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Review

Autonomous field management – An enabler of sustainable future in agriculture

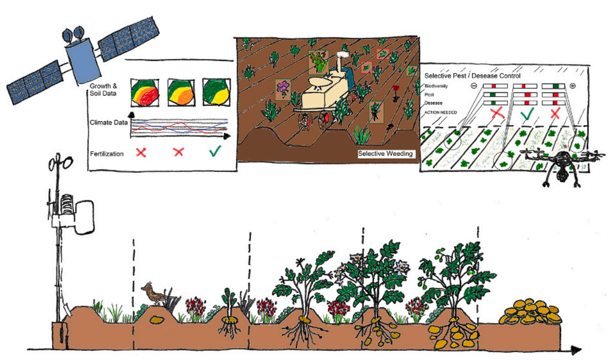
David Gackstetter [a,1], Malte von Bloh [b,1], Veronika Hannus [a,c], Sebastian T. Meyer [d], Wolfgang Weisser [d], Claudia Luksch [a], Senthold Asseng [a,b,*]

[a] Technical University of Munich, Hans Eisenmann-Forum for Agricultural Sciences (TUM-HEF), Germany
[b] Technical University of Munich, TUM School of Life Sciences, Department of Life Science Engineering, Chair of Digital Agriculture, Germany
[c] Technical University of Munich, TUM School of Management & TUM School of Life Sciences, Department of Life Science Systems, Chair for Agricultural Production and Resource Economics, Germany
[d] Technical University of Munich, TUM School of Life Sciences, Department of Life Science Systems, Terrestrial Ecology Research Group, Germany

HIGHLIGHTS

- Context: This review includes the state of the art in the four most important technology sectors that are needed for autonomous farming.
- Objective: Robotics, AI, Big Data – the important topics are developing quickly. We show how this technology can positively impact the system.
- Results: There is a lack of interconnection between different technologies. If this is made possible, it can reconcile sustainability and production.
- Conclusion: Autonomous field management can produce more resource-efficiently and incorporate objectives such as sustainability.
- Significance: Many reviews of the individual technologies exist. However, there are hardly any that consider them integrated within a common system.

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: Technological innovations in agriculture are mainly driven by the maxim: increase productivity at any costs. Today, in the face of climate change and an unprecedented loss of biodiversity, this approach is reaching its limits. Meeting global nutrition needs while achieving sustainability is one of the greatest challenges for modern agriculture.
OBJECTIVE: Autonomous field management represents the next evolutionary step in agricultural technology. It is characterized by an end-to-end automation of agricultural production processes and by that – for the first time in history - independence from labor constraints. Although literature has provided solutions for individual

* Corresponding author at: Technical University of Munich, TUM School of Life Sciences, Department of Life Science Engineering, Chair of Digital Agriculture, Germany.
E-mail address: senthold.asseng@tum.de (S. Asseng).
[1] These two authors contributed equally

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New farming systems
Autonomous farming

components of these new technological systems, integrating those components into a common, fully autonomous process has not yet been achieved.
METHODS: We analyzed the technological, agronomic, environmental, and related, interdisciplinary literature in the context of automated, and digital field crop management.
RESULTS AND CONCLUSION: The review shows the disruptive potential of fully autonomous, labor-independent crop management systems to guarantee the required food security by simultaneously allowing sustainable factors to be equally incorporated into the agricultural decision-making process. The integration of multifaceted objectives into a common decision-making process poses a great challenge to human farmers and their capacities. Liberated from labor constraints, autonomous systems have the potential to align decisions with the complex requirements of multiple – even contradicting – goals more easily, and to execute them accordingly without exhaustion. We show barriers that explain, why fully autonomous crop management is not yet present in today's agricultural practice, despite the fact that the majority of technological sub-components has reached a maturity stage beyond the proof of concept. Substantial technological progress will still be required with respect to the robustness in varying application settings and the standardization of interfaces to integrate diverse subsystems. For the adoption of autonomous cropping systems, societal engagement will be required including extensive research and discussion on public acceptance, legal frameworks, and the human farmers' future role as crucial success factors.
SIGNIFICANCE: Aligning autonomous cropping systems to domain-overarching objectives can make these technological solutions not only another, next stage of more efficiently producing technologies, but a game changer for new, environmentally sustainable cropping systems. Field management practice can leave the currently persisting, oversimplified management strategies, characterized by large-scale, and standardized field arrangements, toward more complex approaches with small-scale, diversely structured fields, which consider local particularities and the heterogeneity of the natural landscape.

1. Introduction

Global agricultural output has increased by 2%–2.5% annually since the 1960s due to additional land use, to input intensification, and largely to efficiency gains from technological innovations and labor savings (Coomes et al., 2019). The labor cost rise led to increasingly efficient and larger field technologies, which promoted increasing field sizes and monocultures(Bowman and Zilberman, 2013). Simultaneously, undesirable externalities of agriculture, such as soil degradation, water pollution, and greenhouse gas emissions, have intensely increased (Montgomery, 2007; Baumhardt et al., 2015; Bhattacharyya et al., 2015; Food and Agriculture Organization of the United Nations (FAO), 2015; 2021). Decades ago, unprecedented rates of biodiversity loss had been recorded(Rosenberg et al., 2019; Seibold et al., 2019; Burns et al., 2021), affecting the provision of ecosystem services(Cardinale et al., 2012) and eventually impacting negative feedbacks on crop productivity(Foley et al., 2005). Areas with intense agriculture practices have been linked with greater biodiversity losses(Chase et al., 2020). Thus, new solutions for agricultural food production systems are needed(Asseng and Asche, 2019; Zabel et al., 2019; Barrett et al., 2020; Basso and Antle, 2020) to mitigate the challenges of continuously augmenting global food demand (Wood and Ludwig, 2020) while improving ecological sustainability.

