Agricultural Systems 233 (2026) 104593

Contents lists available at ScienceDirect

Agricultural Systems

journal homepage: www.elsevier.com/locate/agsy

From technological fixes to systemic change: Vision-led innovation for Europe's crop farming systems

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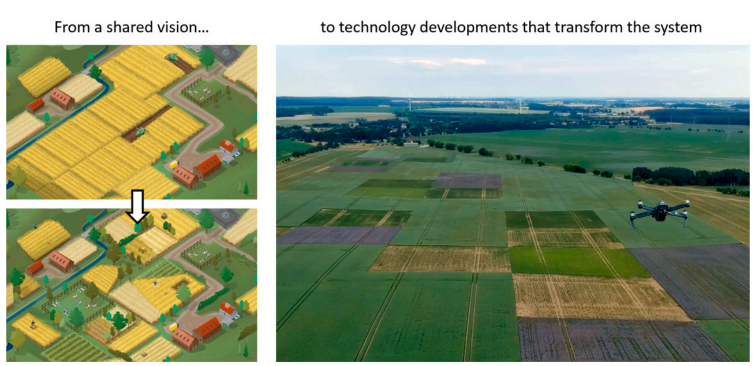
HIGHLIGHTS

- Past technological advances have mostly responded to immediate market signals.
- Future technological advances shall more strongly follow a strategic vision.
- Enabling innovations in sensing, robotics, AI, breeding, and environmental monitoring.
- These innovations allow for novel systems that are more diverse and sustainable.
- Important to develop visions inclusively, and anticipate risks, costs, and trade-offs.

GRAPHICAL ABSTRACT



ARTICLE INFO

Editor: Guillaume Martin

Keywords:
Agricultural technology

ABSTRACT

So far, agricultural technologies have mostly been developed to economize on expensive production inputs or to expand production in response to demand. The interplay of these individual, narrow-focused technology developments has profoundly transformed agricultural systems. In particular, economies of scale have led to large machinery, for which fields had to be made larger, more homogeneous, and more regularly shaped. This has

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https://doi.org/10.1016/j.agsy.2025.104593
Received 12 September 2025; Received in revised form 20 November 2025; Accepted 24 November 2025

Smart farming
Agro-ecology
Digital transformation
Responsible innovation
Mission-oriented innovation

considerably increased agricultural productivity, but has also come with considerable costs, such as soil degradation and biodiversity loss. We here propose a new paradigm for agricultural technology development, in which a vision for a more sustainable agricultural system is developed first, followed by the advancement of the required technologies, alongside complementary institutional reforms, policy changes, and novel business models to achieve it. In this paper, we systematically take stock of where we are in this process, i.e., how to identify target systems, what is the current technological frontier in sensing, robotics, AI modeling, breeding, and environmental monitoring, and which policy and business model innovations are now needed to realize the highest economic and environmental benefits at the lowest cost (financially and non-financially). This crucially includes anticipation of risks and the management of trade-offs.

1. Introduction

Crop productivity varies considerably around the world (Fig. 1, a-c). A key reason is technology (Gollin et al., 2021). High productivity is pivotal for food security and balanced diets, as well as for minimizing agricultural expansion (Baldos et al., 2025). However, technological progress has so far simplified fields and landscapes (Larsen and Noack, 2021), increased pollution (Schulte-Uebbing et al., 2022), and reduced biodiversity (Fig. 1d).

To achieve the Sustainable Development Goals, high agricultural productivity and environmental conservation need to be achieved together (FAO, 2025a, 2025b). Although technological progress is just one part of the solution bundle (Qaim et al., 2024; Zhu et al., 2023; Scown et al., 2020), we consider it an important one. We focus here specifically on Europe, as a global leader in technology and environmental policy (van Dijk et al., 2025; Wuepper et al., 2024). Solutions developed in Europe are globally relevant – directly (e.g., technology transfers) and indirectly (e.g., providing examples).

We propose that in order to create more sustainable and resilient agricultural production systems, a fundamental shift is required: So far, production systems have been adapted to new technological developments, but now, we can move towards first identifying desirable properties of target systems and based on these, identify innovation needs. Importantly, technological change must go hand in hand with business and policy innovations to achieve new system configurations with, e.g., more diverse landscapes (Ewert et al., 2023) or more precise, location-adapted practices (Finger, 2023). This requires advances in sensing, robotics, artificial intelligence, breeding, as well as institutional-, business-, and policy- innovations, to be coherently aligned (Finger, 2023; Khanna et al., 2024; Storm et al., 2024).[1] This has also been called "mission-oriented innovation" (Mazzucato, 2018).

