity-related factors are not obvious to stakeholders, which may be due to lack of evidence base, or insufficient communication between researchers and other stakeholders.

5.4. Reflections on the method

Our study introduces a novel approach to assessing the impacts of agricultural digitalization through the application of a participatory BBN. Namely, our approach sets itself apart from other studies examining stakeholder perceptions of agricultural digitalization, such as through group concept mapping (Monteiro et al., 2023) or the socio-cyber-physical systems framework (Metta et al., 2022), by explicitly incorporating uncertainties into a probabilistic modelling framework. As such, the scenario-driven analysis enabled by BBNs provides a more dynamic exploration of stakeholders perception, including thier uncertainties, on digitalization's multi-dimensional impacts. Moreover, unlike other stakeholder engagement methods commonly employed in the field, such as surveys (Kernecker et al., 2020) and interviews (Fleming et al., 2018; Barrett and Rose, 2022), which primarily focus on unidirectional acquisition of knowledge, the participatory BBN approach provides an interactive means for facilitating dialogue and co-creation of knowledge among stakeholders and researchers, culminating in the development of a formalized, consensus-driven model. This type of consensus building is particularly critical in contexts characterized by high uncertainty, where causal relationships are complex and stakeholders possess diverse, often conflicting values (Moallemi et al., 2023), as is the case of assessing the impacts of agricultural digitalization and many other envrinmontel problems.

Consensus was derived through an iterative process of constructing the BBN, where through a visual representation of causal dependencies and quantification of uncertainties via probabilities, stakeholders were able to transparently see how their knowledge was incorporated in the model over time. In this way, the procces of consturing the BBN helped to focus communication, facilitating discussion and learning (Barbrook-Johnson and Penn, 2022). As such, the BBN served as a 'boundary object' (Kenny and Castilla-Rho, 2022), bridging the different perceptions of the participants, providing a mutual understanding on the issues at hand, while helping to mitigate emotion to the greatest possible extent during discussions. This process of creating a collective understanding, or co-learning, is arguably the key product behind participatory modelling (Yassine et al., 2020; Voinov and Bousquet, 2010; Gray, 2016). In other words, the process of creating the BBN as a boundary object helped stakeholders engage with and gain a deeper understanding of the implications of digital agriculture, which might even be considered as more useful than the output of the BBN itself (Barbrook-Johnson and Penn, 2022). This highlights the notion that participatory BBNs are better suited as a tool for thinking, rather than serving as a rigid decision support tool (Cain, 2001).

Greater clarity and mutual understanding could be attained by utilizing indicators as selected by our group of stakeholders. While indicators are frequently applied in quantitative studies, their incorporation of stakeholder perspectives often remains limited. In contrast, qualitative studies often deal with themes or topics that are broad and less well defined. Through the substantiation of variables with quantitative indicators, the combined strengths from both quantitative and qualitative domains can be utilized, as demonstrated by this study. Nevertheless, it is essential to acknowledge that the indicators employed in our BBN were tailored to the unique circumstances of Brandenburg. As the efficacy of the BBN as a boundary object is contingent upon the contextual understanding and the consensus among the participants who constructed it, it may not be easily replicable in different settings. Therefore, transferring the results of the BBN to another context poses challenges due to differences in local agricultural and environmental condition, as well as variations in in stakeholder perceptions and priorities.

5.5. Limitations

In our study, stakeholders from diverse groups including farmers, researchers, civil society organizations, and public administration were included in the workshops, providing a broad range of perspectives on digital agriculture in the Brandenburg region. However, the absence of other agri-food system actors including agri-tech companies, farm advisors, supply chain actors, retailers, consumer representatives or small-scale farmers might have limited the scope of feedback, potentially overlooking impacts related to market dynamics, technology provision, consumer acceptance and equity concerns. Limiting the number of participants in workshops, however, is a necessary trade-off for facilitating highly engaging, semi-guided methods such as participatory BBNs. Ensuring more focused discussions and effective engagement requires smaller groups, which reduces sample size and potentially compromises the robustness and generalizability of the quantification outcomes of the BBN. Due to this, it is important to carefully select participants through stakeholder mapping and proper vetting procedures while acknowledging biases when interpreting results.

One possible artefact of methodological bias in our study relates to an absence of negative impacts from digitalization included in the BBN. This finding is unexpected considering the numerous concerns raised in existing literature and the initial scepticism expressed by participants. Although we attempted to conceptualize digital agriculture by discussing and selecting specific digital technologies and describing their use in various scenarios, it's important to note that understanding of digital technologies and the definition of digital agriculture may vary across different contexts and individual perspectives. Generally speaking, the farmers in our study could be considered non-adopters as they only appeared to make use of basic digital tools like farming apps, GPS-guided tractors, and social media and did not report using more complex digital technologies such as robotics, AI, or remote sensing technologies. Even though the farmers in our study had some degree of knowledge about advanced digital applications, there were varying and somewhat emotional opinions concerning their implementation. For example, some participants held scepticisms regarding the effectiveness of digital technologies, such as FMIS, questioning their ability to match the value of traditional experience and expertise (Barnes et al., 2019b). These same individuals simultaneously believed that digital tools could simplify certain tasks in the future. Here, a general lack of knowledge of digital technologies may have led to an overly optimistic view of digital agriculture. Furthermore, it is important to recognize that stakeholders' prior technical familiarity with digital agriculture technologies, or lack thereof, may have resulted in overestimation or underestimation of impacts (Kuhnert et al., 2010), affecting the reliability of probability estimates and outputs of the BBN. To address issues of potential bias in future research, assessing stakeholder knowledge both before and after the PM exercise could help determine the influence of bias in the outcomes of the BBN. Additionally, the literature frequently indicates that the advantages of digitalization, such as enhanced efficiency and productivity, tend to benefit large-scale enterprises primarily. Consequently, as previously noted regarding labor-saving aspects, the potential negative impacts of digital agriculture on smaller farms might have been neglected due to a focus on large scale arable farming in the study.

Although it was possible to derive probability estimates for the majority of CPTs within the given timeframe of the workshops, several CPTs were left blank due to time limitations. To overcome this, we suggest the use of an alternative elicitation method. For example, 3-point elicitation methods may reduce fatigue of participants by simplifying the probability estimation process (Cain, 2001). Use of improved elicitation methods will enhance data completeness, maintain participant engagement, and ultimately improve the overall quality and reliability of results.

6. Conclusions

The transition to digital agriculture is poised to bring about significant systemic changes that will have far-reaching impacts on production, consumption, governance, and the environment of agricultural systems. Digitalization will not necessarily happen overnight, but will most likely occur as a gradual, background transition over the next decades (Klerkx and Rose, 2020). While it appears that we are at the beginning of this transition, society has an opportunity to guide agriculture digitalization toward sustainability through anticipation and inclusion. The objective of this study, therefore, was to investigate the impacts of digitalization on agricultural systems by engaging stakeholder knowledge and values, specifically focusing on the Brandenburg region. To achieve this, our study employed a participatory modelling approach to co-construct a Bayesian belief network with key stakeholder groups from the area, including farmers, researchers and representatives from civil society organizations and public administration.

