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Research priorities to leverage smart digital technologies for sustainable crop production

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A B S T R A C T

Agriculture faces several challenges including climate change and biodiversity loss while, at the same time, the demand for food, feed, biofuels, and fiber is increasing. Sustainable intensification aims to increase productivity and input-use efficiency while enhancing the resilience of agricultural systems to adverse environmental conditions through improved management and technology. Recent advances in sensing, machine learning, modeling, and robotics offer opportunities for novel smart digital technologies to enable sustainable intensification. However, developing smart digital technologies and putting them into agricultural practice, requires closing major research gaps, related in particular to (1) the utilization of multi-scale multi-sensor monitoring in space and time, (2) using artificial intelligence for linking process and data-driven methods, (3) improving decision making and intervention in plant production, and finally (4) modeling conditions and consequences of farmers acceptance. Closing these gaps requires an interdisciplinary approach. Here, we present a research agenda and steps forward to steer research efforts, highlighting research priorities, and identifying required interdisciplinary research collaboration. Following this agenda will leverage the full potential of smart digital technologies for sustainable crop production.

1. Introduction

One of the greatest challenges for humanity is to produce sufficient food, feed, fiber, and biofuel, while simultaneously adapting to climate change, reducing agriculture's environmental footprint, and dealing with pressure on labor supply (FAO, 2017). These challenges require a new way of thinking about crop production and field management. Smart digital technologies can enable innovative approaches, such as autonomous light-weight robots and drones, high-resolution monitoring of the crop and field status, linkage of data to simulation models, and

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artificial intelligence (AI) (Asseng and Asche, 2019; Basso and Antle, 2020; Grieve et al., 2019; Khanna et al., 2022; Kumar and Sharma, 2020; Ramin Shamshiri et al., 2018). The rapid decline in the cost of sensors, robots, and computing power, as well as rapid advances in AI, offer opportunities for sustainable intensification (Grieve et al., 2019). Existing precision agriculture tools are becoming increasingly connected, accurate, efficient, and widely applicable (Finger et al., 2019). Combining these tools with process-based agro-ecosystem models enables new ways of crop management by predicting plant ideotypes for specific environments (Lynch et al., 2022), by predicting the performance of crops in a specific environment, the development of diseases, pests, and weeds or the demand for nutrients (Caubel et al., 2017; Colbach et al., 2014; Seidel et al., 2021). These models also enable the assessment of the impacts of novel technologies from local to landscape or regional scales (Duru et al., 2015; Kersebaum et al., 2015), which may contribute to the design of more effective policies and regulations and enable new field arrangements.

While the potential of those tools is substantial, their realization remains an open challenge. To address this challenge, multidisciplinary collaborations (Ramin Shamshiri et al., 2018) and the right institutional settings connecting research, governmental support, regulation, and education programs are required (Grieve et al., 2019). In this article, we discuss four major research gaps (RG1–4) that need to be closed to realize these opportunities. These include (RG1) multi-scale multi-sensor monitoring in space and time, (RG2) combining process and data-driven methods, (RG3) improving decision-making and intervention, and (RG4) modeling conditions and impacts of upscaling. Along three examples (E1–3) we demonstrate how closing the research gaps contributes to addressing concrete practical agricultural sustainability challenges: (E1) real-time optimization of nitrogen (N) fertilization, (E2) automated selective weeding and detection of plant diseases, and (E3) implementing novel field arrangements such as patch cropping and mixed cropping.

Existing literature highlighted the potential of smart digital technologies for sustainable intensification (Asseng and Asche, 2019; Basso and Antle, 2020; Grieve et al., 2019). However, they did not discuss which type of research and particularly research collaboration is required to realize the potential. We fill this gap by outlining a broad research agenda combining the views of an interdisciplinary group of experts. We also present the current state of research, drawing on examples from our ongoing large-scale interdisciplinary research project "PhenoRob - Robotics and Phenotyping Towards Sustainable Crop Production". Finally, we discuss steps forward to tackle the major challenges by outlining the required institutional settings.

2. Research gaps

We discuss four major research gaps that need to be closed on the way towards integrated smart digital solutions for sustainable crop production. For each gap, we first discuss its importance, major challenges, and what disciplines must collaborate to address them.

2.1. RG1: Multi-scale multi-sensor monitoring in space and time

Crop status information is fundamental for crop breeding, where functional and structural crop traits need to be characterized to guide the selection of promising genotypes, crop management, where real-time information on the plant status and field situations guides management actions, and crop modeling, where relationships between resource availability, physiological processes, yield, and ecosystem (dis) services are investigated.

Monitoring of fields is often done with destructive or labor-intensive methods (Atkinson et al., 2019; Cai et al., 2016; Jones, 2004; Muñoz-Huerta et al., 2013). Increasingly, non-invasive optical methods, such as multi- and hyperspectral imaging or laser scanning, have been developed to provide higher throughput (Fiorani et al., 2012; Jin et al., 2021; Watt et al., 2020). The precision of optical methods has greatly improved and nowadays Unmanned Aerial Vehicles (UAVs) measure at mm-ground resolution, opening the possibility for detailed single-plant monitoring and the detection of subtle, small-scale features, including the identification of diseases (Mahlein et al., 2019). Currently, there is no reliable high-throughput method for non-invasive root measurements or quantifying root distributions in the field, however, novel root phenotyping approaches are being developed (Atkinson et al., 2019; Tracy et al., 2020).