Key to integrating all innovation elements is to co-create a joint vision of the target system or landscape. This is beyond the scope of this paper, but is discussed elsewhere, e.g., how to involve living labs (see Gardezi et al., 2024), and how to combine sustainability assessments with responsible innovation (Ehlers et al., 2025). Ultimately, the success of the vision-led innovation approach rests on its perceived legitimacy and inclusiveness to address all actors' preferences, needs, and concerns, and particularly, the farmers need to be acknowledged as key agents of change.

2. Theoretical embedding

Agricultural innovation processes are driven by factor scarcity and prices, and involve both technological and institutional innovations, as described by the theory of induced innovation (Pardey et al., 2010; Ruttan, 1997). Today, the scarce factor (or service in demand) increasingly consists of non-market agricultural sustainability. As a result, some of the new technologies we discuss below are already profitable without policy support. Others would become profitable if governments were to price in all environmental externalities of different agricultural practices (taxing and regulating harmful ones, supporting and subsidizing beneficial ones) (Mirzabaev and Wuepper, 2023; Shang et al., 2023). Sustainable agriculture has been a goal of governments for a long time (Wuepper et al., 2024; Zilberman, 2014). However, truly transformative institutional and policy change will produce winners and losers among food system actors, including consumers. Technological progress is key to make the required transformation affordable and enhances its governability.

Vision-led innovation thus fundamentally also comes with the challenge of governing responsibly, sustainably, and efficiently, anticipating and addressing potential positive and negative transformational impacts (i.e. as in the concept of responsible innovation, see Kihoro et al., 2025; Gargani et al., 2024; Bellon-Maurel et al., 2022). Responsible innovation consists of four building blocks: Anticipation, reflexivity, inclusion, and responsiveness (Ehlers et al., 2025). In large heterogeneous regions like Europe, vision-led innovation may often require bottom-up or territorial approaches (Torre, 2023) embedded in local and regional agricultural knowledge systems (Fieldsend et al., 2021) to leverage the responsible innovation potential of diverse target systems.

3. Current technological developments

Over the past decade, large research clusters have been established in several countries to advance technological progress while identifying opportunities, constraints, and risks (Storm et al., 2024). Whereas technologies and economies of scales have favored towards larger and simplified fields and landscapes, current and future research increasingly facilitates more flexible technologies that perform well across a broad range of environments, including complex arrangements of patches and fields (Grahmann et al., 2024), with many structural elements that are environmentally and socially desirable but unsuitable for large machines (Finger, 2023) (Fig. 2).

3.1. Advances in sensing, AI and modeling

Novel sensing technology, in combination with artificial intelligence, is a key enabler for autonomous agricultural machinery to operate in complex field and landscape structures and to allow for plant-level treatment (Bongomin et al., 2020; Cisternas et al., 2020). A key achievement is the growing ability to extract information from complex spatiotemporal data to detect weeds (Ahmadi et al., 2024), predict plant diseases (Günder et al., 2025; Okole et al., 2024), stress (Zhou et al., 2021), and nutrient deficiencies (Yi et al., 2024). This information can be made available to farmers within decision support tools. Digital twins in agriculture go a step further (Purcell and Neubauer, 2023), leveraging these capabilities to build a real-time virtual representation of the underlying system and, in addition, provide the possibility of simulating interventions. These digital technologies, together with the right policies, can allow farmers to farm under more challenging conditions (such as on diverse and complex fields) and reduce agricultural pollution. A key open research question is how to combine machine learning approaches, process-based simulation models, and data from diverse sources to better predict events that are not part of the training data (Storm et al., 2024). A promise of AI is that it can self-improve and adapt

[1] This also requires parallel transformations on the consumption side, but here we focus on the production side.

to changing conditions (Grieve et al., 2019). However, we still need to learn more about the conditions under which farmers are willing to follow AI-generated recommendations and support the required experimentation that is crucial for these methods to improve and spread (Khanna et al., 2024).