Through our study, we found that there is a significant amount of uncertainty among stakeholders regarding the impact of digital agriculture on landscape heterogeneity and biodiversity, pointing to a research gap. Once more evidence is ascertained on this topic, it will be important for research and policy endeavours to effectively communicate these effects to stakeholders. Here, effective communication between research, the public as well as decision makers still seems to be lacking. On the other hand, the results of our study showed there was more certainty regarding the socioeconomic benefits of digitalization, specifically in terms of promoting economic stability through enhanced risk management, labour saving improvements, as well as postivie knock-on effects of improved resource use efficiency on certain environmental factors. In this case, stakeholders' perceptions validate general claims already made regarding resource use efficiency. However the consensus among stakeholders regarding the interplay between digitalization, risk management, and diversification warrants closer attention, as it is currently under researched and could potentially serve as a strong lever in the future for promoting economic robustness.

Ultimately, the instrumentalization of digital agriculture, or the objectives for which it is being used to achieve, depends on the underlying paradigm it is associated with. For instance, within the sustainable intensification paradigm, digitalization is a means to mitigate environmental pollution and land expansion pressures by enhancing efficiency and productivity through improved input management (Lindblom et al., 2017). From the angle of conventional agriculture, the potential efficiency and productivity gains of digitalization are typically considered from a profit-maximization perspective, with less concern for wider impacts on social sustainability and ecosystem services (Lajoie-O'Malley et al., 2020). From an alternative perspective, digitalization and ecology can be seen as complementary (Schnebelin et al., 2021; Brunori, 2023), where technology is used to promote multifunctional and diversified agriculture landscapes by building on principles of agroecology (Mouratiadou et al., 2023). In this way, digital agriculture has the potential to shape the future of farming, including sustainability outcomes, based on the values and priorities of the system in which it is embedded. It is therefore useful not to view digital agriculture as a paradigm in itself, but as a versatile tool adaptable to different agricultural visions and normative framings.

Our study makes important contributions to our understanding of the various perspectives about digitalization according to key stakeholder groups in the region, which can direct future research initiatives in conveying the opportunities and risks of digital agriculture to a larger societal audience. In general, by recognizing and addressing differing perspectives, we can bridge the gap between stakeholders, researchers and policy makers, facilitating a more inclusive and informed dialogue and, consequently, promoting research that is socially, economically and environmentally more responsible.

CRediT authorship contribution statement

Joseph MacPherson: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Anna Rosman:** Writing – original draft, Visualization, Investigation, Formal analysis, Data curation. **Katharina Helming:** Writing – review & editing, Supervision, Methodology, Investigation, Conceptualization. **Benjamin Burkhard:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2024.104222.

Data availability

Data will be made available on request.

References

Amt für Statistik Berlin-Brandenburg, 2016. Struktur der land- und forstwirtschaftlichen Betriebe. Agrarstrukturerhebung (ASE). EVAS: 41121. Potsdam, Germany.

Amt für Statistik Berlin-Brandenburg, 2021. Getreide und Winterraps in Brandenburg - Ernte 2021 unterdurchschnittlich. Berlin, Germany. Kurz, Regina. Available online at https://www.statistik-berlin-brandenburg.de/211-2021. checked on 6/20/2022.

Balafoutis, Athanasios, Beck, Bert, Fountas, Spyros, Vangeyte, Jurgen, Wal, Tamme, Soto, Iria, et al., 2017. Precision agriculture technologies positively contributing to GHG emissions mitigation, farm productivity and economics. Sustainability 9 (8), 1339. https://doi.org/10.3390/su9081339.

Balafoutis, Athanasios T., van Evert, Frits K., Fountas, Spyros, 2020. Smart farming technology trends: economic and environmental effects, labor impact, and adoption readiness. Agronomy 10 (5), 743. https://doi.org/10.3390/agronomy10050743.

Balasundram, Siva K., Shamshiri, Redmond R., Sridhara, Shankarappa, Rizan, Nastaran, 2023. The role of digital agriculture in mitigating climate change and ensuring food security: an overview. Sustainability 15 (6), 5325. https://doi.org/10.3390/su15065325.

Barbrook-Johnson, Pete, Penn, Alexandra S. (Eds.), 2022. Systems Mapping. Springer International Publishing, Cham.

Barnes, A.P., Soto, I., Eory, V., Beck, B., Balafoutis, A., Sánchez, B., et al., 2019a. Exploring the adoption of precision agricultural technologies: a cross regional study of EU farmers. Land Use Policy 80, 163–174. https://doi.org/10.1016/j.landusepol.2018.10.004.

Barnes, A.P., Soto, I., Eory, V., Beck, B., Balafoutis, A.T., Sanchez, B., et al., 2019b. Influencing incentives for precision agricultural technologies within European arable farming systems. Environ. Sci. Pol. 93, 66–74. https://doi.org/10.1016/j.envsci.2018.12.014.

Barrett, Hannah, Rose, David Christian, 2022. Perceptions of the fourth agricultural revolution: what's in, what's out, and what consequences are anticipated? Sociol. Rural. 62 (2), 162–189. https://doi.org/10.1111/soru.12324.

Basso, Bruno, Antle, John, 2020. Digital agriculture to design sustainable agricultural systems. Nat. Sustain. 3 (4), 254–256. https://doi.org/10.1038/s41893-020-0510-0.

Bernhardt, Heinz, Schumacher, Leon, Zhou, Jianfeng, Treiber, Maximilian, Shannon, Kent, 2021. Digital Agriculture Infrastructure in the USA and Germany (Engineering Proceedings, 9).

Binder, Claudia R., Feola, Giuseppe, Steinberger, Julia K., 2010. Considering the normative, systemic and procedural dimensions in indicator-based sustainability assessments in agriculture. Environ. Impact Assess. Rev. 30 (2), 71–81. https://doi.org/10.1016/j.eiar.2009.06.002.

Birner, Regina, Daum, Thomas, Pray, Carl, 2021. Who drives the digital revolution in agriculture? A review of supply-side trends, players and challenges. Appl. Econ. Perspect. Policy 43 (4), 1260–1285. https://doi.org/10.1002/aepp.13145.

Bloch, R., Bellingrath-Kimura, S.D., 2020. Smart Farming – Eine Chance für nachhaltige Agrarsysteme? In: Göpel, M., Leitschuh, H., Brunnengräber, A., Ibisch, P., Loske, R., Müller, M., et al. (Eds.), Die Ökologie der digitalen Gesellschaft. Jahrbuch Ökologie 2019/2020. Stuttgart: S. Hirzel, pp. 110–116.