Digitization of agriculture possesses the huge potential of improving land use and food production, ensuring a more sustainable and efficient farming(Lindblom et al., 2017; Finger et al., 2019; Barrett et al., 2020; Basso and Antle, 2020). Key technological innovations include varying levels in the Internet of Things (IoT) such as sensor technology, robotics, artificial intelligence (AI), and big data(Tzounis et al., 2017). Although the literature has provided solutions for individual components of these new technological systems, integrating those components into a single process has not yet been achieved. Therefore, a major setback in achieving a fully autonomous crop management system is developing technologies for integrating the individual components, which require digital technologies and robotics linking across multiple layers. Fig. 1 illustrates the flow of information that collects real-world crop and environmental conditions via sensor technology and diverse context information ("Capturing"). Following the information basis, intelligent, big data processing and algorithm-based technologies decide on actions to perform next ("Thinking"), which are executed in the field by autonomous robot technology ("Acting"). In addition, overarching technologies ("Connecting") are further responsible for linking the components of Capturing, Thinking, and Acting. The framework for implementing and optimizing the respective technologies is provided by defined economic, social, and environmental objectives (Fig. 1).

Food production and economic revenue are continually the prime objectives of agricultural activities. However, additional objectives, like reducing environmental side effects, are increasingly required by society. For example, small autonomous robots can be deployed automatically to apply fertilizer and pesticides site-specifically and only when needed by a crop, leading to improved environmental sustainability (Table 1).

However, efficiency gains obtained through an autonomous field management system are not sustainable intrinsically. More precise land management permits lower inputs and reduces negative external effects (Bach and Mauser, 2018; Mahlein et al., 2018; Finger et al., 2019; Librán-Embid et al., 2020). For example, weeding robots make herbicides superfluous and may even leave some wildflowers within a crop field. A plant-species recognition algorithm allows the elimination of noxious weeds and tolerates plants with less harmful effects on crops (Fig. 2). Yet, autonomous systems can also increase productivity without taking into account negative external effects, e.g. when used to remove any weeds at any time in a field, the negative effects on biodiversity increase(Daum, 2021).

Subsequently, we reviewed the major challenges and possible solutions in integrating new technologies into a fully autonomous farming system. We also analyzed how such integrated solutions can assist in making agriculture more productive and concurrently more environmentally sustainable. Recent literature reviews on digital farming have focused either on specific scientific perspectives, such as big data analysis benefits, or digital tools impact on crop production(Kamilaris et al., 2017; Tummers et al., 2019; Klerkx and Rose, 2020), single technologies like farm management information systems or IoT networks(Tummers et al., 2019; Navarro et al., 2020; Sishodia et al., 2020; Aboubakar et al., 2021; Odebiri et al., 2021), or single tasks such as precision weeding and spraying or harvesting(Aravind et al., 2017; Vougioukas, 2019; Fue et al., 2020). Our review outlines the requirements that will make autonomous crop management a game changer for a future environmentally sustainable agriculture. Finally, to autonomously manage the entire cropping process in a single field, we review the technical, agronomic, environmental, and sustainability literature on digital solutions for field cropping, as illustrated in Fig. 2.

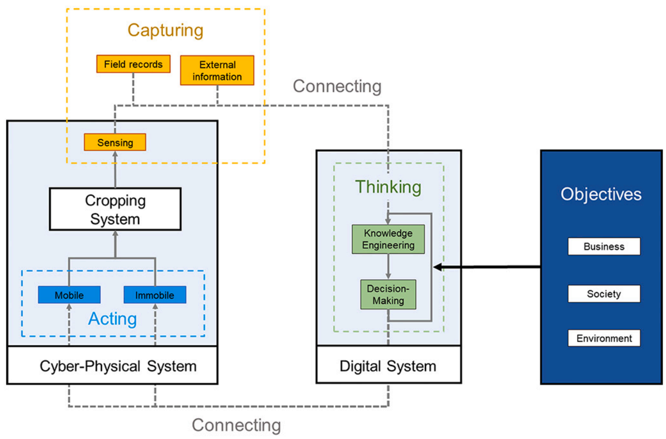

Fig. 1. Process cycle of a fully autonomous crop management system.

2. Capturing

Farmers capture a variety of past, present, and forecasted information from different sources on or off the farm to efficiently and productively manage crops(Kamilaris et al., 2017; Tummers et al., 2019; Saiz-Rubio and Rovira-Más, 2020). This information ranges from non-interpreted, raw machine data to site-specific human expert consultancy. Capturing information in machine-readable data packets represents the basis for machines to "understand" situations, develop decisions, and execute control actions, and is therefore the foundation for autonomous crop management systems (Fig. 1)(Wolfert et al., 2017; Gonzalez-de-Santos et al., 2020; Verdouw et al., 2021).

