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Cyber-Agricultural Systems for Crop Breeding and Sustainable Production

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Feature Review

Cyber-agricultural systems for crop breeding and sustainable production

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The cyber-agricultural system (CAS) represents an overarching framework of agriculture that leverages recent advances in ubiquitous sensing, artificial intelligence, smart actuators, and scalable cyberinfrastructure (CI) in both breeding and production agriculture. We discuss the recent progress and perspective of the three fundamental components of CAS – sensing, modeling, and actuation – and the emerging concept of agricultural digital twins (DTs). We also discuss how scalable CI is becoming a key enabler of smart agriculture. In this review we shed light on the significance of CAS in revolutionizing crop breeding and production by enhancing efficiency, productivity, sustainability, and resilience to changing climate. Finally, we identify underexplored and promising future directions for CAS research and development.

Highlights

The cyber-agricultural system (CAS) integrates cybersystems with the physical world of agriculture via sensing, modeling, and actuation, and leverages the three pillars of functional cyber-physical systems (CPSs): computation, control, and communication:

Advances in computation (i.e., ubiquitous, multimodal sensing, modeling/reasoning enabled by complex computation capabilities, and off-the-shelf deep learning models) have opened up numerous opportunities in CAS.

Progress in control/actuation is characterized by advanced agricultural machinery and the rise of agricultural robotics (e.g., dexterous manipulation and harvesting, interactive sensing, precision spraying, mechanical operations, and weed culling).

Advanced communication is enabling sensors, actuators, and platforms to coordinate and collaborate using internet of things (IoT) principles/tools.

Agricultural cyber-physical systems

Cyber-physical systems (**CPSs**; see Glossary) are natural or human-engineered systems that deeply integrate computation (cyber) and physical processes. In a CPS, the physical space is the source of information, and the cyberspace uses the generated information to make decisions which are then implemented back into the physical space [1]. In addition to memory, computation, and communication constraints, the information processing and control algorithms in the cyberspace also consider the aspects of physical constraints such as time, energy, and safety. A typical CPS comprises three modules, namely **sensing**, **modeling**, and **actuation**, that form a closed-loop system that leverages the three functional pillars – communication, computation, and control (Figure 1A, Key figure).

In a CPS, the sensing devices 'sense' or collect specific information from the physical system or environment that is being monitored and controlled. The sensed data are either processed *in situ* or transmitted through communication channels to the servers for storage, further processing, and analysis. Data analysis often involves **cloud computing**, which not only offers cost-effectiveness and flexibility but also demonstrates resource elasticity to allow dynamic allocation and scaling of computing resources based on demand. The sensing module is followed by the modeling module which utilizes decision-making algorithms such as **machine learning (ML)** models to extract actionable information from the data and construct computational models. These models enable reasoning and control of the underlying system, thus allowing predictive analytics, anomaly detection, and optimization. Finally, the control and actuation module regulates the CPS to achieve the desired performance safely and efficiently. Although a CPS can be a monolithic system such as an autonomous vehicle, it can also be a distributed system (e.g., an electric power grid) through which many subsystems are connected via a communication network [2,3].

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Key figure

Overview of cyber-agricultural systems (CASs)