BMEL, 2019. Discussion Paper 2035 Arable Farming Strategy. Bundesministerium für Ernährung und Landwirtschaft. Available online at https://www.bmel.de/SharedDocs/Downloads/EN/Publications/ackerbaustrategie-en.html. checked on 10/1/2022.

Bronson, Kelly, 2019. Looking through a responsible innovation lens at uneven engagements with digital farming. In NJAS: Wageningen Journal of Life Sciences 90-91 1, 1–6. https://doi.org/10.1016/j.njas.2019.03.001.

Bosch, P., Gabrielson, P., 2003. Environmental Indicators: Typology and Use in Reporting. In European Environment Agency, Copenhagen, pp. 1–20.

Breitschuh, Gerhard, 2008. Kriteriensystem nachhaltige Landwirtschaft (KSNL). Ein Verfahren zur Nachhaltigkeitsanalyse und Bewertung von Landwirtschaftsbetrieben / [Gerhard Breitschuh … et al.; unter Mitarb. von Günter Bachmann … et al.]. Darmstadt: Kuratorium für Technik und Bauwesen in der Landwirtschaft (KTBL-Schrift, 0173–2811, 466).

Bromley, J., Jackson, N.A., Clymer, O.J., Giacomello, A.M., Jensen, F.V., 2005. The use of Hugin® to develop Bayesian networks as an aid to integrated water resource planning. Environ. Model Softw. 20 (2), 231–242. https://doi.org/10.1016/j.envsoft.2003.12.021.

Brunori, Gianluca, 2023. Agriculture and rural areas facing the "twin transition": principles for a sustainable rural digitalisation. Rea 77 (3), 3–14. https://doi.org/10.36253/rea-13983.

Cain, Jeremy, 2001. Planning Improvements in Natural Resource Management. Guidelines for Using Bayesian Networks to Support the Planning and Management of Development Programmes in the Water Sector and beyond. Centre for Ecology and Hydrology, Wallingford.

Carmona, G., Varela-Ortega, C., Bromley, J., 2011. The use of participatory object-oriented Bayesian networks and agro-economic models for groundwater management in Spain. Water Resour. Manag. 25 (5), 1509–1524. https://doi.org/10.1007/s11269-010-9757-y.

Carolan, Michael, 2020. Automated agrifood futures: robotics, labor and the distributive politics of digital agriculture. J. Peasant Stud. 47 (1), 184–207. https://doi.org/10.1080/03066150.2019.1584189.

Celio, E., Gret-Regamey, A., 2016. Understanding farmers' influence on land-use change using a participatory Bayesian network approach in a pre-Alpine region in Switzerland. J. Environ. Plan. Manag. 59 (11), 2079–2101. https://doi.org/10.1080/09640568.2015.1120713.

Chopin, Pierre, Mubaya, Chipo P., Descheemaeker, Katrien, Öborn, Ingrid, Bergkvist, Göran, 2021. Avenues for improving farming sustainability assessment with upgraded tools, sustainability framing and indicators. A review. Agron. Sustain. Dev. 41 (2), 155. https://doi.org/10.1007/s13593-021-00674-3.

Clapp, Jennifer, Ruder, Sarah-Louise, 2020. Precision technologies for agriculture: digital farming, gene-edited crops, and the politics of sustainability. Glob. Environ. Polit. 20 (3), 49–69. https://doi.org/10.1162/glep_a_00566.

Cochrane, Willard W., 1958. Farm Prices: Myth and Reality. U of Minnesota Press.

Da Silveira, Franco, Da Silva, Sabrina Letícia Couto, Machado, Filipe Molinar, Barbedo, Jayme Garcia Arnal, Amaral, Fernando Gonçalves, 2023. Farmers' perception of the barriers that hinder the implementation of agriculture 4.0. Agricultural Systems 208, 103656. https://doi.org/10.1016/j.agsy.2023.103656.

Daum, Thomas, 2021. Farm robots: ecological utopia or dystopia? Trends Ecol. Evol. 36 (9), 774–777. https://doi.org/10.1016/j.tree.2021.06.002.

Daum, Thomas, Buchwald, Hannes, Gerlicher, Ansgar, Birner, Regina, 2018. Smartphone apps as a new method to collect data on smallholder farming systems in the digital age: a case study from Zambia. Comput. Electron. Agric. 153, 144–150. https://doi.org/10.1016/j.compag.2018.08.017.

Dehnen-Schmutz, Katharina, Foster, Gemma L., Owen, Luke, Persello, Séverine, 2016. Exploring the role of smartphone technology for citizen science in agriculture. Agron. Sustain. Dev. 36 (2). https://doi.org/10.1007/s13593-016-0359-9.

Deutsche Bauerbund Dokumentation (2001): 10 Jahre Umstrukturierung der ost-deutschen Landwirtschaft. 2. Auflage, IGW Berlin, 75 S. Methodenbuch (1955): Bd.1, Radebeul und Berlin.

Deutsche Bundesregierung, 2018. Deutsche Nachhaltigkeitsstrategie. Aktualisierung 2018. Die Bundesregierung.

Donat, Marco, Geistert, Jonas, Grahmann, Kathrin, Bloch, Ralf, Bellingrath-Kimura, Sonoko D., 2022. Patch cropping- a new methodological approach to determine new field arrangements that increase the multifunctionality of agricultural landscapes. Comput. Electron. Agric. 197, 106894. https://doi.org/10.1016/j.compag.2022.106894.

Dönitz, E, Voglhuber-Slavinsky, A, Moller, B, 2020. Agribusiness in 2035—Farmers of the Future. Frauenhofer Institute for Systems and Innovation Research ISI, Karlsruhe, Germany.

Döring, Thomas F., Reckling, Moritz, 2018. Detecting global trends of cereal yield stability by adjusting the coefficient of variation. Eur. J. Agron. 99, 30–36. https://doi.org/10.1016/j.eja.2018.06.007.

Duncan, Emily, Abdulai, Abdul-Rahim, Fraser, Evan D.G., 2021. Modernizing agriculture through digital technologies: Prospects and challenges. In: James, Harvey S. (Ed.), Handbook on the Human Impact of Agriculture. Edward Elgar Publishing, Cheltenham UK, Northampton MA.

Duspohl, M., Doll, P., 2016. Causal networks and scenarios: participatory strategy development for promoting renewable electricity generation. J. Clean. Prod. 121, 218–230. https://doi.org/10.1016/j.jclepro.2015.09.117.

Eastwood, Callum R., Renwick, Alan, 2020. Innovation uncertainty impacts the adoption of smarter farming approaches. Front. Sustain. Food Syst. 4. https://doi.org/10.3389/fsufs.2020.00024. Article 24.

Eastwood, C., Klerkx, L., Ayre, M., Dela Rue, B., 2019. Managing socio-ethical challenges in the development of smart farming: from a fragmented to a comprehensive approach for responsible research and innovation. J. Agric. Environ. Ethics 32 (5–6), 741–768. https://doi.org/10.1007/s10806-017-9704-5.