Manual field inspections are time-consuming and rarely all-encompassing, depending on the size of a farm. Due to their nature, human farmers can only take samples of a certain location at a specific time and can track only field characteristics within the scope of their available human senses. In contrast, machines can work nonstop with much larger field of sight covering up to several fields (e.g. satellites, drones), and may be equipped with sensors that capture information beyond human capabilities (e.g. parts of the non-visible light spectrum) (Mahlein et al., 2018; Sishodia et al., 2020). Thus, this implies the potential of missing important developments in some parts of the fields, like the emergence of crop disease in a potato crop (Fig. 2). There are already many inventions and innovations in agriculture-specific sensor technologies that support farmers in automating and enlarging the coverage of field inspections. These technologies operate on different temporal and spatial scales, ranging from seconds to days and millimeters to several kilometers of resolution (Table 2). Their applications comprise the wide scope of field inspection tasks from crop, via substrate to environmental monitoring. A farmer may choose between different sensing systems ranging from in situ sensors that capture physical and chemical parameters through direct contact (e.g., electrical conductivity) with the local environment or material (e.g., air, soil, or crop), to remote sensing(Navarro et al., 2020). The latter category comprises various light-based (e.g., camera, laser scanner) and some sound-based sensing approaches at different heights, including large-scale images from satellites, aerial images from sensor-equipped unmanned aerial vehicle (UAV), or very detailed images of individual plant organs using field robots (Table 2). Selective weeding relies, for instance, on field-level, remote sensing technologies. Different types of cameras can capture both the visible appearance and non-visible spectral emissions of the underlying crop and weeds with high resolutions(Sishodia et al., 2020).

Most sensing technologies were initially developed to increase crop productivity. They however also enable ecologically motivated environmental monitoring, for instance to assess plant diversity in a field with satellites and UAVs(Wang and Gamon, 2019; Librán-Embid et al., 2020; Abdi et al., 2021) or to estimate bird populations with microphone stations(Tuncer et al., 2021). A rare example of a mixed use of production-related and ecological monitoring represent yellow sticky traps that capture valuable information both on pest risks and local insect populations(Musters et al., 2021). A diverse scope of technologies already exists to monitor several main production parameters for crop management, as indicated in Table 2 and in the potato example in Fig. 2. However, the set of available sensing solutions does not yet address all requirements of commercial farming. Still many techniques have only been applied under controlled, academic conditions. As a consequence, they are often not sufficiently precise, reproducible, and applicable in real-world farm settings. This implies the necessity for additional research on automated systems that adjust sensor processing workflows to local situations(Librán-Embid et al., 2020; Sishodia et al., 2020; Tian et al., 2020; Monteiro et al., 2021).

Farmers obtain various information from farm documentation and third-party information sources. The farmers' knowledge, partly recorded in farm documentation, illustrates the basis for the crop management since it provides all relevant information about past and current

Table 1
New technologies in agriculture with positive environmental impact.

Technology	Positive effect	Saving/improvement potential (up to)	Reference
Spot-spraying weeds	Reduced pesticide use	>85% (on multiple crops)	(Aravind et al., 2017; Fountas et al., 2020)
	Selective spraying / Integrated weed management (IWM)	Only undesirable weeds are targeted, harmless/ rare/ endangered weeds could be left in the field, Up to 18% more species richness using IWM	(Clements et al., 1994; Gerhards et al., 2022)
Camera-based mechanical weeding	Avoidance of herbicides	100% less herbicides	(McCool et al., 2018; Gonzalez-de-Santos et al., 2020)
	Selective weeding / Integrated weed management	Only undesirable weeds are targeted, harmless/ rare/ endangered weeds could be left in the field; Up to 18% more species richness using IWM	(Clements et al., 1994; Gerhards et al., 2022)
Site-specific fertilization (nitrogen)	Reduced fertilizer use, less fertilizer loss	45% less fertilizer (on grain crops)	(Colaço and Bramley, 2018)
	Reduced greenhouse gas emissions (GHG)	Up to 34% less of GHG	(Balafoutis et al., 2017)
	Increased nitrogen efficiency	48% more nitrogen efficiency (on grain crops)	(Colaço and Bramley, 2018)
Sensor-based irrigation systems	Reduced irrigation demand	75% less water use (in drip irrigation systems); 26% (in site-specific irrigation)	(Evans et al., 2013; Velasco-Muñoz et al., 2018)
Small autonomous robots	Small field sizes	For example, nine small fields resulted in much higher species richness than four large fields	(Batáry et al., 2017)
	Increased biodiversity and plant health	50%–100% increase in predator species richness (in apple orchards); 30%–40% less reduced disease incidence	(Brooker et al., 2015)