The increasing availability of field data with higher temporal and spatial resolution does not automatically satisfy the need for better crop status information. In contrast, it raises multiple challenges, which need to be tackled to make use of all the information. (i) The development of novel or the adaption of existing below- and above-ground sensing technologies is needed with a focus on in-field capability, automation, and non-invasiveness. This enables for example large-scale studies on above and below-ground phenology as one of the future directions identified in Piao et al. (2019). (ii) Methods for spatial and temporal registration of heterogeneous data are needed, enabling the combination of coordinate-based and plot-based measurements, and making information relatable to soil, genotypes, weather, and management data. This includes finding adequate data representations and formats and their storage in a common database, which is searchable and minable. Based on this it is possible to derive "urgently needed (Piao et al., 2019)" methods for multiple-scale and spatio-temporal data fusion. (iii) Methods to fuse models and data are needed as part of the monitoring process. This may be data assimilation into process-based models, but also the extraction of model parameters from data (e.g., light extinction coefficients) or the extraction of complex functional traits from model/data combinations (e.g. carbon assimilation rate, light use efficiency, water use efficiency).

A close collaboration between plant and agricultural science, computer science, and robotics, as well as geodesy, is necessary to address aspects such as databases, measurement automation, sensor technology, spatial registration, phenotyping, and crop modeling, and to utilize sensor data with an agronomic meaning.

2.2. RG2: Combining data-driven and process-based modeling

Realizing the opportunities offered by smart technology hinges on our ability to model and predict the development of crops and agro-ecosystems under different management and environmental conditions and thus to allow seasonal predictions. Process-based and data-driven models are two conceptually different approaches for this, but they are currently largely distinct. Process-based models start from the available theoretical knowledge and parameter calibration using available data to accurately predict real-world outcomes. These models typically require extensive information on initial states, parameters, and boundary conditions, which are often not completely available, limiting their application under real field conditions. Data-driven machine learning models excel at prediction tasks, particularly with large high-quality data. However, they are limited with insufficient data, for predicting rare or unseen phenomena, and are usually trained for a specific environment–transfer to other environments is challenging. Machine learning will benefit from prior structural or procedural knowledge (Karpatne et al., 2017; Sabour et al., 2017; von Rueden et al., 2020), however, incorporating domain knowledge and existing crop models in a principled fashion is challenging. Combining process-based and machine-learning approaches could help to overcome their specific weaknesses and help to move from correlation-based learning to the creation of explainable and causal models.

To advance the usability of both approaches, we need to improve our capabilities to identify relevant features and dependencies of variables obtained from sensor data and develop hybrid learning systems that integrate expert knowledge with data-driven approaches. Since data are of heterogeneous origin and nature, ranging from existing models to various sensor measurements, machine learning methods also need to be capable of working with both in an integrated fashion. Scaling these methods to large-scale applications is an additional open research issue. Further, active learning approaches might allow us to identify sparsely populated areas in the input-output space and request additional labeled data to strengthen the model. Addressing this research gap needs interaction between plant and crop modelers, agricultural domain experts, and machine learning scientists.

2.3. RG3: Improving decision-making and intervention

To maximize resource use efficiency and optimize management decisions, we need to be able to localize, recognize, and treat individual field patches, plots, and ideally single plants in a targeted manner. Management decisions may also be increasingly executed via autonomous interventions.

Improving decision-making includes field arrangement, species, and cultivar choice, sowing date, fertilization, irrigation management, as well as weed and disease management. Ideally, these decisions are based on predictions of the outcome, such as the potential yield or ecological (dis)services, with and without the intervention across alternatives, and quantification of the uncertainty in outcomes and the associated costs. For example, deciding if a weed individual should be removed requires specifying which weed species and quantity are economically acceptable and ecologically desired. Also, individual preferences of farm managers will have to be taken into account for autonomous solutions to support widespread adoption. Addressing these challenges requires sensing technology (RG1) and improved simulation modeling tools (RG2) to carry out counterfactual simulations. Frequently cited tools for the latter are process-based agroecosystem simulation models (Chenu et al., 2017; Enders et al., 2023).

However, model-based real-time management decisions require an integrated multi-scale approach to modeling crop growth with real-time measurements of soil-crop-atmosphere variables and fluxes (Kersebaum et al., 2015) and data assimilation approaches within an integrated, operational framework. This gap needs to be bridged by fusing real-time management information with important prognostic information on the dynamics of crop systems. Apart from the challenge of making an economic management decision based on available information, simulations, and predictions, the actual execution of the intended action requires special collaborations. Here, robotic perception, planning, and control methods need to be combined with the necessary robustness from classical agricultural machinery and geospatial data management with accurate geolocation from geoinformation and geodesy.

2.4. RG4: Modeling conditions and consequences of uptake

Despite substantial research and development, current adoption rates of technology remain low (Lowenberg-DeBoer and Erickson, 2019). Also, adoption may lead to unintended consequences (Basso and Antle, 2020). Both aspects crucially determine the overall environmental impact of technology. Hence, governing the speed and direction of technology uptake is as important as technology development.