Eastwood, C.R., Edwards, J.P., Turner, J.A., 2021. Review: anticipating alternative trajectories for responsible Agriculture 4.0 innovation in livestock systems. Animal 15 (Suppl. 1), 100296. https://doi.org/10.1016/j.animal.2021.100296.

Eastwood, C.R., Turner, F.J., Romera, A.J., 2022. Farmer-centred design: an affordances-based framework for identifying processes that facilitate farmers as co-designers in addressing complex agricultural challenges. Agric. Syst. 195, 103314. https://doi.org/10.1016/j.agsy.2021.103314.

Ehlers, Melf-Hinrich, Huber, Robert, Finger, Robert, 2021. Agricultural policy in the era of digitalisation. Food Policy 100, 102019. https://doi.org/10.1016/j.foodpol.2020.102019.

Ehlers, Melf-Hinrich, Finger, Robert, El Benni, Nadja, Gocht, Alexander, Sørensen, Claus Aage Grøn, Gusset, Markus, et al., 2022. Scenarios for European agricultural policymaking in the era of digitalisation. Agric. Syst. 196, 103318. https://doi.org/10.1016/j.agsy.2021.103318.

European Commission, 2020. F2F strategy: for a fair, healthy and environmentally-friendly food system. Available online at https://ec.europa.eu/food/farm2fork_en. checked on 10/1/2022.

European Environment Agency, 2019. CORINE Land Cover 2018 (Raster 100 M), Europe, 6-Yearly - Version 2020_20u1. May 2020.

Fahrig, Lenore, Baudry, Jacques, Brotons, Lluís, Burel, Françoise G., Crist, Thomas O., Fuller, Robert J., et al., 2011. Functional landscape heterogeneity and animal biodiversity in agricultural landscapes. Ecol. Lett. 14 (2), 101–112. https://doi.org/10.1111/j.1461-0248.2010.01559.x.

FAO, 2013. SAFA Sustainability Assessment of Food and Agriculture Systems Indicators. FAO, Rome, Italy.

Fielke, Simon J., Garrard, Robert, Jakku, Emma, Fleming, Aysha, Wiseman, Leanne, Taylor, Bruce M., 2019. Conceptualising the DAIS: implications of the 'digitalisation of agricultural innovation systems' on technology and policy at multiple levels. NJAS Wagening. J. Life Sci. 90-91 (1), 1–11. https://doi.org/10.1016/j.njas.2019.04.002.

Finger, Robert, 2023. Digital innovations for sustainable and resilient agricultural systems. Eur. Rev. Agric. Econ. 50 (4), 1277–1309. https://doi.org/10.1093/erae/jbad021.

Finger, Robert, Swinton, Scott M., El Benni, Nadja, Walter, Achim, 2019. Precision farming at the Nexus of agricultural production and the environment. Ann. Rev. Resour. Econ. 11 (1), 313–335. https://doi.org/10.1146/annurev-resource-100518-093929.

Fleming, Aysha, Jakku, Emma, Lim-Camacho, Lilly, Taylor, Bruce, Thorburn, Peter, 2018. Is big data for big farming or for everyone? Perceptions in the Australian grains industry. Agron. Sustain. Dev. 38 (3). https://doi.org/10.1007/s13593-018-0501-y.

Fleming, Aysha, Jakku, Emma, Fielke, Simon, Taylor, Bruce M., Lacey, Justine, Terhorst, Andrew, Stitzlein, Cara, 2021. Foresighting Australian digital agricultural futures: applying responsible innovation thinking to anticipate research and development impact under different scenarios. Agric. Syst. 190 (4), 103120. https://doi.org/10.1016/j.agsy.2021.103120.

Gao, Demin, Sun, Quan, Hu, Bin, Zhang, Shuo, 2020. A framework for agricultural pest and disease monitoring based on internet-of-things and unmanned aerial vehicles. Sensors (Basel, Switzerland) 20 (5). https://doi.org/10.3390/s20051487.

Garske, Beatrice, Bau, Antonia, Ekardt, Felix, 2021. Digitalization and AI in European agriculture: a strategy for achieving climate and biodiversity targets? Sustainability 13 (9), 4652. https://doi.org/10.3390/su13094652.

Gil, Gustavo, Casagrande, Daniel Emilio, Cortés, Leonardo Pérez, Verschae, Rodrigo, 2023. Why the low adoption of robotics in the farms? Challenges for the establishment of commercial agricultural robots. Smart Agric. Technol. 3, 100069. https://doi.org/10.1016/j.atech.2022.100069.

Gocht, Alexander, Ciaian, Pavel, Bielza, Maria, Terres, Jean-Michel, Röder, Norbert, Himics, Mihaly, Salputra, Guna, 2017. EU -wide economic and environmental impacts of CAP greening with high spatial and farm-type detail. J. Agric. Econ. 68 (3), 651–681. https://doi.org/10.1111/1477-9552.12217.

Godoy, Eduardo Paciência, Tangerino, Giovana Tangerino, Tabile, Rubens André, Inamasu, Ricardo Yassushi, Porto, Arthur José Vieira, 2012. Networked control system for the guidance of a four-wheel steering agricultural robotic platform. J. Control Sci. Eng. 2012, 1–10. https://doi.org/10.1155/2012/368503.

Grahmann, Kathrin, Reckling, Moritz, Hernández-Ochoa, Ixchel, Donat, Marco, Bellingrath-Kimura, Sonoko, Ewert, Frank, 2024. Co-designing a landscape experiment to investigate diversified cropping systems. Agric. Syst. 217, 103950. https://doi.org/10.1016/j.agsy.2024.103950.

Gray, Steven, 2016. Environmental Modeling with Stakeholders. Theory, Methods, and Applications. Springer Science+Business Media, New York NY.

Grenz, J., Thalmann, C., Schoch, M., Stalder, S., Studer, C., 2012. RISE (Response-Inducing Sustainability Evaluation), version 2.0. In: School of Agriculture, Forest and Food Science, HAFL. Bern University of Applied Science, Bern.

Groher, Tanja, Heitkämper, Katja, Walter, Achim, Liebisch, Frank, Umstätter, Christina, 2020. Status quo of adoption of precision agriculture enabling technologies in Swiss plant production. Precis. Agric. 21 (6), 1327–1350. https://doi.org/10.1007/s11119-020-09723-5.

Gutzler, C., Helming, K., Balla, D., Dannowski, R., Deumlich, D., Glemnitz, M., et al., 2015. Agricultural land use changes – a scenario-based sustainability impact assessment for Brandenburg, Germany. Ecol. Indic. 48, 505–517. https://doi.org/10.1016/j.ecolind.2014.09.004.

Hackfort, Sarah, 2021. Patterns of inequalities in digital agriculture: a systematic literature review. Sustainability 13 (22), 12345. https://doi.org/10.3390/su132212345.