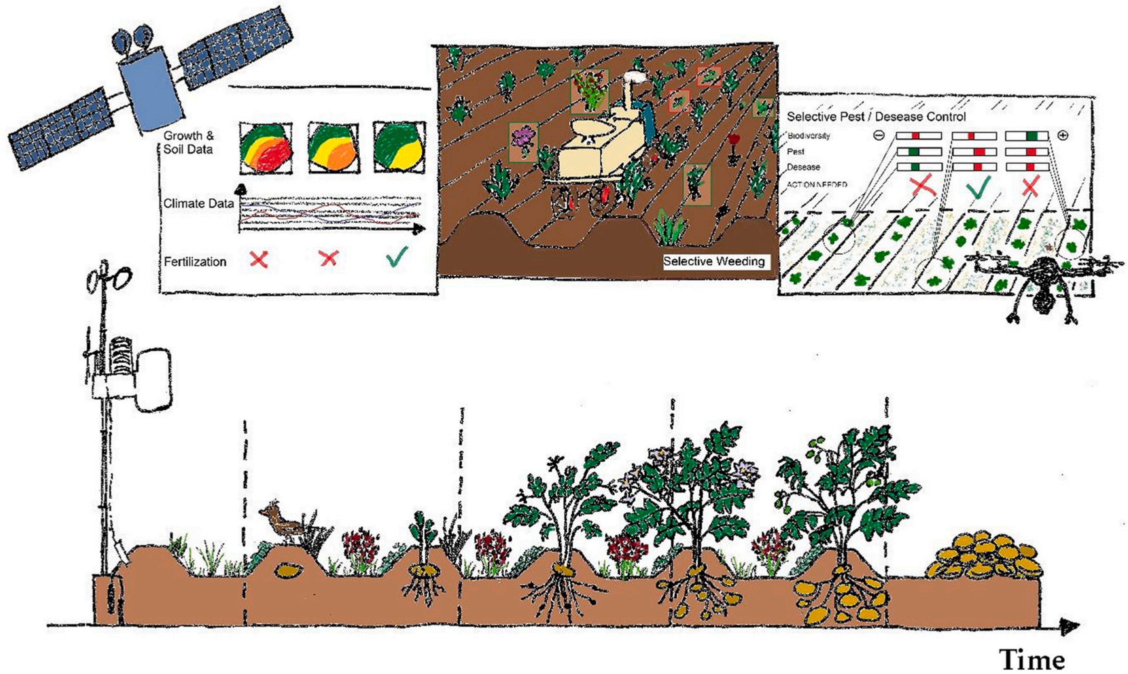

Fig. 2. Examples of the scope of information needed to be captured, the decisions to be developed and the field actions to be executed throughout an entire crop production process, shown for a potato (*Solanum tuberosum*) crop, which is aligned with both productivity and sustainability objectives.

activities and states of the field, and related production resources (e.g., intensity and spatial distribution of conducted weeding or applied fertilizer in previous field activities). Farm management information systems (FMIS) support automating and digitizing the documentation of field records on digital platforms (Fountas et al., 2015a; Munz et al., 2020). Moreover, third-party information integration provides the framework of possibilities and limitations (e.g., environmental regulations) and farm overarching, external information that a farm operator, either human or machine-driven, must adhere to when optimizing the crop production system(Sørensen et al., 2011; Tummers et al., 2019). Legal regulations, for instance, on pesticide amounts to apply at a specific location (e.g., near nature reserves) or water to withdraw for irrigation limit the range of actions to manage a field. In addition, a forecast of next-day weather or the cropping season climate (e.g., dryer as usual) influences fertilizer or pesticide applications or irrigation scheduling. The major challenge for farm documentation systems is not a lack of available data but the automated integration of these information sources into the decision-making process. Such integration still needs standardized semantic data formats and open exchange interfaces so that data is automatically obtainable from and interpretable by different platforms (compare with "Connecting" *sec*tion)(Sørensen et al., 2011; Paraforos et al., 2017; Tummers et al., 2019; Moshrefzadeh et al., 2020).

3. Connecting

Crop management systems represent complex systems of dynamically changing elements and interacting subsystems (Paraforos et al., 2017; Navarro et al., 2020). In its entirety, an information-based control system can be described as a network of nodes and links, each node representing a discrete and standalone element in the network, ranging from a source of information via data processing tools to task executing field actuators (e.g., robots) (Medhi and Ramasamy, 2018; Saiz-Rubio and Rovira-Más, 2020). Furthermore, the nodes need to be connected through links to form a network; these are the basis for information flows between nodes and the entire system.

In today's combined human-machine cropping systems, human farmers still supply a majority of essential tasks. in autonomous field management however exclusively technical solutions need to provide the necessary system components and processes, i.e. nodes and links (Asseng and Asche, 2019). With the diverse requirements in cropping operation, research and industry have developed several digital and cyber-physical solutions to perform "Capturing", "Thinking", and "Acting"-related tasks (Saiz-Rubio and Rovira-Más, 2020). Moreover, for linking these multiple technological subcomponents, a great need for connectivity solutions equally exists ("Connecting") (Fig. 1). According to the Open Systems Interconnection (OSI)-reference model for computer networks, a link consists of two major elements: transport and application-oriented functionalities. The former includes the physical transmission of data packages from one location to another. The latter focuses on translating and processing the data packages into digital representations (data) applicable for a specific purpose(Park et al., 2003).

Physical transmission technologies can be divided into cable-bound and radio-based technologies. The cable-bound network technologies such as the Ethernet or Controller Area Network (CAN) standards are mostly used for stationary systems. They enable direct connection to or the extension of cyber-physical devices by additional components (e.g., connecting a robot platform with a selective weeding implement) (Fountas et al., 2015b; Paraforos et al., 2019). In addition, these technologies persist through stable connections and transmission rates of up to several terabits per second(Secondini, 2020). However, common agricultural field conditions with large areas and mobile field technologies often make cable-bound technologies usage impossible as they are attributed to high costs, and disturbances to field activities. This is the situation where wireless, radio-based solutions compel.