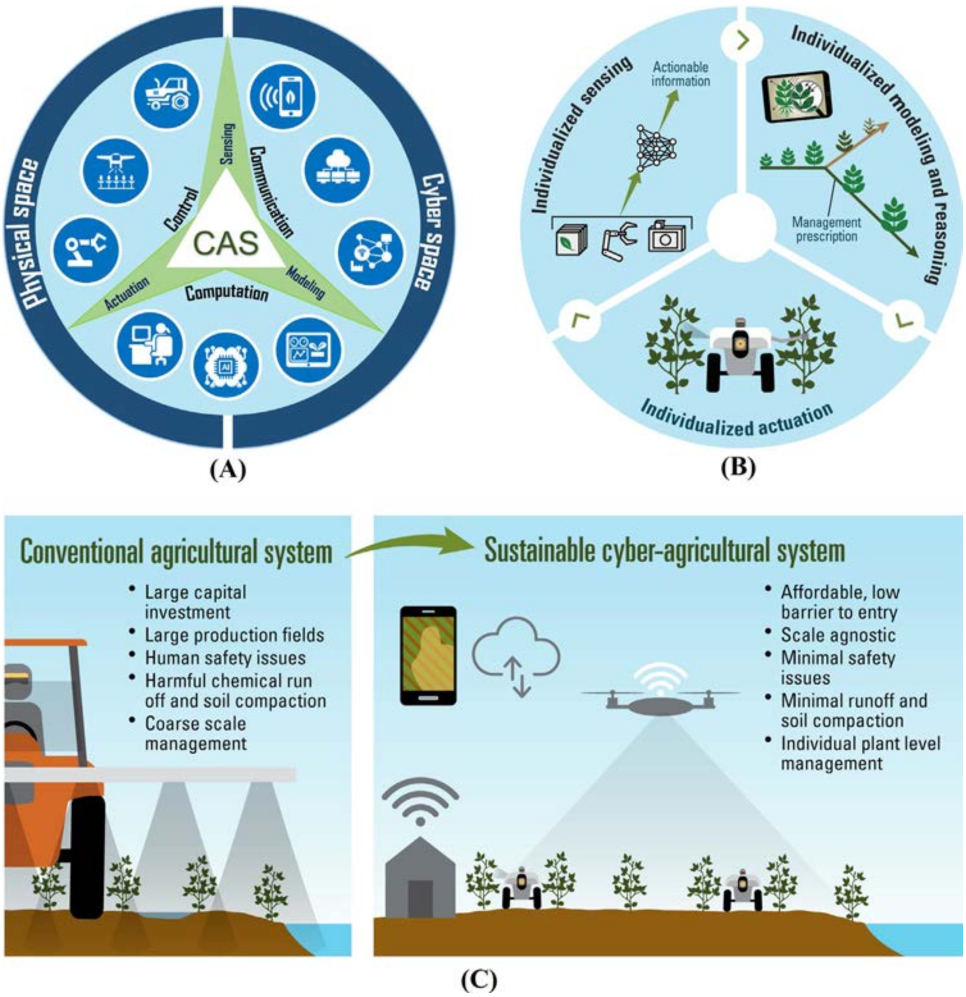

Figure 1. (A) Cyber-physical systems (CPSs) are engineered systems with deep integration between the physical and the cyberspace. The three technical modules of CPS – sensing, modeling, and actuation – leverage the three functional pillars – communication, computation, and control. (B) The future vision of CAS – an individualized plant management paradigm that senses and models up to basal individual plants and organs and applies treatments at the plant level rather than the field level by replacing heavy machinery with multiple small, lightweight units. (C) The CAS vision to transform conventional agriculture into a highly sustainable system by reducing the disadvantages of widespread chemical usage and significant capital input required by conventional large-scale farming, for example leading to chemical runoff and soil compaction. Advanced automation improves the abilities of farmers to manage their operations by reducing work stress, improving accuracy and precision, reducing physical strain, and minimizing safety concerns.

In this age of **Industry 4.0** [4], examples of real-world CPS applications can be found in every sector – from smart cities, smart power grids, autonomous vehicles, and intelligent transportation systems to advanced manufacturing and industrial control systems, and robotic systems. Exactly as in all these sectors, the CPS paradigm is poised to fundamentally change agriculture, making it significantly more efficient, profitable, sustainable, and safe. The objective of this review is to present the significance of CPS in plant agriculture. The vision of agricultural CPS or **cyber-agricultural systems (CASs)**, as illustrated in Figure 1B, is already showing immense possibilities by leveraging the power of advanced sensing, **artificial intelligence (AI)**, ML, computational modeling, robotics, wireless communication, and scalable **cyberinfrastructure (CI)**.