This implies major challenges. For example, farm-scale interactions are expected to strongly affect uptake but empirical quantification is still limited (Shang et al., 2021). To steer adoption processes, we also need to identify drivers of adoption decisions and how policymakers, technology developers, or extension services can modulate these drivers. Further, improved modeling capabilities to assess the socio-economic and environmental impacts at different scales are needed. Sectoral and general economy models exist with links to biophysical models or assessment indicators (Ewert et al., 2011; von Lampe et al., 2014). However, they consider technology adoption as exogenous, use representative, only statically interacting agents, and have limited resolution in representing technology and management decisions. Some of these limitations are addressed by Agent-Based Models (ABM) (Shang et al., 2021), which can reflect relevant social and market-level spatio-temporal dynamic interactions. However, existing ABMs are limited to small regions because of computational constraints. We also face limitations in terms of the available data to assess what technology is currently used on farms (Lowenberg-DeBoer and Erickson, 2019). This means that even describing the reference point against which we compare novel technologies is hardly possible, particularly in a spatially explicit manner. To ease the transfer of knowledge from research to industry, we need to develop efficient routes for adopting novel technologies into agricultural practice.

Closing the research gap requires collaboration with modelers and empirical scientists within agricultural economics, complemented by environmental, crop, ecology, and landscape scientists, particularly to quantify the expected environmental impacts of novel technologies. To assess technology options and describe their characteristics, collaboration with engineers and technology experts is required.

3. Benefits of closing the gaps: examples from our research

Drawing on our research activities in PhenoRob we present three examples (E1–3) that demonstrate how closing the research gaps contributes to addressing concrete practical agricultural sustainability challenges. It should be pointed out that the examples here are not an exhaustive list but aim as an illustration. There are other equally important areas, for example, irrigation management or optimized breeding, where closing the identified research gaps could have a substantial impact.

3.1. E1: Real-time optimization of nitrogen fertilization

Typically, farmers estimate the nitrogen (N) fertilizer demand based on pre-sowing soil N status measurements or based on sensors mounted on tractors as well as on expected yields. Lacking reliable tools for estimating the actual soil N status of the rooted soil and the crop N demand during the growing season can easily lead to suboptimal management.

In our ongoing interdisciplinary research project PhenoRob, we developed a data assimilation framework called Digital Agricultural Avatar using agro-ecosystem models (Fig. 1k, l), ground- and drone-based remote sensing data (Fig. 1d, g), and ground reference observations from plants, roots, and soils including the critical N-turnover component nitrate (Fig. 1e, f, h, i). The Avatar is a digital twin of the respective field, which provides continuous online information on the N status of the soil and crop. A conceivable product could be a crop- and site-specific model-based tool (e.g., decision support system) for farmers providing information on an optimal N fertilization strategy on patches across fields and larger scales. It would also enable the quantification of certain ecosystem (dis)services (e.g., N and C gaseous emissions and nitrate leaching) as well as uncertainties.

The proposed framework requires real-time measurements of relevant soil-crop-atmosphere variables and fluxes that need to be preprocessed and provided to the model (RG1, RG2). We monitor soil water content and soil water potential continuously and provide the data wirelessly in real-time (Fig. 1a, b, i). Besides, we use a spectral electric impedance tomography sensing device to observe root system extension. A mobile system monitors reactive N species based on gaseous intermediate products which can be related to the current soil N status (Fig. 1j). Imagery collected by drones is used to estimate crop leaf area index and/or biomass (Fig. 1g, h). For a given field, high-resolution crop and soil data can be collected and used by the model as input or for data assimilation (Tewes et al., 2020). We downscale a fully coupled subsurface-land surface and atmospheric model from the continental scale to the field scale and then model the field with dedicated agro-ecosystem models that can resolve the within-field variability. Currently, the data is used to run an agro-ecosystem model not in real-time but in retrospect. Soil N status as well as leaf area index