Hamidov, Ahmad, Daedlow, Katrin, Webber, Heidi, Hussein, Hussam, Abdurahmanov, Ilhom, Dolidudko, Aleksandr, et al., 2022. Operationalizing water-energy-food nexus research for sustainable development in social-ecological systems: an interdisciplinary learning case in Central Asia. E&S 27 (1). https://doi.org/10.5751/ES-12891-270112.

Härtel, Ines, 2021. Agrar-Digitalrecht für Agrarsysteme der Zukunft. at - Automatisierungstechnik 69 (4), 278–280. https://doi.org/10.1515/auto-2021-0004.

Henriksen, H.J., Kjaer, J., Brush, W., Jacobsen, L.B., Jensen, J.D., Grinderslev, D., Andersen, P., 2007. Environmental benefits and social cost - an example of combining Bayesian networks and economic models for analysing pesticide management instruments. Nord. Hydrol. 38 (4–5), 351–371. https://doi.org/10.2166/nh.2007.017.

Hermanns, Till, Helming, Katharina, König, Hannes J., Schmidt, Katharina, Li, Qirui, Faust, Heiko, 2017. Sustainability impact assessment of peatland-use scenarios: confronting land use supply with demand. Ecosyst. Serv. 26 (Suppl. 1), 365–376. https://doi.org/10.1016/j.ecoser.2017.02.002.

Hernández-Ochoa, Ixchel M., Gaiser, Thomas, Kersebaum, Kurt-Christian, Webber, Heidi, Seidel, Sabine Julia, Grahmann, Kathrin, Ewert, Frank, 2022. Model-based design of crop diversification through new field arrangements in spatially heterogeneous landscapes. A review. Agron. Sustain. Dev. 42 (4). https://doi.org/10.1007/s13593-022-00805-4.

Ingram, Julie, Maye, Damian, Bailye, Clive, Barnes, Andrew, Bear, Christopher, Bell, Matthew, et al., 2022. What are the priority research questions for digital agriculture? Land Use Policy 114, 105962. https://doi.org/10.1016/j.landusepol.2021.105962.

Jakku, Emma, Taylor, Bruce, Fleming, Aysha, Mason, Claire, Fielke, Simon, Sounness, Chris, Thorburn, Peter, 2019. “If they don’t tell us what they do with it, why would we trust them?” Trust, transparency and benefit-sharing in smart farming. NJAS Wagening. J. Life Sci. 90-91 (1), 1–13. https://doi.org/10.1016/j.njas.2018.11.002.

Kamilaris, Andreas, Kartakoullis, Andreas, Prenafeta-Boldú, Francesc X., 2017. A review on the practice of big data analysis in agriculture. Comput. Electron. Agric. 143, 23–37. https://doi.org/10.1016/j.compag.2017.09.037.

Kaplan, Sarah, Tripsas, Mary, 2008. Thinking about technology: applying a cognitive lens to technical change. Res. Policy 37 (5), 790–805. https://doi.org/10.1016/j.respol.2008.02.002.

Keller, Thomas, Sandin, Maria, Colombi, Tino, Horn, Rainer, Or, Dani, 2019. Historical increase in agricultural machinery weights enhanced soil stress levels and adversely affected soil functioning. Soil Tillage Res. 194 (10), 104293. https://doi.org/10.1016/j.still.2019.104293.

Kenny, Daniel C., Castilla-Rho, Juan, 2022. No stakeholder is an island: human barriers and enablers in participatory environmental modelling. LAND 11 (3), 340. https://doi.org/10.3390/land11030340.

Kernecker, Maria, Knierim, Andrea, Wurbs, Angelika, Kraus, Teresa, Borges, Friederike, 2020. Experience versus expectation: farmers’ perceptions of smart farming technologies for cropping systems across Europe. Precis. Agric. 21 (1), 34–50. https://doi.org/10.1007/s11119-019-09651-z.

Kjaerulff, Uffe B., Madsen, Anders L., 2013. Bayesian Networks and Influence Diagrams. A Guide to Construction and Analysis, 2nd ed. Springer (Information science and statistics), New York NY.

Klerkx, Laurens, Rose, David, 2020. Dealing with the game-changing technologies of Agriculture 4.0: how do we manage diversity and responsibility in food system transition pathways? Glob. Food Secur. 24 (1), 100347. https://doi.org/10.1016/j.gfs.2019.100347.

Klerkx, Laurens, Jakku, Emma, Labarthe, Pierre, 2019. A review of social science on digital agriculture, smart farming and agriculture 4.0: new contributions and a future research agenda. NJAS Wagening. J. Life Sci. 90-91 (1), 1–16. https://doi.org/10.1016/j.njas.2019.100315.

Knierim, Andrea, Kernecker, Maria, Erdle, Klaus, Kraus, Teresa, Borges, Friederike, Wurbs, Angelika, 2019. Smart farming technology innovations – insights and reflections from the German Smart-AKIS hub. NJAS Wagening. J. Life Sci. 90-91 (1), 1–10. https://doi.org/10.1016/j.njas.2019.100314.

König, Hannes Jochen, Uthes, Sandra, Schuler, Johannes, Zhen, Lin, Purushothaman, Seema, Suarma, Utia, et al., 2013. Regional impact assessment of land use scenarios in developing countries using the FoPIA approach: findings from five case studies. J. Environ. Manag. 127 (Suppl), S56–S64. https://doi.org/10.1016/j.jenvman.2012.10.021.

Kuhnert, Petra M., Martin, Tara G., Griffiths, Shane P., 2010. A guide to eliciting and using expert knowledge in Bayesian ecological models. Ecol. Lett. 13 (7), 900–914. https://doi.org/10.1111/j.1461-0248.2010.01477.x.

Kutter, T., Tiemann, S., Siebert, R., Fountas, S., 2011. The role of communication and co-operation in the adoption of precision farming. Precis. Agric. 12 (1), 2–17. https://doi.org/10.1007/s11119-009-9150-0.

Lajoie-O’Malley, Alana, Bronson, Kelly, van der Burg, Simone, Klerkx, Laurens, 2020. The future(s) of digital agriculture and sustainable food systems: an analysis of high-level policy documents. Ecosyst. Serv. 45, 101183. https://doi.org/10.1016/j.ecoser.2020.101183.

Land Brandenburg, 2019. 5G-STRATEGIE Brandenburg. MWAE - Ministerium für Wirtschaft, Arbeit und Energie des. Available online at https://mwae.brandenburg.de/media/bb1.a.3814.de/5G_Strategie_Brandenburg.pdf. updated on 2022, checked on 2021.

Lange, Steffen, Pohl, Johanna, Santarius, Tilman, 2020. Digitalization and energy consumption. Does ICT reduce energy demand? Ecol. Econ. 176, 106760. https://doi.org/10.1016/j.ecolecon.2020.106760.