For example, in the case of US agriculture, CAS has the ability to alter the current paradigm of large farms (~70% of US farmland is in holdings of >500 acres) that are characterized by large machinery and a large swath of chemical applications that have increased input costs [5,6]. Conventional big agricultural practices have helped to improve agricultural outputs but have also produced unintended negative consequences that affect farm economic health and environmental sustainability [7,8], especially when combating plant pathogens, weeds, and insects that reduce US crop yields. For example, US agriculture loses US$60.66 per acre due to soybean diseases [9], and global estimates suggest 21.4% yield loss [10]. Large farms counteract these stressors by large-scale and frequent application of chemicals such as fertilizers, pesticides, and herbicides [11]. However, this increased chemical application directly affects run-off, which impacts on water quality across all watershed scales, including the oceans [12]. Large-scale chemical applications also deteriorate the quality of soil and impact on the food chain; overuse of chemicals results in chemical resistance with cascading negative consequences [13]. The vision of CAS can alleviate many of these challenges by achieving ultra-**precision agriculture** with integration of improved sustainability, profitability, and technology, as shown in Figure 1C. It is worth noting that the principles of CAS have been previously applied to crop improvement [14] and protection, encompassing sensing (e.g., phenotyping), modeling (e.g., breeding methodologies), and actuation (e.g., selection decisions and farm management). However, with advances in sensing, communication, data management, AI, and robotics technologies, this process has become more efficient and intelligent in recent times. Specifically, to address crop breeding problems, efficient sensing, monitoring, analysis, and characterization of plant traits, known as phenomics or plant phenotyping, is crucial. Several research questions pertaining to breeding and phenomics are illustrated in [15].

Although the notion of precision agriculture has been demonstrated and adopted in recent years to some extent, the framework of CAS can push the boundary further. It can enable an individualized plant management paradigm (enabled by individualized sensing, individualized modeling, and individualized actuation, as illustrated in Figure 1B) that applies treatments (i.e., actuation) at the plant level rather than the field level by replacing heavy machinery with multiple small, lightweight platforms [4]. We refer to this individualized CAS paradigm as ultra-precision agriculture because it offers greater flexibility of scale (i.e., scale-agnostic, equally effective for small and large fields), higher functionality (more effective management and outcomes), increased resilience (e.g., ability to adapt to changing climate), greater profitability (e.g., reduced costs of operations), enhanced autonomy, and reduced soil compaction by utilizing small and lightweight platforms. For example, the authors of [16] describe a CAS framework with a monitoring, managing, and adapting (MMA) approach. They also discuss how connectivity is ensured among the **edge computing** devices to perform cloud computing and dissemination of real-time or near real-time information in production agriculture. In summary, the concept of CAS lies at the intersection of precision agriculture, **digital agriculture**, and **smart agriculture** that can address various efficiency, sustainability, and resiliency issues faced by current agricultural practices.

In the following sections we discuss the three fundamental components (sensing, modeling, and actuation) of CAS (Figure 2 for a conceptual illustration of these three components), followed by a brief discussion of agricultural **digital twins (DTs)**, a recently emerging concept in the context of CAS. Finally, we provide a discussion on CI, a key enabler of the CAS paradigm.

Glossary

Actuation: translating the decisions and actions of a control system into physical actions by controlling the physical environment via actuators.
Artificial intelligence (AI): a branch of computer science that aims to build intelligent machines to perform tasks similar to intelligent beings.
Augmented reality (AR): a technology that overlays digital information onto the real world interactively, creating a mixed reality experience that enhances the user's perception of their surroundings.
Cloud computing: allows users to access computer resources on-demand through the internet, using a network of remote servers for a variety of services such as data management, storage, computing, and tool development.
Computer vision (CV): a field of AI that enables computers to 'see' and interpret visual data.
Convolutional neural network (CNN): a class of deep neural networks designed to automatically analyze and extract higher-value information from visual data.
Cyber-agricultural systems (CASs): an agricultural framework that leverages the power of advanced sensing, artificial intelligence, machine learning, computational modeling, robotics, wireless communication, and scalable CI to optimize agricultural processes, enhance productivity, sustainability, and resilience in a connected and digital environment.
Cyberinfrastructure (CI): a technological infrastructure that supports advanced data acquisition, data storage, data management, data integration, data exchange and sharing, data analytics, data visualization, and other computing and information processing services.
Cyber-physical systems (CPSs): engineered systems that are created from the continuous integration of computation and physical components. CPSs involve close integration of different elements such as computing devices, control and actuation systems, networking infrastructure, and sensors.
Digital agriculture: a farm strategy that involves seamless integration of digital technologies to improve agricultural production.
Digital twins (DTs): computer-generated models designed to precisely reflect the state and behavior of an intended or actual physical system for