Short-range radio technologies are common for applications requiring connectivity range within 10 m(Jawad et al., 2017). However, many outdoor field management applications require mid- to long-range radio connections to communicate with the closest radio base station, ranging from several hundred meters to many kilometers of distance, such as for standalone in situ moisture sensors in precision irrigation (Ojha et al., 2015). Cellular mobile networks (e.g., 5G) offer suitable features, when requiring high data rates (i.e., several megabits per second) and low latency (e.g., for video streaming and remote control of

Table 2
Overview on sensing technologies for information capturing in crop production.

Sensing level	Task	Example applications	Spatial resolution	Temporal resolution[1]	Reference(s)
In situ	Crop monitoring	Crop growth parameters (e.g., leaf wetness, stem perimeter, plant water transport)	<1 cm^2	sec - min	(Vilenski et al., 2019; Navarro et al., 2020)
	Soil monitoring	pH value, chemical elements (e.g., nitrate), temperature and moisture		sec - min	(Navarro et al., 2020; Monteiro et al., 2021)
	Environment monitoring	Ambient conditions (e.g., air temperature and humidity, solar radiation, precipitation, wind speed, etc.)		sec -min	(Kamilaris et al., 2017; Navarro et al., 2020)
Remote | space	Crop monitoring	Growth states, phenotyping (e.g., leaf size), pests and diseases (type and extent), water stress, etc.	<1 m^2 to several square-kilometers	d	(Kamilaris et al., 2017; Sishodia et al., 2020)
	Soil monitoring	Soil organic carbon, soil moisture, soil temperature		d	(Sishodia et al., 2020; Odebiri et al., 2021)
	Environment monitoring	Ambient conditions (e.g., air temperature, soil humidity)		d	(Sishodia et al., 2020)
		Biodiversity monitoring (e.g., plant diversity assessment)		d	(Wang and Gamon, 2019; Abdi et al., 2021)
Remote | aerial and field-level (including field robots and drones)	Crop monitoring	Growth states, phenotyping (e.g., leaf size and number), pests and diseases (type and extent), water stress, etc.	<1 cm^2–10 m^2	h - d	(Huang et al., 2019; Librán-Embid et al., 2020)
	Soil monitoring	Soil organic carbon, soil moisture, soil roughness		h - d	(Huang et al., 2019; Librán-Embid et al., 2020)
	Environment monitoring	Ambient conditions (e.g., air temperature and air humidity)		h - d	(Huang et al., 2019; Librán-Embid et al., 2020)
		Biodiversity monitoring (e.g., acoustic bird detection, camera-based insect detection)			(Wang and Gamon, 2019; Musters et al., 2021; Tuncer et al., 2021)

[1] sec, seconds; min, minutes; h, hours; d, days.

a mechanical weeding field robot). In contrast, Low-Power Wide-Area Networks (LPWAN) are suitable for applications with low data rates (i.e., <100 kilobits per second) and strong energy restrictions (e.g., outdoor animal trackers that run on a single battery for several years) (Jawad et al., 2017). In recent years, radio connectivity to space has become an emerging field. Satellite-based networks enable connectivity anywhere on the planet(Bembe et al., 2019), making them attractive for remote locations with little or no infrastructure (e.g., mountainous pasture management or animal population monitoring). The comprehensive availability of different connectivity solutions fulfills the connectivity requirements of most agricultural applications in theory. However in practice, the coverage and reliability of radio networks vary depending on local conditions; this represents one of the major challenges to the widespread implementation of digital farming technologies (Villa-Henriksen et al., 2020). One solution to overcome this challenge is the flexible management of data transfers and processing. Data processing can be conducted temporarily on a machine at a field ("edge"), during periods of low connectivity. Once connectivity is re-established data transfer and processing can be allocated to a remote place ("cloud") such as a computer at the farm site(Aboubakar et al., 2021).

Application-oriented technologies (translation and processing of information into purpose-oriented data) are equally important. They build on the transport-oriented functional layers (physical transfer of data from one place to another) and create a uniform framework for storing, semantic understanding, and exchanging of data between software applications(Park et al., 2003). For instance, farm-specific data and context information are stored and processed on this level. Within integrated crop management, cyber-physical devices, software tools and data typically originate from a several domains and organizations(Fountas et al., 2015a; Paraforos et al., 2017; Tummers et al., 2019). Therefore, to use the full potential of such a decentralized system for a common automated application, standardized data formats and programming interfaces must be available (Paraforos et al., 2017; Moshrefzadeh et al., 2020). They enable the automatic information flow across different system components and through this functional interoperability. Such standards are common in web programming, where it is a basic requirement to communicate in a unified language between different web services(Tightiz and Yang, 2020). As a counterexample, in the past, hardware manufacturers, particularly suppliers of farm machinery, developed own, proprietary solutions not adhering to common standards, thus leading to a lack of interoperability and a barrier to automated interconnections between systems of different manufacturers' products(Oksanen et al., 2005; Fountas et al., 2015b). Initiatives that develop functional and semantic standards are increasingly on the rise to establish domain-specific interoperability (e.g., for biodiversity-related data)(Oksanen et al., 2005; Reichardt, 2017; Paraforos et al., 2019; Hartl et al., 2021; Huber et al., 2021). These semantic standards are an important basis for domain-overarching, multi-objective optimization processes, since they provide context and interpretability to the underlying data (e.g., for quantifying the aim conflict between productivity and sustainability).