Landesregierung Brandenburg (Ed.) (2021): Digitalprogramm des Landes Brandenburg 2025. Digital. Vernetzt. Gemeinsam. Version für das öffentliche Konsultationsverfahren. Potsdam, Germany. Available online at https://digitalesbb.de/wp-content/uploads/2021/12/211214_dp25_Konsultationsfassung.pdf, checked on 6/23/2022.

Latruffe, Laure, Diazabakana, Ambre, Bockstaller, Christian, Desjeux, Yann, Finn, John, Kelly, Edel, et al., 2016. Measurement of sustainability in agriculture: a review of indicators. Stud. Agr. Econ. 118 (3), 123–130. https://doi.org/10.7896/j.1624.

Leroux, C., 2020. Reflecting on the carbon footprint of digital technologies in the AgTech and Precision Agriculture sectors. Available online at https://www.aspexit.com/en/reflecting-on-the-carbon-footprint-of-digital-in-the-agtech-and-precision-agriculture-sectors/. checked on 4/1/2023.

Lindblom, Jessica, Lundström, Christina, Ljung, Magnus, Jonsson, Anders, 2017. Promoting sustainable intensification in precision agriculture: review of decision support systems development and strategies. Precis. Agric. 18 (3), 309–331. https://doi.org/10.1007/s11119-016-9491-4.

Lioutas, Evagelos D., Charatsari, Chrysanthi, de Rosa, Marcello, 2021. Digitalization of agriculture: a way to solve the food problem or a trolley dilemma? Technol. Soc. 67, 101744. https://doi.org/10.1016/j.techsoc.2021.101744.

Lowenberg-DeBoer, James, Erickson, Bruce, 2019. Setting the record straight on precision agriculture adoption. Agron. J. 111 (4), 1552–1569. https://doi.org/10.2134/agronj2018.12.0779.

Lowenberg-DeBoer, James, Huang, Iona Yuelu, Grigoriadis, Vasileios, Blackmore, Simon, 2020. Economics of robots and automation in field crop production. Precis. Agric. 21 (2), 278–299. https://doi.org/10.1007/s11119-019-09667-5.

Macholdt, J., Hadasch, S., Piepho, H.-P., Reckling, M., Taghizadeh-Toosi, A., Christensen, B.T., 2021. Yield variability trends of winter wheat and spring barley grown during 1932–2019 in the Askov long-term experiment. Field Crop Res. 264, 108083. https://doi.org/10.1016/j.fcr.2021.108083.

MacPherson, Joseph, Voglhuber-Slavinsky, Ariane, Olbrisch, Mathias, Schöbel, Philipp, Dönitz, Ewa, Mouratiadou, Ioanna, Helming, Katharina, 2022. Future agricultural systems and the role of digitalization for achieving sustainability goals. A review. Agron. Sustain. Dev. 42 (4), 70. https://doi.org/10.1007/s13593-022-00792-6.

Marcot, Bruce G., 2012. Metrics for evaluating performance and uncertainty of Bayesian network models. Ecol. Model. 230, 50–62. https://doi.org/10.1016/j.ecolmodel.2012.01.013.

Martin, Théo, Gasselin, Pierre, Hostiou, Nathalie, Feron, Gilles, Laurens, Lucette, Purseigle, François, Ollivier, Guillaume, 2022. Robots and transformations of work in farm: a systematic review of the literature and a research agenda. Agron. Sustain. Dev. 42 (4). https://doi.org/10.1007/s13593-022-00796-2.