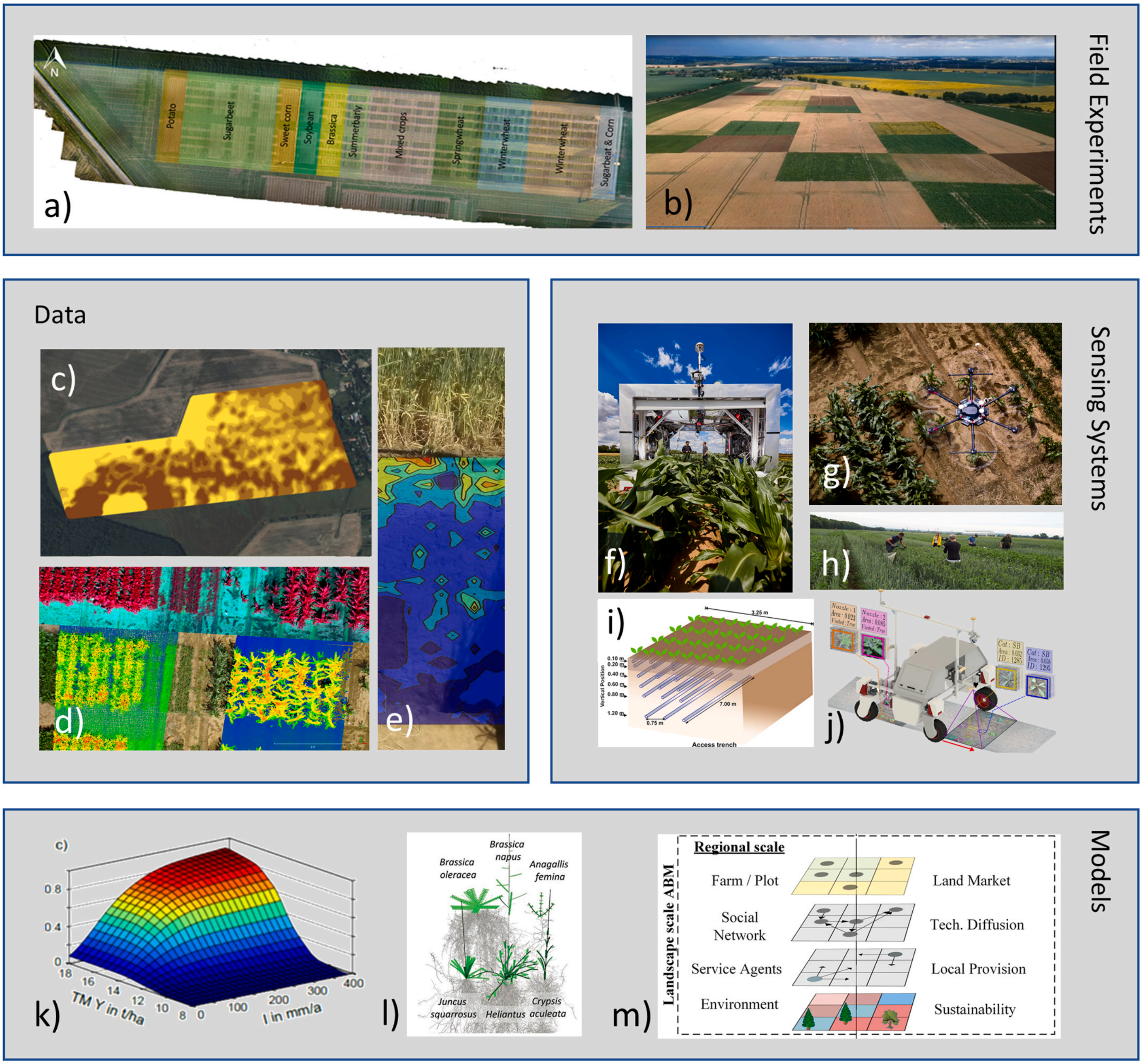

Fig. 1. a) PhenoRob Central Experiment, Bonn, Germany b) Patch Crop Experiment (photo by H. Schneider, ZALF PR) c) topsoil clay content (proximally sensed soil electrical resistivity, Geophilus), kindly provided by Anna Engels d) Combination of UAV Lidar, UAV multispectral imagery, and in-field mobile laser scanning e) Root distribution f) Ground robot with high-resolution optical sensors (photo by V.Lannert) g) UAV system (photo by V. Lannert) h) Classical fieldwork in a crop mixture experiment i) Scheme of the rhizotron facility at Selhausen, kindly provided by Lena Lärm j) Robot for targeted weed management (Ahmadi et al., 2022) k) Schematic crop model output showing the relationship between irrigation water input and yield l) Functional–structural plant models (Zhou et al., 2020) m) Agent-based model to upscale technology adoption.

products derived from remotely sensed imagery exist but a real-time automated retrieval of these products is pending. The real-time data assimilation into the model is under current research.

The model can be used to optimize crop N fertilization while considering ecosystem disservices, uncertainty and costs (RG3). However, even with such a tool available, it remains uncertain if this alone is sufficient to limit excessive N use and N leaching or if other measures (e.g. policies or regulations) are required in addition. Assessing this requires economic modeling of technology adoption and crop choice modeling at the landscape/regional scale (RG4) (Fig. 1m).

3.2. E2: Selective weeding and plant disease detection

Smart digital technologies have a great potential to reduce the required amount of applied chemicals for weed or plant disease control through targeted treatment on a plant or patch level.

Agricultural weeding robots equipped with different actuators can execute the treatments only where it is needed and can also select the most effective treatment for the targeted plant or weed (Fig. 1j). It is also possible to decide if a weed needs to be treated at all, as there are weeds that do not harm the crop or are even beneficial in supporting pollinator diversity and ecosystem services. Selective weeding requires a robust real-time plant classification system that reliably identifies the crop and both the stem location of dicotyl weeds and also the extent of grass weeds given by its leaf area (RG1). Operational systems for the online detection and classification of weeds from ground robots and UAVs have already been presented (Halstead et al., 2021; Lottes et al., 2020; Weyler et al., 2021). Based on these, multiple movable tools have been developed for our weed management and sensing robot (Ahmadi et al., 2022). Current investigations focus on deciding which weed to keep due to its contribution to biodiversity and/or low impact on yield and which to remove (RG3). This needs advanced thresholds and ecosystem models considering the current state of the crop and the environment as well as judging potential benefits of keeping the weed. Current studies also analyze whether farmers are interested in adopting selective weeding technologies, with the option to leave environmentally beneficial weeds, which depends on the motives and objectives of farmers (RG4).