3.2. Advances in robotics

Robots in agricultural crop management provide the opportunity to leverage advances in sensing into autonomous interventions for plant protection, fertilization, and harvesting (Yang et al., 2023). The developments are closely tied to advances in AI that are the basis for targeted, fast, and safe operations (Muhammad et al., 2021). Robots in the context of crop management hold two main promises: (1) more precise, eco-friendly crop management and (2) decreasing the economies of scale associated with single crops on large and regularly shaped fields required for the use of much of the current machinery (Estrada-Carmona et al., 2022; Hernández-Ochoa et al., 2022; Pearson et al., 2022). Additionally, robotic systems can address the growing issue of labor scarcity (Kondratieva et al., 2022). The combination of robots with AI algorithms capable of reinforcement learning opens the possibility of self-learning systems that continuously optimize themselves, leveraging increasing amounts of data generated by own and other robots' operation (Gautron et al., 2022; Khanna et al., 2024). Challenges, however, include finding suitable business models for heterogeneous farms and contexts, legal barriers to data exchange, and ethical issues of autonomous operations (Gil et al., 2023; Sparrow and Howard, 2021).

3.3. Advances in breeding

Advances in plant breeding have been an important source of productivity growth throughout the history of agriculture (Qaim, 2020). With the advent of modern biotechnology and new genomic techniques, the speed and precision of plant breeding are, however, increasing. High-throughput genome sequencing technologies in combination with advances in computation, machine learning, and new gene-editing tools allow faster developments of crops that are high-yielding, more resistant to pests and diseases, and more robust to weather shocks (Steinwand and Ronald, 2020; Zhang et al., 2020). Many of the new genomic techniques are relatively low-cost and can therefore also be used to improve minor crops that were previously often neglected by commercial breeding programs. Advances in breeding could play an important role in making European agriculture more diverse, sustainable, resilient, and locally adapted. Currently, however, the number of genetically engineered crops and traits in practical use is still small, mainly due to security concerns, misconceptions about potential risks and benefits, and costly and politicized regulatory processes (Noack et al., 2024). A constructive public debate and more efficient regulations would be needed to leverage the full potential of new breeding technologies for sustainable agriculture in the EU (Fischer and Rock, 2023).

3.4. Advances in environmental monitoring

New technologies are now paving the way towards the automated monitoring of entire ecological communities (Besson et al., 2022), offering powerful new tools to enhance the design and management of sustainable agricultural systems. Important developments include autonomous recorders for passive acoustic monitoring (Hill et al., 2019), embedded vision cameras (Darras et al., 2025), UAVs (Barrasso et al., 2024), and eDNA analysis (Kestel et al., 2022). These technologies enable standardized spatiotemporal biodiversity data collection while minimizing human observer error and providing rich metadata (e.g., timestamps and taxonomic uncertainties; Hartig et al., 2024). When combined with AI-based species identification tools such as BirdNET (Kahl et al., 2021), they offer unprecedented opportunities to advance our understanding of the complex relationships between biodiversity and agricultural management.

Greenhouse gas (GHG) emission monitoring is profiting from similar technological developments (Al Hamwi et al., 2024). Automated chambers allow for intra-daily GHG flux measurements (Pavelka et al., 2018) and can be controlled by robots (Vaidya et al., 2021). However, their use in croplands remains challenging. Fast sensors for nitrous oxide