Despite the comprehensive advances in standardization and connectivity, a major challenge toward autonomous agricultural systems still includes the interoperable flow of information across technical subsystems of different hardware, software, and information providers. Non-compatible components lead to inefficient solutions for farmers, including potential long-term supplier dependencies ("vendor lock-in"), extra expenses for the establishment of customized solutions to overcome lacking interoperability between subsystems, or higher production inputs from an incomplete information base (Opara-Martins et al., 2016; Coomes et al., 2019; Finger et al., 2019). In the future, these system components must be designed to interact seamless and automatically to unleash their full individual and joint potential within a common autonomous field management system.

4. Thinking

Each season require farmers to make multiple decisions on their crop management; some are strategic, while others are tactic and weather- or seasonal dependent and are out of their control. Strategic decision in agriculture mostly focus on maximizing economic return, but some also include a risk assessment, social acceptance, and environmental sustainability for which farmers must consider external and internal factors (Rajagopalan, 1993; Darnhofer, 2010). Strategic decisions are related to

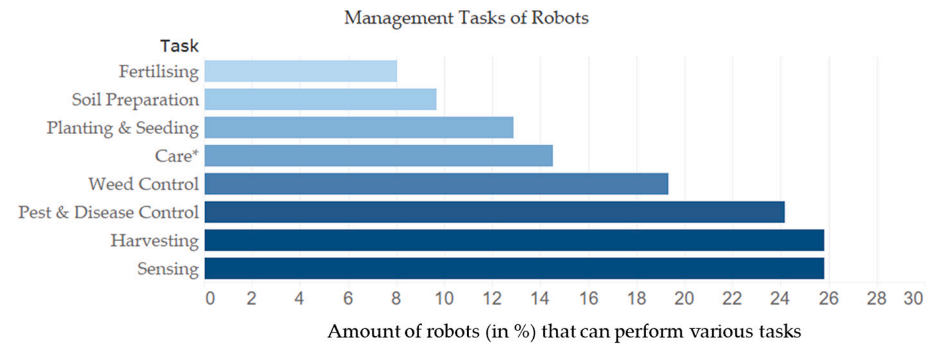

Fig. 3. Autonomous field robots by tasks and use type based on a survey of 63 agricultural robots. *Care tasks promote plant condition but do not affect external factors (such as weeding or spraying) and are mainly used in horticultural crops, like pruning or trimming.

the type of crop, choice of cultivars and location. Tactic decisions are made in an operational business process during the season in conjunction with current growing conditions (e.g. wetness of soil) and weather (e.g. wind and rainfall). Tactic decisions deal for example with the amount of fertilizer to apply, the right time for pest control, or to harvest a crop and must be adapted to current situations (e.g., stage of crop development, crop nutrition status, weed and disease occurrence, weather conditions etc.). For strategic decisions exist climate crop models that can be used, e.g., to forecast the long-term risk at a farm location arising for instance due to climate change or substantial socio-economic changes (e.g. vegetarian trends). However, in field management the majority of decisions are on a tactical level for which there are a wide range of decision support systems and algorithms.

Simulation crop models and rule-based expert systems have a long history in research (Cook and Bramley, 1998; Liao, 2005). They incorporate biophysical knowledge from agricultural experiments and experts (Hoogenboom et al., 2020). They can also be applied to crop management optimization, including fertilizer (Asseng et al., 2012) and pesticide application (Mahaman et al., 2003). They can also be used for yield forecasting (Basso et al., 2013), but require a range of field and crop-specific information for model execution. Crop models require detailed information about weather data, soil characteristics (e.g., water-holding capacity of soil layers, bulk density, soil organic carbon content), and cultivar-specific parameter (Oteng-Darko et al., 2013). While several decision support tools for operating cropping systems have been developed, they are seldom practically utilized, mostly due to the detailed data requirements for such models (Rose et al., 2016; Lindblom et al., 2017).

Recently, an increase in statistically based, self-learning algorithms such as machine learning algorithms has occurred driven by access to big data and hardware innovation allowing computer to calculate complex models, previously not feasible 10–15 years ago (LeCun et al., 2015; Cai et al., 2019). Today, machine learning is also used in farming and has become a standard approach, especially in image processing (Chlingaryan et al., 2018; Kamilaris and Prenafeta-Boldú, 2018). For example, in weeding, an automatic differentiation between weeds and a crop has been achieved by deep learning methods using artificial neural networks (ANN)-based approaches (Liakos et al., 2018). ANN can learn abstract patterns to identify and locate individual plant and output probabilities on whether a captured image shows a weed or a crop and, in some cases, differentiate even specific types of weed (Wang et al., 2019). Such technology allows to decide whether to destroy a weed in a field or not, according to a defined objective (Liakos et al., 2018). Machine learning models can be powerful, but their performance depends on the data used for their training. However, incorrect or skewed data can lead to poor or unintended results, sometimes even discriminatory (Zou and Schiebinger, 2018). Significantly more validated data from field and crop management are needed to overcome the biased data set problem and improve decision support systems that are robust and trustworthy (Wolfert et al., 2017; Kamilaris and Prenafeta-Boldú, 2018; Tantalaki et al., 2019).