In the case of plant diseases, one main challenge is to accurately detect their occurrence and distribution for, potentially site-specific, pesticide applications. Currently, monitoring is done mainly by costly and error-prone visual inspection by humans (Bock et al., 2021; Mahlein et al., 2018). Improving this requires the establishment of applicable sensor systems (RG1) and their integration into modeling approaches for data analysis (RG2) and decision-making (RG3). Site-specific pesticide applications require research on the epidemiology of plant pathogens, and exhaustive datasets of UAV field monitoring from different years and different sites. These have been established within PhenoRob (Barreto Alcántara et al., 2022). Based on these unique datasets and deep learning approaches, an accurate estimate of disease severity and intensity in time and space is possible and will be further improved. One result of the current studies may be that well-established threshold systems for decision-making in plant protection need to be reconsidered and adapted. We expect that smart digital technologies provide a tremendous potential to reduce the amount of pesticides applied, and will be one technology to comply with ambitious pesticide reduction plans. However, a substantial research gap still exists in the characterization of multiple stresses (mixed infections or combined biotic and abiotic stress) by sensor systems which needs to be further investigated.

3.3. E3: Spatial field arrangement on patchy soils and mixed cropping

Simplifications of landscapes, large field sizes, narrowing of crop rotations, and monocultures have resulted in a loss of biological and landscape diversity (Batáry et al., 2017). Smart digital technologies could enable smaller field sizes with single crops, following the patchiness of soils in a heterogeneous landscape (Fig. 1c), or crop mixtures with the same or lower labor inputs (Fig. 1b). However, the response of the biophysical system and the economic system is largely unknown. Current models are ill-suited to determine optimal mixture composition and management at the field and farm scale, limiting possibilities to give suitable recommendations for farmers. We also lack tools to evaluate or design policies that would reward the adoption of new field arrangements that maximize beneficial landscape effects (Barghusen et al., 2021).

Current research aims to identify and evaluate new field arrangements for diversified cropping systems such as crop mixtures and adapted field geometries ('patch cropping') with respect to their impact on agro-ecosystems (Hernández-Ochoa et al., 2022). Developing the required field- and landscape models, benefits from newly developed advanced data acquisition and analysis tools to evaluate the performance of diversified cropping systems (RG1, RG2) as well as methods for assimilation of monitoring data with high spatial and temporal resolution into crop and agro-ecosystem models (RG2, RG3). Improved sensing and modeling also enable defining crop traits indicative of mixing compatibility and rules for improved decision-making to identify optimal field sizes, shapes, and neighbourhoods and to quantify ecosystem (dis)services. To assess the full potential of new field arrangements at a landscape scale, it is crucial to assess the diffusion process as well as potential feedback effects (RG4). Further effects might strongly depend on where patchy or mixed cropping is applied (e.g., potential larger effect in more homogenous landscapes) requiring spatially explicit modeling of adoption (RG4).

Important first steps have already been realized within our research project PhenoRob. Approaches to estimate the crop cover per species using high-resolution RGB imagery (Marashdeh et al., 2022), as well as species-specific measurements of the below-ground competition in cereal/legume mixtures, were developed to improve field-scale agro-ecosystem models. Additionally, we set up a large field experiment making positive use of field heterogeneities (Fig. 1b). Smaller plots, with diverse and site-specific crop rotations, help to strengthen synergies and interactions between crops and landscape elements such as flower strips. Non-invasive soil sensing such as gamma spectroscopy, x-ray fluorescence, and mid-wavelength infrared readings are currently implemented for apriori providing soil information to the optimization of the field designs (Fig. 1c). The results of those experiments allow for setting up newly developed crop mixture models and simulating performance and ecosystem service provision of a large range of cropping systems (Fig. 1k, m).

4. Steps forward to close the gaps

So far, we have pointed out, which major research gaps need to be closed on the way towards integrated smart digital solutions for sustainable crop production. We also illustrated ideas on how to close the gaps and the benefits of closing them by giving some examples from our related research activities. In every involved scientific community, there are certainly ideas for addressing specific challenges in the context of the mentioned gaps. However, as we outlined before, we strongly believe, that closing the gaps requires a strong interdisciplinary collaboration between plant and agricultural science, computer science, ecologists, economists, robotics, and geodesy. However, this is easier said than done. Fostering and enabling this interdisciplinary collaboration requires strategic research programs that coherently align complementary scientific expertise around relevant use cases. Based on our experience from our own large-scale interdisciplinary research project "PhenoRob - Robotics and Phenotyping Towards Sustainable Crop Production" we propose several measures for this. The measures consist of (i) common experimental platforms and central databases, (ii) interdisciplinary training, and (iii) institutional cooperation and networks.