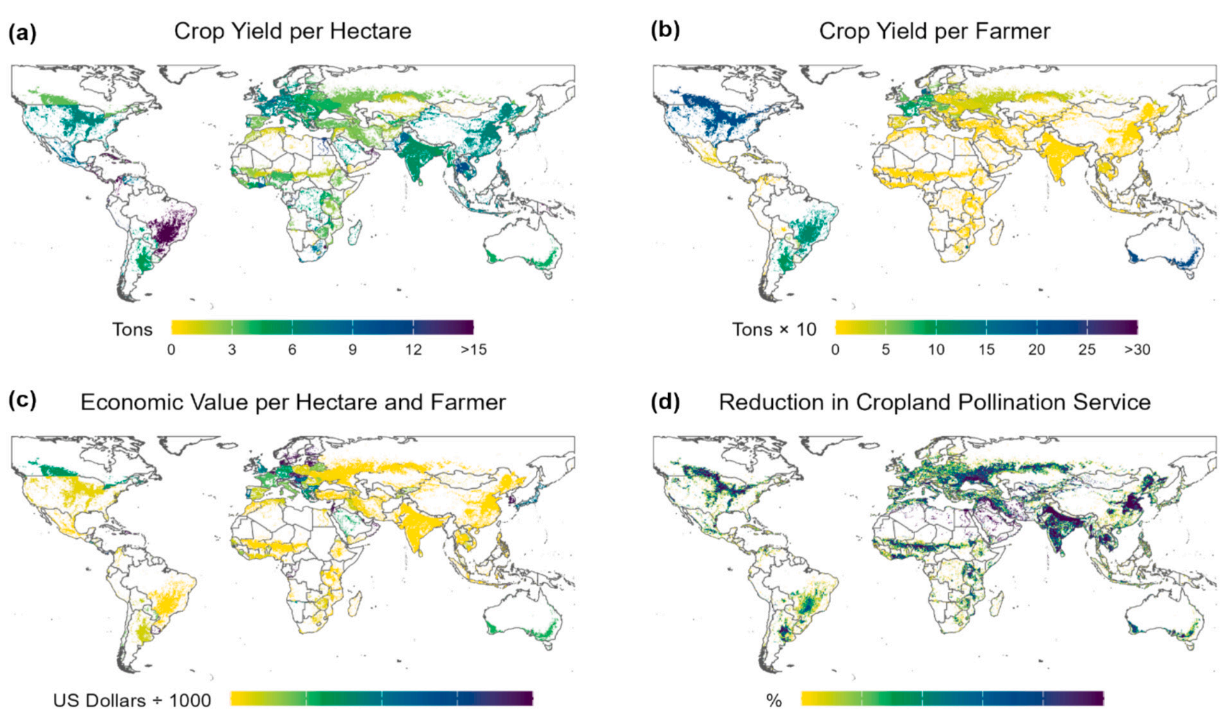

Fig. 1. European Agriculture in Global Context (ca. 2020). (a) Land productivity (b) Labor productivity (c) Economic value created per land and labor (d) Loss of natural pollination services. Data from FAO (2025b), World Bank (2025), Ru et al. (2022), Von Jeetze et al. (2023).

and methane, together with the existing ones for carbon dioxide, allow for flux measurements at high temporal resolution over entire fields (Maier et al., 2022), while new mobile sensors offer opportunities for survey measurements. Currently, these techniques are still costly and technically demanding but promising approaches are being developed combining remote sensing and machine learning (Adler et al., 2024).

3.5. Enabling conditions: policy and business model innovations

Leveraging the benefits promised by technological innovations will require new policies and business models (Fig. 3). In turn, new technologies will also enable innovations in policy and business models. For example, with improved sensing and modeling capabilities, agri-environmental payments can be redesigned and improved. Currently, most payment schemes are either paying farmers for their actions, or when results-based, focus on narrow indicators (Hagemann et al., 2025). The range of indicators can now be expanded, but also action-based payments can be improved (Massfeller et al., 2025).

Europe – because of the EU - has many agri-environmental regulations (Wuepper et al., 2024). Regulations can be both a barrier and a driver for agricultural transformation. Some regulations constrain farmers' option space and stifle innovation. However, tightening environmental regulations can also be a driver of directed technological change (Aghion et al., 2019). As such, to transform Europe's crop production system, it is important to carefully reform regulations, to incentivize and enable green entrepreneurship (Zilberman et al., 2022), while avoiding expensive overregulation.

Another policy-relevant issue is that farmers might not adopt novel technology if they need to take all risks involved and do not sufficiently benefit from sustainability improvements. Innovative insurance solutions have potential (Lefebvre et al., 2024). With farmers learning and technologies improving over time, the costs of such insurance products fall. However, insurances must be carefully designed and targeted, as they can otherwise lead to unintended effects and even increase environmental pollution (Dalhaus et al., 2023; Möhring et al., 2020a). Moreover, farmers require loans, as most of the discussed innovations are expensive. Subscription-based models and contractors, however, can particularly help smaller farmers (Chappell et al., 2019; Wang et al., 2022).

Not only are new policies required, but also new cooperation along the entire value chain, as well as new business models (Birner et al., 2021; Möhring et al., 2020b). First, value chains need to adapt storage, logistics, and market structures to new cropping systems. Second, demand from consumers and value chains can provide a push, e.g., through price premia (Möhring and Finger, 2022Third, novel business models may enable easier and more equitable access to new technologies: Two examples are cross-company collaborations and moving from products to services (Raineau et al., 2024; Tukker, 2004). The former involves different companies working together to come up with mutually beneficial business ideas, such as combining software and hardware expertise, or different partners having access to different kinds of data. For this, regulations need to be adjusted to allow regulated data-sharing (Meemken et al., 2024; Sauvagerd et al., 2024). The move from products to services changes incentives for industry in supplying resource-efficient technology. Similarly, supporting machinery rings or contractors could lead to a faster spread of innovations (Wang et al., 2022). Side effects like changes in power structures need to be carefully considered (Dalhaus et al., 2023; Sauvagerd et al., 2024). Even though impressive technological advances have been made over the last decade, more investments in research and development are still necessary (Khanna et al., 2024; Storm et al., 2024).