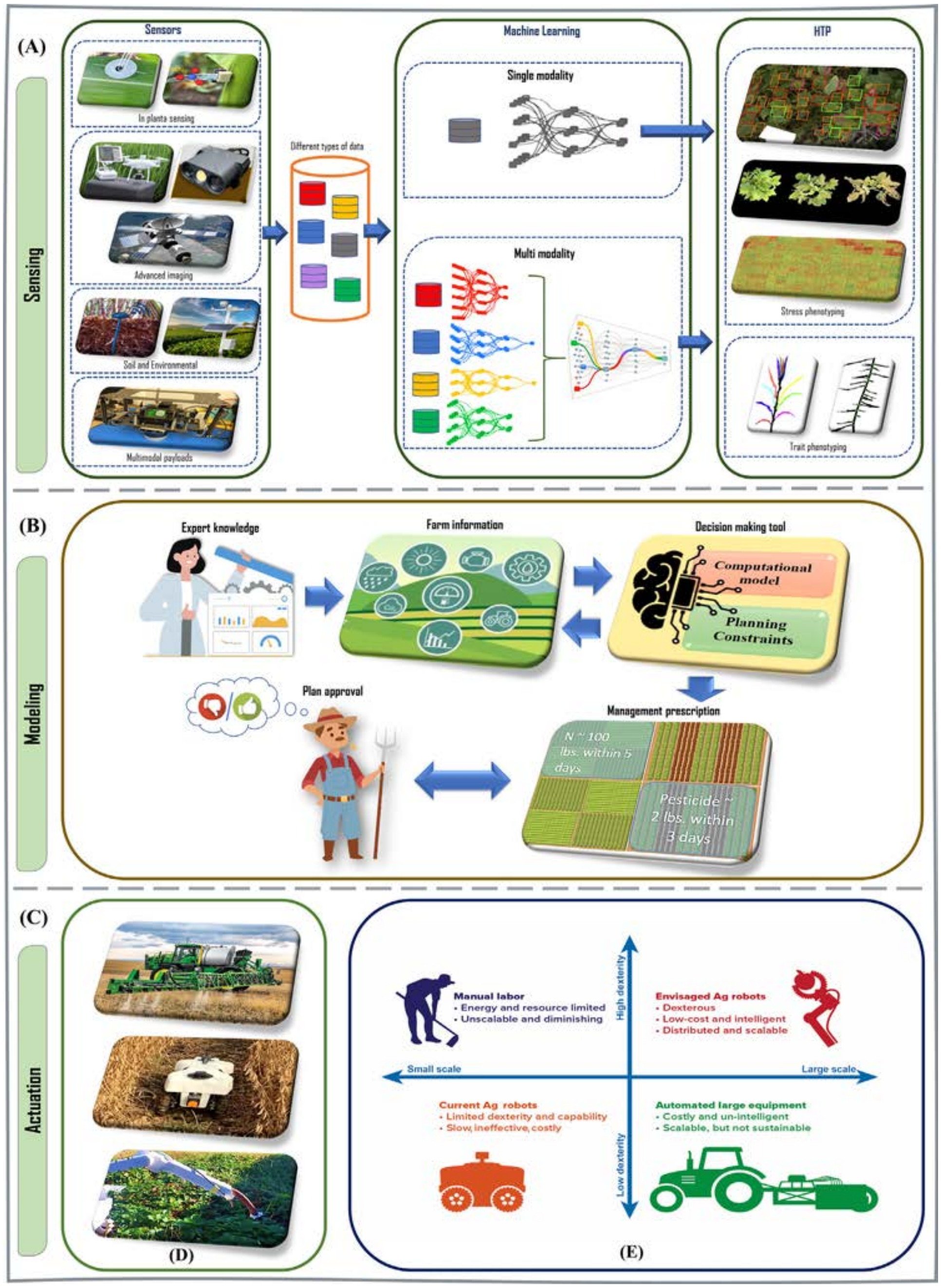

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Figure 2. Cyber-agricultural system (CAS) sensing, modeling, and actuation modules. (A) CAS sensing: advanced sensing technology of different modalities, leveraging heterogeneous platforms; recent advances in information processing methods, enabled by computer vision and machine learning, lead to high-throughput phenotyping (HTP) of important plant traits and stresses. (B) CAS modeling and reasoning: computational modeling at a plant to field to regional scale involving both domain knowledge and data; computational models are then used to make optimal reasoning, planning, and control for agricultural decisions. (C) CAS actuation and in-field intelligence. (D) Advanced actuation such as precision spraying, autonomous scouting robots, and dexterous robotic arms for plant manipulation can realize the great potential of the CAS framework. (E) Technical challenges in creating robotic cyber-physical systems (CPSs) for agriculture that are highly dexterous while at the same time are engineered to be scaled to millions of acres of agriculture at low cost. Abbreviation: Ag, agricultural.