As an implementation of an automated decision-making system is also part of the farmer's decision-making process, the question arises if algorithm-based decisions are an advantage and what damage might be caused by incorrect predictions? Studies show that the economic threshold of weeds varies between crops but lies between 2 and 42 plants per m^2, while current algorithms reach accuracies of 83%–95% the needed threshold might not always be achieved and can result in yield loss (Cousens, 1987; Pannell, 1990; Swanton et al., 1999; Wang et al., 2019). The application of pesticides is one of the most critical tactile decisions to be made and a wrong management can lead to enormous, up to a complete yield loss or long-term negative effects on pest resistance. Algorithm should not fail, but modern detection methods do not cover the whole range or are robust enough, yet (Barbedo, 2018).

However, also conducted by humans, a decision making process may not be entirely optimal; as emotions often play a central role it is always biased toward the sensitivity of probability variation (Loewenstein et al., 2001; Slovic et al., 2005; Fenton-O'Creevy et al., 2011). Beyond, there is usually a limited amount of information a human can process at once; an information overload can reduce the decision-making quality and substantially increase time for decision-making (Hwang and Lin, 1999). In contrast, algorithmic decision-making is free of these limitations, at least in theory. However, reliability, robustness and ability of generalization are still major barriers toward full reliance on computer-driven decision in agriculture (Barbedo, 2018).

Promising new concepts are integrating the farmers knowledge and simultaneously gain the benefit of rational acting algorithms in a "human-in-the-loop" approach (Wu et al., 2022). Such hybrid systems monitor the autonomous actions and integrate the farmer in the model decision-making process at decisions with high impact (e.g., pest control).

5. Acting

The computational crop management decision must interact with some form of hardware (e.g., weeding robot) in a fully automated way (Fig. 1). Therefore, autonomous machinery and self-driving vehicles possess great potential in this context since they can enable more sustainability in various economic sectors, providing increased safety and inspiring new business models(Shamshiri et al., 2018; Lowenberg-DeBoer et al., 2020). Recent years have shown that autonomous farming robots are no longer limited to research laboratories but can fulfill practical farming tasks. Most are designed for field use. Fig. 3 shows results from a survey that demonstrates that agricultural robots are used for crop sensing and harvesting (26% each), with pest-disease control (24%) and mechanical weed control (19%). In total 50 individual research and review articles were analyzed including 63 different

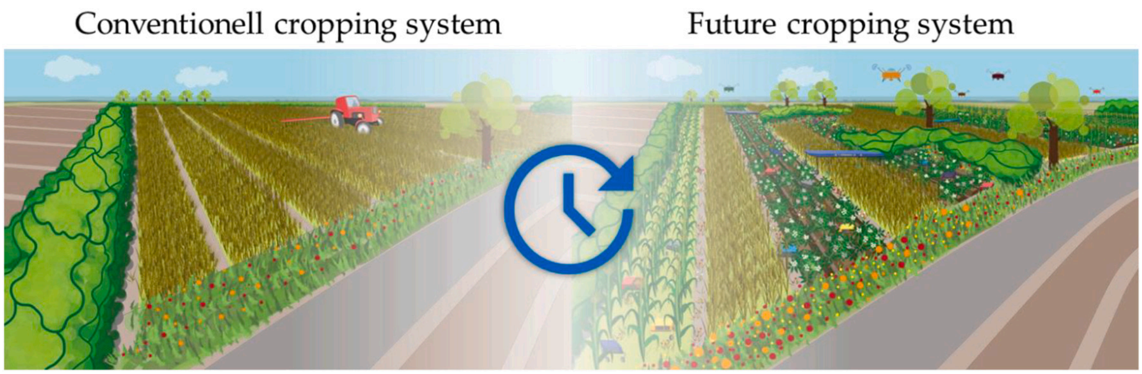

Fig. 4. The overall integration of sensors, network technology, intelligent decision models, and robotics can lead to a transformation of today's agricultural system into one that takes environmental sustainability into account, in addition to crop productivity, and enables sustainable agriculture for future generations.

agricultural robotic applications for cropping systems.

The navigation of an autonomous driving robot on a field involves movement in unknown terrain and changing environmental conditions; thus, it requires obstacle detection and reliable safety considerations (Hussain and Zeadally, 2018). However, different technologies are used concurrently for data collection (e.g., LiDAR, radar, RGB cameras), processing (e.g., rule-based systems, heuristic approaches), safety under all conceivable scenarios persist as a major challenge(Yurtsever et al., 2020; Badue et al., 2021). Safeguarding autonomous actors operating in a mixed-traffic system and in-vehicle safety, including external safety, e.g., against hackers or malware, is crucial for practical application (Hussain and Zeadally, 2018; Cui et al., 2019). However, non-technical challenges like accepting robots, willingness to purchase a robot, consent for innovation, and trust by consumers and stakeholders regarding safety are highly important, consequently impacting the proliferation of autonomous vehicles(Hussain and Zeadally, 2018; Jing et al., 2020). Furthermore, ethical questions must be clarified before self-acting vehicles are released to the public and for the involvement of society (Shariff et al., 2017; Gkartzonikas and Gkritza, 2019). For instance, in road traffic, ethical evaluation is required for situations where an autonomous vehicle in an unavoidable accident must decide which lives to be spared and how this can be transferred to all areas in which autonomous systems interact in a mixed human-robot environment(Lin, 2016; Hussain and Zeadally, 2018).