4. Risks

A shift to smart farming also comes with risks. Here, we discuss five distinct categories of risk.

4.1. Sustainability is not guaranteed

Smart farming is widely expected to increase sustainability. In reality, however, it rather has the *potential* to make agriculture more sustainable, and whether this potential is realized depends on how technologies are utilized and what adjustments follow (Dalhaus et al., 2024; Walter et al., 2017). Depending on the context, there is the possibility that farmers adopt smart farming and increase short-term profits by increasing both the precision of agrochemical applications, as well as the amounts used (Oui, 2025). There are even direct sustainability threats, such as drones bothering local wildlife (Brisson-Curadeau et al., 2025).

4.2. Increasing market power and inequality

Another concern regards the strengthening of oligopolies and the widening of inequalities. Many smart farming innovations are capital-intensive, both financially and in terms of required human capital, and they regularly substitute for labor, all potentially leaving behind smaller, more resource-constrained farms. On the business side, the more information a company gathers, the better its provided services, and the more a single company provides all the different innovations, the better they can be integrated, potentially increasing the concentration of market power (Khanna et al., 2024; Sauvagerd et al., 2024).

4.3. Incentives for over- and misregulation

The growing availability of data is generally a boon for policy making, e.g., allowing novel agri-environmental payment schemes and extension services. However, there exist pitfalls. First, policymakers might be tempted to focus on outcomes that can be measured well with the new technologies, instead of those that are most relevant (Elmiger et al., 2023). Secondly, constant technological advances can incentivize policymakers to constantly adjust policies, creating an unpredictable and bureaucratic policy environment. Finally, there is the risk of overregulation in two ways: First, improved monitoring could lead to ever more instructions to the farmers on how to manage their farms, and secondly, policymakers' risk aversion could lead to regulations that make innovations unprofitable (Lowenberg-DeBoer et al., 2022;

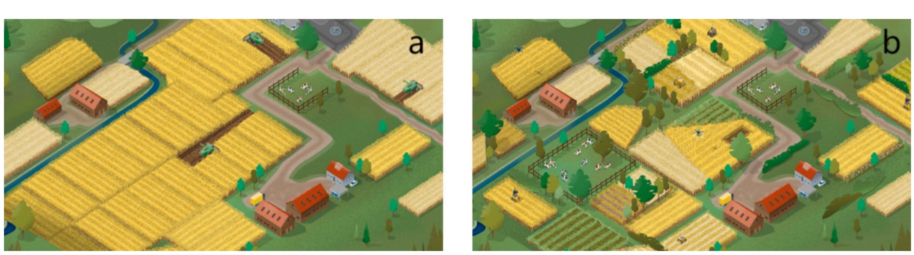

Fig. 2. Towards diversified, sustainable, and productive crop farming systems. Enabled by new technologies and changes in policies and business models, future crop production in Europe might look much more like panel b than panel a. Images: ©ZALF (institutional repository).