Martinez-Feria, Rafael A., Basso, Bruno, 2020. Unstable crop yields reveal opportunities for site-specific adaptations to climate variability. Sci. Rep. 10 (1), 2885. https://doi.org/10.1038/s41598-020-59494-2.
McFadden, Jonathan, Casalini, Francesca, Griffin, Terry, Antón, Jesús, 2022. The digitalisation of agriculture. https://doi.org/10.1787/285cc27d-en.
McGrath, Karen, Brown, Claire, Regan, Áine, Russell, Tomás, 2023. Investigating narratives and trends in digital agriculture: a scoping study of social and behavioural science studies. Agric. Syst. 207, 103616. https://doi.org/10.1016/j.agsy.2023.103616.
Melzer, Marvin, Bellingrath-Kimura, Sonoko, Gandorfer, Markus, 2023. Commercial farm management information systems - a demand-oriented analysis of functions in practical use. Smart Agric. Technol. 4, 100203. https://doi.org/10.1016/j.atech.2023.100203.
Metta, Matteo, Ciliberti, Stefano, Obi, Chinedu, Bartolini, Fabio, Klerkx, Laurens, Brunori, Gianluca, 2022. An integrated socio-cyber-physical system framework to assess responsible digitalisation in agriculture: a first application with Living Labs in Europe. Agric. Syst. 203, 103533. https://doi.org/10.1016/j.agsy.2022.103533.
Moallemi, Enayat A., Zare, Fateme, Hebinck, Aniek, Szetey, Katrina, Molina-Perez, Edmundo, Zyngier, Romy L., et al., 2023. Knowledge co-production for decision-making in human-natural systems under uncertainty. Glob. Environ. Chang. 82, 102727. https://doi.org/10.1016/j.gloenvcha.2023.102727.
Monteiro Moretti, Débora, Baum, Chad M., Ehlers, Melf-Hinrich, Finger, Robert, Bröring, Stefanie, 2023. Exploring actors' perceptions of the precision agriculture innovation system – a group concept mapping approach in Germany and Switzerland. Technol. Forecast. Soc. Chang. 189, 122270. https://doi.org/10.1016/j.techfore.2022.122270.
Mouratiadou, Ioanna, Lemke, Nahleen, Chen, Cheng, Wartenberg, Ariani, Bloch, Ralf, Donat, Marco, et al., 2023. The Digital Agricultural Knowledge and Information System (DAKIS): employing digitalisation to encourage diversified and multifunctional agricultural systems. Environ. Sci. Ecotechnol. 16, 100274. https://doi.org/10.1016/j.ese.2023.100274.
Netica V5.18, 2015. Netica Manual. Norsys Software Corp.
Niemeijer, David, de Groot, Rudolf S., 2008. Framing environmental indicators: moving from causal chains to causal networks. Environ. Dev. Sustain. 10 (1), 89–106. https://doi.org/10.1007/s10668-006-9040-9.
Nowak, Benjamin, 2021. Precision agriculture: where do we stand? A review of the adoption of precision agriculture technologies on field crops farms in developed countries. Agric. Res. 10 (4), 515–522. https://doi.org/10.1007/s40003-021-00539-x.
Paustian, Margit, Theuvsen, Ludwig, 2017. Adoption of precision agriculture technologies by German crop farmers. Precis. Agric. 18 (5), 701–716. https://doi.org/10.1007/s11119-016-9482-5.
Pearson, Simon, Camacho-Villa, Tania Carolina, Valluru, Ravi, Gaju, Oorbessy, Rai, Mini C., Gould, Iain, et al., 2022. Robotics and autonomous systems for net zero agriculture. Curr. Robot. Rep. 3 (2), 57–64. https://doi.org/10.1007/s43154-022-00077-6.
Pedersen, Søren Marcus, Lind, Kim Martin, 2017. Precision Agriculture: Technology and Economic Perspectives. Springer.
Pope, Jenny, Annandale, David, Morrison-Saunders, Angus, 2004. Conceptualising sustainability assessment. Environ. Impact Assess. Rev. 24 (6), 595–616. https://doi.org/10.1016/j.eiar.2004.03.001.
Poppe, Krijn J., Wolfert, Sjaak, Verdouw, Cor, Verwaart, Tim, 2013. Information and communication technology as a driver for change in agri-food chains. EuroChoices 12 (1), 60–65. https://doi.org/10.1111/1746-692X.12022.
Prause, Louisa, 2021. Digital agriculture and labor: a few challenges for social sustainability. Sustainability 13 (11), 5980. https://doi.org/10.3390/su13115980.
Reed, Mark S., 2008. Stakeholder participation for environmental management: a literature review. Biol. Conserv. 141 (10), 2417–2431. https://doi.org/10.1016/j.biocon.2008.07.014.
Regan, Áine, 2019. 'Smart farming' in Ireland: a risk perception study with key governance actors. NJAS Wagening. J. Life Sci. 90-91 (1), 1–10. https://doi.org/10.1016/j.njas.2019.02.003.
Reichelt, Nicole, Nettle, Ruth, 2023. Practice insights for the responsible adoption of smart farming technologies using a participatory technology assessment approach: the case of virtual herding technology in Australia. Agric. Syst. 206, 103592. https://doi.org/10.1016/j.agsy.2022.103592.
Reyer, Christopher, Bachinger, Johann, Bloch, Ralf, Hattermann, Fred F., Ibisch, Pierre L., Kreft, Stefan, et al., 2012. Climate change adaptation and sustainable regional development: a case study for the Federal State of Brandenburg, Germany. Reg. Environ. Chang. 12 (3), 523–542. https://doi.org/10.1007/s10113-011-0269-y.
Rijswijk, Kelly, Klerkx, Laurens, Bacco, Manlio, Bartolini, Fabio, Bulten, Ellen, Debruyne, Lies, et al., 2021. Digital transformation of agriculture and rural areas: a socio-cyber-physical system framework to support responsibilisation. J. Rural. Stud. 85, 79–90. https://doi.org/10.1016/j.jrurstud.2021.05.003.
Rohleder, B., Krüsken, B., Reinhardt, H., 2020. Digitalisierung in der Landwirtschaft 2020. Bitkom; Deutscher Bauernverband; Rentenbank, Berlin, Germany.
Rose, David Christian, Chilvers, Jason, 2018. Agriculture 4.0: broadening responsible innovation in an era of smart farming. Front. Sustain. Food Syst. 2, 571. https://doi.org/10.3389/fsufs.2018.00087.
Rose, David Christian, Wheeler, Rebecca, Winter, Michael, Lobley, Matt, Chivers, Charlotte-Anne, 2021. Agriculture 4.0: making it work for people, production, and the planet. Land Use Policy 100, 104933. https://doi.org/10.1016/j.landusepol.2020.104933.
Rotz, Sarah, Duncan, Emily, Small, Matthew, Botschner, Janos, Dara, Rozita, Mosby, Ian, et al., 2019a. The politics of digital agricultural technologies: a preliminary review. Sociol. Rural. 59 (2), 203–229. https://doi.org/10.1111/soru.12233.
Rotz, Sarah, Gravely, Evan, Mosby, Ian, Duncan, Emily, Finnis, Elizabeth, Horgan, Mervyn, et al., 2019b. Automated pastures and the digital divide: how agricultural technologies are shaping labour and rural communities. J. Rural. Stud. 68, 112–122. https://doi.org/10.1016/j.jrurstud.2019.01.023.
Salliou, N., Barnaud, C., Vialatte, A., Monteil, C., 2017. A participatory Bayesian belief network approach to explore ambiguity among stakeholders about socio-ecological systems. Environ. Model Softw. 96, 199–209. https://doi.org/10.1016/j.envsoft.2017.06.050.
Schimmelpfennig, David, 2016. Farm Profits and Adoption of Precision Agriculture.
Schnebelin, Éléonore, Labarthe, Pierre, Touzard, Jean-Marc, 2021. How digitalisation interacts with ecologisation? Perspectives from actors of the French agricultural innovation system. J. Rural. Stud. 86, 599–610. https://doi.org/10.1016/j.jrurstud.2021.07.023.
Shaaban, Mostafa, 2022. The Viability of the Social-Ecological Agroecosystem (ViSA) Spatial Agent-based Model: CoMSES Net.
Shepherd, Mark, Turner, James A., Small, Bruce, Wheeler, David, 2020. Priorities for science to overcome hurdles thwarting the full promise of the 'digital agriculture' revolution. J. Sci. Food Agric. 100 (14), 5083–5092. https://doi.org/10.1002/jsfa.9346.
Singh, Narendra, Ogunseitan, Oladele A., 2022. Disentangling the worldwide web of e-waste and climate change co-benefits. Circ. Econ. 1 (2), 100011. https://doi.org/10.1016/j.cec.2022.100011.
Sparrow, Robert, Howard, Mark, 2021. Robots in agriculture: prospects, impacts, ethics, and policy. Precis. Agric. 22 (3), 818–833. https://doi.org/10.1007/s11119-020-09757-9.
Späti, Karin, Huber, Robert, Finger, Robert, 2021. Benefits of increasing information accuracy in variable rate technologies. Ecol. Econ. 185, 107047. https://doi.org/10.1016/j.ecolecon.2021.107047.
Spykman, O., Gabriel, A., Ptacek, M., Gandorfer, M., 2021. Farmers' perspectives on field crop robots – evidence from Bavaria, Germany. Comput. Electron. Agric. 186, 106176. https://doi.org/10.1016/j.compag.2021.106176.
Stilgoe, Jack, Owen, Richard, Macnaghten, Phil, 2013. Developing a framework for responsible innovation. Res. Policy 42 (9), 1568–1580. https://doi.org/10.1016/j.respol.2013.05.008.
Tamburini, Giovanni, Bommarco, Riccardo, Wanger, Thomas Cherico, Kremen, Claire, van der Heijden, Marcel G.A., Liebman, Matt, Hallin, Sara, 2020. Agricultural diversification promotes multiple ecosystem services without compromising yield. Sci. Adv. 6 (45). https://doi.org/10.1126/sciadv.aba1715.
Thompson, Nathanael M., Bir, Courtney L., Mintert, James R., Widmar, David, 2019. Farmer perceptions of precision agriculture technology benefits. J. Agric. Appl. Econ. 51 (1), 142–163. https://doi.org/10.1017/aae.2018.27.
Thomson, Allison M., Ellis, Erle C., Grau, Héctor Ricardo, Kuemmerle, Tobias, Meyfroidt, Patrick, Ramankutty, Navin, Zeleke, Gete, 2019. Sustainable intensification in land systems: trade-offs, scales, and contexts. Curr. Opin. Environ. Sustain. 38, 37–43. https://doi.org/10.1016/j.cosust.2019.04.011.
Troegel, T., Schulz, C., 2016. Ergebnisse der Agrarstrukturerhebung 2016 für das Land Brandenburg. In: Zeitschrift für amtliche Statistik Berlin Brandenburg, 2016. Available online at https://www.statistik-berlin-brandenburg.de/publikationen/aufsaetze/2018/HZ_201801-08.pdf.
Tscherning, Karen, Helming, Katharina, Krippner, Bernd, Sieber, Stefan, Paloma, Sergio Gomez, y., 2012. Does research applying the DPSIR framework support decision making? Land Use Policy 29 (1), 102–110. https://doi.org/10.1016/j.landusepol.2011.05.009.
Tummers, J., Kassahun, A., Tekinerdogan, B., 2019. Obstacles and features of farm management information systems: a systematic literature review. Comput. Electron. Agric. 157, 189–204. https://doi.org/10.1016/j.compag.2018.12.044.
Uusitalo, Laura, 2007. Advantages and challenges of Bayesian networks in environmental modelling. Ecol. Model. 203 (3–4), 312–318. https://doi.org/10.1016/j.ecolmodel.2006.11.033.
van der Burg, Simone, Bogaardt, Marc-Jeroen, Wolfert, Sjaak, 2019. Ethics of smart farming: current questions and directions for responsible innovation towards the future. NJAS Wagening. J. Life Sci. 90-91 (1), 1–10. https://doi.org/10.1016/j.njas.2019.01.001.
Vicente-Vicente, José Luis, Sanz-Sanz, Esther, Napoléone, Claude, Moulery, Michel, Piorr, Annette, 2021. Foodshed, agricultural diversification and self-sufficiency assessment: beyond the isotropic circle foodshed—a case study from Avignon (France). Agriculture 11 (2), 143. https://doi.org/10.3390/agriculture11020143.
Voglhuber-Slavinsky, Ariane, Lemke, Nahleen, MacPherson, Joseph, Dönitz, Ewa, Olbrisch, Mathias, Schöbel, Philipp, et al., 2023. Valorization for biodiversity and ecosystem services in the agri-food value chain. Environ. Manag. 72 (6), 1163–1188. https://doi.org/10.1007/s00267-023-01860-7.
Voinov, A., Bousquet, F., 2010. Modelling with stakeholders. Environ. Model Softw. 25 (11), 1268–1281. https://doi.org/10.1016/j.envsoft.2010.03.007.
Voinov, Alexey, Jenni, Karen, Gray, Steven, Kolagani, Nagesh, Glynn, Pierre D., Bommel, Pierre, et al., 2018. Tools and methods in participatory modeling: selecting the right tool for the job. Environ. Model Softw. 109, 232–255. https://doi.org/10.1016/j.envsoft.2018.08.028.
von Czettritz, Hannah Jona, Hosseini-Yekani, Seyed-Ali, Schuler, Johannes, Kersebaum, Kurt-Christian, Zander, Peter, 2023. Adapting cropping patterns to climate change: risk management effectiveness of diversification and irrigation in Brandenburg (Germany). Agriculture 13 (9), 1740. https://doi.org/10.3390/agriculture13091740.
Walter, Achim, Finger, Robert, Huber, Robert, Buchmann, Nina, 2017. Opinion: smart farming is key to developing sustainable agriculture. Proc. Natl. Acad. Sci. USA 114 (24), 6148–6150. https://doi.org/10.1073/pnas.1707462114.