(i) Central elements in a research program on sustainable crop production are core experimental platforms, which could be agricultural field and landscape experiments of different spatial and temporal scales and foci. All data collected in the experiments should be stored and managed in a dedicated customized database and should be accessible by all researchers of the programme. These experimental platforms and the database provide a collaboration and communication environment for researchers from different disciplines. Data with different spatial and temporal resolutions play a major role in all of the mentioned disciplines, but how to create them, how to process them, and especially how to use them can be very different. Building a common language and understanding around the creation, representation, provision, and utilization of any kind of data in the agricultural context is a booster for the necessary interdisciplinary work.

(ii) Additional measures to foster interdisciplinary collaboration and to develop a common language are seminar and lecture series, and interdisciplinary undergraduate and graduate teaching activities (including joint PhD supervision). It is important, that the seminars and lectures are specially designed to enable the understanding of the questions and methods used in other disciplines of the research program. This training should be implemented throughout all levels of scientific work, ranging from undergraduates to professors.

(iii) A third important structural measure is the development of institutional cooperation and networks. They should be promoted at national and international levels to pool resources, knowledge, and expertise to foster innovation, improve efficiency, and create shared value. One example in this direction is the *DigiCrop.Net* network, which has been set up in the context of technology-driven approaches towards sustainable crop production. Beyond research cooperations, collaboration should include stakeholder networks, including companies, farmers, and start-ups to address collective challenges, to drive innovation, and to create positive social impact.

5. Conclusion and outlook

Smart digital technologies offer opportunities for sustainable crop production. In this paper, we present a research agenda that needs to be addressed by such programs. By focusing on high-risk/high-reward research questions they can provide innovation impulses to existing public and private Research and Development (R&D) that develop digital farming technology for specific applications and accelerate the transformation towards sustainable crop production.

CRediT authorship contribution statement

Uwe Rascher: Writing – review & editing. **Lasse Klingbeil:** Writing – review & editing, Writing – original draft, Conceptualization. **Chris McCool:** Writing – review & editing. **Sabine Julia Seidel:** Writing – review & editing, Writing – original draft, Conceptualization. **Anne-Katrin Mahlein:** Writing – review & editing. **Hugo Storm:** Writing – review & editing, Writing – original draft, Conceptualization. **Juergen Gall:** Writing – review & editing. **Sven Behnke:** Writing – review & editing. **Cyrill Stachniss:** Writing – review & editing, Writing – original draft, Conceptualization. **Wulf Amelung:** Writing – review & editing. **Andrea Schnepf:** Writing – review & editing. **Harry Vereecken:** Writing – review & editing, Conceptualization. **Stefan Wrobel:** Writing – review & editing. **Frank Ewert:** Writing – review & editing, Writing – original draft, Conceptualization. **Thomas Döring:** Writing – review & editing. **Jan Börner:** Writing – review & editing. **Maren Bennewitz:** Writing – review & editing. **Heiner Kuhlmann:** Writing – review & editing, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

No data was used for the research described in the article.

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References

Ahmadi, A., Mccool, C., Halstead, M., 2022. BonnBot-I: a precise weed management and crop monitoring platform. : Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS) 10.

Asseng, S., Asche, F., 2019. Future farms without farmers. Sci. Robot. 4, 2–4.

Atkinson, J.A., Pound, M.P., Bennett, M.J., Wells, D.M., 2019. Uncovering the hidden half of plants using new advances in root phenotyping. Curr. Opin. Biotechnol. 55, 1–8.

Barghusen, R., Sattler, C., Deijl, L., Weebers, C., Matzdorf, B., 2021. Motivations of farmers to participate in collective agri-environmental schemes: the case of Dutch agricultural collectives. Ecosyst. People 17, 539–555.

Barreto Alcántara, A.A., Ispizua Yamati, F.R., Varrelmann, M., Paulus, S., Mahlein, A.-K., 2022. Disease incidence and severity of Cercospora leaf spot in sugar beet assessed by multispectral unmanned aerial images and machine learning. Plant Dis. 0, null.

Basso, B., Antle, J., 2020. Digital agriculture to design sustainable agricultural systems. Nat. Sustain. 3, 254–256.

Batáry, P., Gallé, R., Riesch, F., Fischer, C., Dormann, C.F., Mußhoff, O., Császár, P., Fusaro, S., Gayer, C., Happe, A.-K., Kurucz, K., Molnár, D., Rösch, V., Wietzke, A., Tscharntke, T., 2017. The former Iron Curtain still drives biodiversity–profit trade-offs in German agriculture. Nat. Ecol. Evol. 1, 1279–1284.

Bock, C.H., Pethybridge, S.J., Barbedo, J.G.A., Esker, P.D., Mahlein, A.-K., Del Ponte, E. M., 2021. A phytopathometry glossary for the twenty-first century: towards consistency and precision in intra-and inter-disciplinary dialogues. Trop. Plant Pathol. 1–11.

Cai, G., Vanderborght, J., Klotzsche, A., van der Kruk, J., Neumann, J., Hermes, N., Vereecken, H., 2016. Construction of minirhizotron facilities for investigating root zone processes. Vadose Zone J. 15, vzj2016.05.0043.