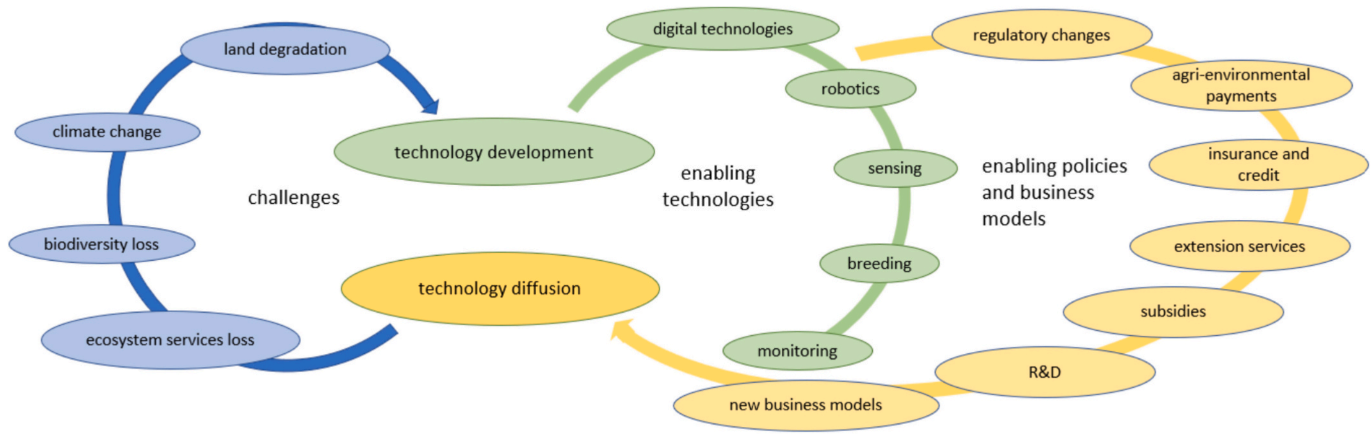

Fig. 3. Scaling Up Sustainable Crop Farming Innovations. In order to address the large sustainability challenges that the European farming system is facing, multiple technological innovations are being developed. For their widespread diffusion, enabling policies are required, consisting of push and pull factors that need to be combined in order to transform the European crop production system towards more diversity and environmental sustainability, while remaining productive and profitable.

Shockley et al., 2022).

4.4. Technology failures

Smart farming relies on frontier technologies that are often novel and complex. This makes them vulnerable in three distinct ways. First, everyone along the value chains needs to learn how to use and integrate them (Zilberman et al., 2022). Secondly, technologies can fail by themselves. For example, AI-based weeding robots might make an error with a potentially large economic impact (e.g., ignore a novel pest that was not in the training data, or destroy a crop, mistaking it for a weed). Third, the more digital the farming system, the more it can become vulnerable to cyber-attacks.

4.5. Substitution effect

A final risk to consider are adjustments to smart farming advances. The goal is that smart farming contributes to a sustainable agricultural system by synergistically complementing other solutions, such as cutting food waste, changing diets, and large-scale ecosystem restoration. If instead, smart farming takes pressure off pursuing these other aspects, the net benefit is smaller (Gil, 2021).

5. Towards a technology-enabled systemic change

Current crop production systems in Europe have evolved mainly to meet the requirements of productivity-enhancing technologies. Now, game-changing agricultural technologies are becoming available that enable a fundamental sustainability transformation to new European crop production systems that account better for societal costs and benefits. For this, we need a co-created vision, a joint target of how crop production systems shall look like, and aligns technological, institutional, business, and policy innovation. The success of such an innovation system will depend on advances in several areas: (1) Co-creating visions of agricultural production systems that locally address societal demands (2) understanding what technologies are key to enable such systems; (3) considering societal preferences and ensure there is public support; (4) considering social implications and needs of farming communities through co-design and responsiveness; (5) identifying the macro-economic and local conditions under which new technologies are profitable for farmers; (6) assessing and designing cost-effective policies and attractive business models to minimize technology risks and create conditions for sustainable use.

These points imply a cross-disciplinary research agenda, and alignment with policy and the private sector. This allows targeted and responsible innovation for European cropping systems. It facilitates progress that is aware of the promises but also risks involved.

CRediT authorship contribution statement

David Wuepper: Writing – review & editing, Writing – original draft, Visualization, Conceptualization. **Niklas Möhring:** Writing – review & editing, Writing – original draft, Conceptualization. **Anna F. Cord:** Writing – review & editing, Writing – original draft, Conceptualization. **Ana Meijide:** Writing – review & editing, Writing – original draft. **Hugo Storm:** Writing – review & editing, Writing – original draft, Conceptualization. **Matin Qaim:** Writing – review & editing, Writing – original draft, Conceptualization. **Thomas Heckelei:** Writing – review & editing, Writing – original draft, Conceptualization. **Jan Börner:** Writing – review & editing, Writing – original draft, Conceptualization. **Hadi Hadi:** Writing – original draft, Visualization, Conceptualization. **Heiner Kuhlmann:** Writing – review & editing, Funding acquisition, Conceptualization. **Cyrill Stachniss:** Writing – review & editing, Funding acquisition, Conceptualization. **Frank Ewert:** Writing – review & editing, Writing – original draft, Visualization, Conceptualization.

Declaration of competing interest

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

Acknowledgements

This research has been supported by the German Research Foundation (DFG), under Germany's Excellence Strategy EXC 2070, Grant No. 390732324 - PhenoRob.

Data availability

Data will be made available on request.

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