Webber, Heidi, Lischeid, Gunnar, Sommer, Michael, Finger, Robert, Nendel, Claas, Gaiser, Thomas, Ewert, Frank, 2020. No perfect storm for crop yield failure in Germany. Environ. Res. Lett. 15 (10), 104012. https://doi.org/10.1088/1748-9326/aba2a4.

Weersink, Alfons, Fraser, Evan, Pannell, David, Duncan, Emily, Rotz, Sarah, 2018. Opportunities and challenges for big data in agricultural and environmental analysis. Ann. Rev. Resour. Econ. 10 (1), 19–37. https://doi.org/10.1146/annurev-resource-100516-053654.

Weigel, Robert, Koellner, Thomas, Poppenborg, Patrick, Bogner, Christina, 2018. Crop diversity and stability of revenue on farms in Central Europe: an analysis of big data from a comprehensive agricultural census in Bavaria. PLoS One 13 (11), e0207454. https://doi.org/10.1371/journal.pone.0207454.

Wolfert, Sjaak, Ge, Lan, Verdouw, Cor, Bogaardt, Marc-Jeroen, 2017. Big data in smart farming – a review. Agric. Syst. 153, 69–80. https://doi.org/10.1016/j.agsy.2017.01.023.

Wolff, Saskia, Hüttel, Silke, Nendel, Claas, Lakes, Tobia, 2021. Agricultural landscapes in Brandenburg, Germany: an analysis of characteristics and spatial patterns. Int. J. Environ. Res. 15 (3), 487–507. https://doi.org/10.1007/s41742-021-00328-y.

Yassine, R., Peres, F., Frysou, O., Roux, H., Cassan, L., 2020. Participatory Bayesian modelling for sustainable and efficient river restoration projects: feedback from the case study of the Gave de Pau River, Hautes-Pyrenees, France. J. Conting. Crisis Manag. 28 (3), 355–373. https://doi.org/10.1111/1468-5973.12312.

Yu, Zhilong, Jung, Dongyun, Park, Soyoun, Hu, Yaxi, Huang, Kang, Rasco, Barbara A., et al., 2022. Smart traceability for food safety. Crit. Rev. Food Sci. Nutr. 62 (4), 905–916. https://doi.org/10.1080/10408398.2020.1830262.

Zander, P., Kächele, H., 1999. Modelling multiple objectives of land use for sustainable development. Agric. Syst. 59 (3), 311–325. https://doi.org/10.1016/S0308-521X(99)00017-7.

Zasada, Ingo, Schmutz, Ulrich, Wascher, Dirk, Kneafsey, Moya, Corsi, Stefano, Mazzocchi, Chiara, et al., 2019. Food beyond the city – Analysing foodsheds and self-sufficiency for different food system scenarios in European metropolitan regions. City Cult. Soc. 16 (6), 25–35. https://doi.org/10.1016/j.ccs.2017.06.002.

Zscheischler, Jana, Brunsch, Reiner, Rogga, Sebastian, Scholz, Roland W., 2022. Perceived risks and vulnerabilities of employing digitalization and digital data in agriculture – socially robust orientations from a transdisciplinary process. J. Clean. Prod. 358, 132034. https://doi.org/10.1016/j.jclepro.2022.132034.