Many of the challenges are generic to autonomous vehicles and, thus, valid for agricultural robotics. Moreover, autonomous action in crop production must be completed with similar or higher quality than traditional methods(Bechar and Vigneault, 2016; Fountas et al., 2020; Fue et al., 2020; Gonzalez-de-Santos et al., 2020; Kootstra et al., 2021). For example, in precision weeding, herbicides are applied only on weeds without wasting herbicides on the crops or bare soil, saving >90% of herbicides with less environmental pollution from crop production (Bechar and Vigneault, 2016; Aravind et al., 2017). Other approaches focus on chemical-free weed control, where weed recognition combined with mechanical weed destruction strategies is used in controlling weeds (McCool et al., 2018; Gonzalez-de-Santos et al., 2020). Both approaches combine accurate object identification and executive actuation. However, to date, the speed of robotic manipulators is relatively slow and often cannot compete with conventional large-scale machinery(Gonzalez-de-Santos et al., 2020).

The automated irrigation systems are an example of the "Acting" process(García et al., 2020). In such systems, the spatial and temporal irrigation scale can be regulated to reduce the water required for irrigation without increasing crop water stress(Evans et al., 2013). Another example for non-stationary tasks is small-scale autonomous robots that facilitate new landscape designs(Vougioukas, 2019), which are no longer dependent on large homogeneous fields required for large machinery(Asseng and Asche, 2019). Therefore, fields can be redesigned to soil types and terrain, including additional biodiversity through more field edges or biodiversity land strips and parcels(Fahrig et al., 2015). Moreover, reduced soil compaction from lightweight robots, early detection, and action on weeds and diseases will increase crop productivity with reduced inputs(Asseng and Asche, 2019). When combined with selective weeding and disease control, targeting only the most aggressive weeds and diseases in crop biodiversity can be increased (Wang et al., 2019). Similarly, fertilizer applications tailored to specific regions in the field(Colaço and Bramley, 2018) and linked to weather (Asseng et al., 2016) and/or seasonal forecasting systems(Asseng et al., 2012) via crop simulations will increase crop performance with fewer inputs and fewer external fertilizer losses.

6. Integration challenges

A seamless and automated link of different components within a common process cycle represents the technological basis for autonomous crop management (Fig. 1). A complete cycle must be applied on various spatial and temporal scales. It operates following the overall goals within all different operational hierarchies in crop management as illustrated in the conceptual representation (Fig. 1) and potato crop production in Fig. 2.

Further technological advances in each subcomponent "Capturing," "Thinking," "Acting," and "Connecting" plus integration are needed to achieve a fully automated cropping system. A major obstacle affecting the wide development of autonomous farming and agricultural robotics currently consists of poor economic competitiveness compared with conventional systems. Therefore, technical improvements are needed in sensor fusion, localization, navigation, and human-robot collaboration to develop autonomous vehicles that operate safely and reliably in mixed environments. A major technological hurdle concerns the seamless connection of subsystems, despite a wide range of technical solutions and standardization initiatives. A seamless connection of subsystems would enable connectivity between machines and software applications. However, this is a primary challenge toward fully integrating autonomous agricultural systems with a demand-oriented availability and the harmonized flow of data across diverse technical subsystems. Given the broad availability of already existing solutions, this challenge is less technical but more a question of agreements to use common standards in industry and research (compare section "Connecting").

Beyond the technical questions, societal acceptance of farming and autonomous robots is an additional sticking point. The societal discussion that involves all relevant stakeholders and the public around the use of autonomous systems in terms of acceptance, ethics, and the law must proceed immediately. Until now, developments in autonomous systems were primarily driven by industry due to expensive or limited labor. The agronomic opportunities resulting from small robots and their ecological benefits have scarcely been investigated. One of the key challenges for research is studying the feasibility and benefits of fully autonomous crop management for crop productivity and environmental sustainability to provide a basis for a societal debate.

7. Conclusions

Land use is increasingly becoming the focus issue of societal discussions. Trade-offs exist between the production of agricultural goods, conservation of natural areas, and land use for other social purposes. Interestingly, technology has always been a key element to satisfying the human population's food demands. However, most automation advances in agriculture have solely focused on productivity-related goals. Therefore, fully autonomous crop management could help align the land use decisions with multiple – even contradicting – goals, thereby mitigating some of the current adverse effects of agriculture. We also expect autonomous crop management to pave the way for an entirely new design of land use and agricultural systems. Advertently, such a new land use design will reduce the adverse effects of agriculture on nature by reducing or eliminating pesticides, reducing fertilizer inputs and losses, reducing soil compaction, and increasing in crop and landscape biodiversity (Table 1, Fig. 4). Therefore, to realize such environmental sustainability goals, they must be integrated into the objectives against which autonomous cropping systems are evaluated, in addition to economic performance indicators.

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

Data will be made available on request.

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