Caubel, J., Launay, M., Ripoche, D., Gouache, D., Buis, S., Huard, F., Huber, L., Brun, F., Bancal, M.O., 2017. Climate change effects on leaf rust of wheat: Implementing a coupled crop-disease model in a French regional application. Eur. J. Agron. 90, 53–66.

Chenu, K., Porter, J.R., Martre, P., Basso, B., Chapman, S.C., Ewert, F., Bindi, M., Asseng, S., 2017. Contribution of crop models to adaptation in wheat. Trends Plant Sci. 22, 472–490.

Colbach, N., Busset, H., Roger-Estrade, J., Caneill, J., 2014. Predictive modelling of weed seed movement in response to superficial tillage tools. Soil Tillage Res 138, 1–8.

Duru, M., Therond, O., Martin, G., Martin-Clouaire, R., Magne, M.-A., Justes, E., Journet, E.-P., Aubertot, J.-N., Savary, S., Bergez, J.-E., et al., 2015. How to implement biodiversity-based agriculture to enhance ecosystem services: a review. Agron. Sustain. Dev. 35, 1259–1281.

Enders, A., Vianna, M., Gaiser, T., Krauss, G., Webber, H., Srivastava, A.K., Seidel, S.J., Tewes, A., Rezaei, E.E., Ewert, F., 2023. SIMPLACE - A versatile modelling and simulation framework for sustainable crops and agroecosystems. silico Plants, diad006.

Ewert, F., van Ittersum, M.K., Heckelei, T., Therond, O., Bezlepkina, I., Andersen, E., 2011. Scale changes and model linking methods for integrated assessment of agri-environmental systems. Agric. Ecosyst. Environ. 142, 6–17.

FAO, 2017. The future of food and agriculture. Trends and challenges. https://doi.org/10.4060/cc1024en.

Finger, R., Swinton, S.M., El Benni, N., Walter, A., 2019. Precision farming at the nexus of agricultural production and the environment. Annu. Rev. Resour. Econ. 11, 313–335.

Fiorani, F., Rascher, U., Jahnke, S., Schurr, U., 2012. Imaging plants dynamics in heterogenic environments. Curr. Opin. Biotechnol. 23, 227–235.

Grieve, B.D., Duckett, T., Collison, M., Boyd, L., West, J., Yin, H., Arvin, F., Pearson, S., 2019. The challenges posed by global broadacre crops in delivering smart agri-robotic solutions: a fundamental rethink is required. Glob. Food Secur. 23, 116–124.

Halstead, M., Ahmadi, A., Smitt, C., Schmittmann, O., McCool, C., 2021. Crop agnostic monitoring driven by deep learning. Front. Plant Sci. 12 https://doi.org/10.3389/fpls.2021.786702.

Hernández-Ochoa, I.M., Gaiser, T., Kersebaum, K.-C., Webber, H., Seidel, S.J., Grahmann, K., Ewert, F., 2022. Model-based design of crop diversification through new field arrangements in spatially heterogeneous landscapes. A review. Agron. Sustain. Dev. 42, 1–25.

Jin, X., Zarco-Tejada, P.J., Schmidhalter, U., Reynolds, M.P., Hawkesford, M.J., Varshney, R.K., Yang, T., Nie, C., Li, Z., Ming, B., Xiao, Y., Xie, Y., Li, S., 2021. High-throughput estimation of crop traits: a review of ground and aerial phenotyping platforms. IEEE Geosci. Remote Sens. Mag. 9, 200–231.

Jones, H.G., 2004. Irrigation scheduling: advantages and pitfalls of plant-based methods. J. Exp. Bot. 55, 2427–2436.

Karpatne, A., Atluri, G., Faghmous, J.H., Steinbach, M., Banerjee, A., Ganguly, A., Shekhar, S., Samatova, N., Kumar, V., 2017. Theory-guided data science: a new paradigm for scientific discovery from data. IEEE Trans. Knowl. Data Eng. 29, 2318–2331.

Kersebaum, K.C., Boote, K.J., Jorgenson, J.S., Nendel, C., Bindi, M., Frühauf, C., Gaiser, T., Hoogenboom, G., Kollas, C., Olesen, J.E., Rötter, R.P., Ruget, F., Thorburn, P.J., Trnka, M., Wegehenkel, M., 2015. Analysis and classification of data sets for calibration and validation of agro-ecosystem models. Environ. Model. Softw. 72, 402–417.

Khanna, M., Atallah, S.S., Kar, S., Sharma, B., Wu, L., Yu, C., Chowdhary, G., Soman, C., Guan, K., 2022. Digital transformation for a sustainable agriculture in the United States: opportunities and challenges. Agric. Econ. https://doi.org/10.1111/agec.12733.

Kumar, N., Sharma, B., 2020. Opportunities and challenges with WSN's in smart technologies: A smart agriculture perspective. Handbook of wireless Sensor Networks: Issues and Challenges in Current Scenario's, p. 441–463.

von Lampe, M., Willenbockel, D., Ahammad, H., Blanc, E., Cai, Y., Calvin, K., Fujimori, S., Hasegawa, T., Havlik, P., Heyhoe, E., Kyle, P., Lotze-Campen, H., Mason d'Croz, D., Nelson, G.C., Sands, R.D., Schmitz, C., Tabeau, A., Valin, H., van der Mensbrugghe, D., van Meijl, H., 2014. Why do global long-term scenarios for agriculture differ? An overview of the AgMIP Global Economic Model Intercomparison. Agric. Econ. 45, 3–20.

Lottes, P., Behley, J., Chebrolu, N., Milioto, A., Stachniss, C., 2020. Robust joint stem detection and crop-weed classification using image sequences for plant-specific treatment in precision farming. J. Field Robot. 37, 20–34.

Lowenberg-DeBoer, J., Erickson, B., 2019. Setting the record straight on precision agriculture adoption. Agron. J. 111, 1552–1569.

Lynch, J.P., Mooney, S.J., Strock, C.F., Schneider, H.M., 2022. Future roots for future soils. Plant Cell Environ. 45, 620–636.
Mahlein, A.-K., Kuska, M.T., Behmann, J., Polder, G., Walter, A., 2018. Hyperspectral sensors and imaging technologies in phytopathology: state of the art. Annu. Rev. Phytopathol. 56, 535–558.
Mahlein, A.-K., Kuska, M.T., Thomas, S., Wahabzada, M., Behmann, J., Rascher, U., Kersting, K., 2019. Quantitative and qualitative phenotyping of disease resistance of crops by hyperspectral sensors: seamless interlocking of phytopathology, sensors, and machine learning is needed! Curr. Opin. Plant Biol. 50, 156–162.
Marashdeh, Q., Drees, L., Roscher, R., 2022. Semantic UAV Image Segmentation of Mixed Cropping Fields. in: Proc. of the Dreiländertagung Der DGPF. Der OVG Und Der SGPF in Dreseden - Publikationen Der DGPF, pp. 140–148.
Muñoz-Huerta, R.F., Guevara-Gonzalez, R.G., Contreras-Medina, L.M., Torres-Pacheco, I., Prado-Olivarez, J., Ocampo-Velazquez, R.V., 2013. A review of methods for sensing the nitrogen status in plants: advantages, disadvantages and recent advances. Sensors 13, 10823–10843.
Piao, S., Liu, Q., Chen, A., Janssens, I.A., Fu, Y., Dai, J., Liu, L., Lian, X., Shen, M., Zhu, X., 2019. Plant phenology and global climate change: Current progresses and challenges. Glob. Chang. Biol. 25, 1922–1940.
Ramin Shamshiri, R., Weltzien, C., A. Hameed, I., J. Yule, I., E. Grift, T., K. Balasundram, S., Pitonakova, L., Ahmad, D., Chowdhary, G., 2018. Research and development in agricultural robotics: a perspective of digital farming. Int. J. Agric. Biol. Eng. 11, 1–11.
von Rueden, L., Mayer, S., Sifa, R., Bauckhage, C., Garcke, J., 2020. Combining machine learning and simulation to a hybrid modelling approach: current and future directions. In: Advances in Intelligent Data Analysis XVIII. Springer International Publishing, pp. 548–560.
Sabour, S., Frosst, N., Hinton, G.E., 2017. Dynamic routing between capsules. Adv. Neural Inf. Process. Syst.
Seidel, S.J., Gaiser, T., Ahrends, H.E., Hüging, H., Siebert, S., Bauke, S.L., Gocke, M.I., Koch, M., Schweitzer, K., Schaaf, G., Ewert, F., 2021. Crop response to P fertilizer omission under a changing climate - experimental and modeling results over 115 years of a long-term fertilizer experiment. Field Crops Res. 268, 108174.
Shang, L., Heckelei, T., Gerullis, M.K., Börner, J., Rasch, S., 2021. Adoption and diffusion of digital farming technologies - integrating farm-level evidence and system interaction. Agric. Syst. 190, 103074.
Tewes, A., Montzka, C., Nolte, M., Krauss, G., Hoffmann, H., Gaiser, T., 2020. Assimilation of Sentinel-2 estimated LAI into a crop model: influence of timing and frequency of acquisitions on simulation of water stress and biomass production of winter wheat. Agronomy 10. https://doi.org/10.3390/agronomy10111813.
Tracy, S.R., Nagel, K.A., Postma, J.A., Fassbender, H., Wasson, A., Watt, M., 2020. Crop improvement from phenotyping roots: highlights reveal expanding opportunities. Trends Plant Sci. 25, 105–118.
Watt, M., Fiorani, F., Usadel, B., Rascher, U., Muller, O., Schurr, U., 2020. Phenotyping: new windows into the plant for breeders. Annu. Rev. Plant Biol. 71, 689–712.
Weyler, J., Milioto, A., Falck, T., Behley, J., Stachniss, C., 2021. Joint plant instance detection and leaf count estimation for in-field plant phenotyping. IEEE Robot. Autom. Lett. 6, 3599–3606.
Zhou, X.-R., Schnepf, A., Vanderborght, J., Leitner, D., Lacointe, A., Vereecken, H., Lobet, G., 2020. CPlantBox, a whole-plant modelling framework for the simulation of water- and carbon-related processes. Silico Plants 2. https://doi.org/10.1093/insilicoplants/diaa001.