simulation, system integration, testing, performance monitoring, control, and maintenance.

Edge computing: involves deploying small, low-power computing (edge) devices at the edge of the network, close to the sensors, devices, and other sources of data.

Fog computing: enhances the capabilities of cloud computing to the network edge, enabling data processing and storage in close proximity to the data source.

High-throughput phenotyping (HTP): a rapid, accurate, and non-destructive approach to measure and analyze phenotypic traits using automated technologies.

Industry 4.0: the fourth industrial revolution involves the integration of technologies such as IoT, AI, cloud computing, and CPSs to create a smart, and connected industry.

Internet of things (IoT): a network of physical devices embedded with sensors and connectivity that allow them to interact with the environment over the internet.

Machine learning (ML): involves developing algorithms and models that empower computers to learn from data and make predictions/decisions without the need for explicit programming.

Modeling: creating mathematical models that capture the behavior of a physical system, that are used for simulation, optimization, and decision-making.

Precision agriculture: a farm strategy that accounts for spatial and temporal variability through the use of technology for increased precision and timely management to improve sustainable agricultural production.

Reinforcement learning (RL): a field of machine learning in which a computational agent learns to make optimal decisions to maximize its potential benefits in a given environment.

Sensing: collecting data from the physical world through sensors to estimate the state of the observed system via information processing and analysis.

Smart agriculture: a farm strategy that involves components of precision and digital agriculture, particularly intelligent information gathering and processing, that enables optimized decision making for improved profitability, sustainability, and resiliency in agricultural production.

Virtual reality (VR): a computer-generated environment that is experienced through a headset and specialized controllers, thus allowing users to feel fully immersed in and interact with a digital world.

Sensing and advanced information processing

This section delves into the realm of the sensing element within a CAS, and offers a comprehensive overview of different types of CAS sensors, their measurement capabilities, and advanced and recent information processing techniques employed for analyzing the sensed data.

High-throughput phenotyping

Among various CAS sensing applications, **high-throughput phenotyping (HTP)** or phenomics has recently emerged as one of the most useful frameworks [17]. HTP leverages both state-of-the-art technologies and analytics to provide a significantly faster and non-invasive alternative to conventional phenotyping methods. Moreover, HTP helps to explore the nexus between several forms of 'omics' that together provide a holistic information of plants to better characterize plant health and performance. Hence, it is extremely useful for making many important crop breeding decisions [18,19]. HTP of plants use various remote sensing techniques to allow large-scale non-destructive measurement of plant traits [20]. In addition, for both crop breeding and production, by employing a diverse array of sensors, both proximal and remote, we can facilitate envirotyping and effectively measure and characterize physical and environmental variables. This enables us to model plant–environment relations and unlock the hidden genetic variations within the latent characteristics [21]. In addition to remote sensing tools, plant phenotyping can be carried out using various proximal sensing platforms in which the sensors are not very far from the objects of interest and are installed on platforms such as handheld, fixed installations, robots, tractors, and drones [22,23]. These sensors are predominantly imaging devices (e.g., simple RGB or grayscale cameras, and thermal, multispectral, or hyperspectral cameras) [24]. By contrast, a variety of handheld sensors and *in planta* sensors are used to estimate phenotypes such as plant chlorophyll fluorescence, canopy temperature, leaf area, nitrogen content, and plant height. Instead of directly enabling HTP, these sensors essentially help to provide the ground-truth for validating the model-derived phenotypic estimates [23,25]. However, efforts are ongoing that help to provide a proxy measurement of these traits using digital technologies.

In addition to sensors, CAS also leverages measurements in semi- or high-throughput manner. For example, plant morphological traits are phenotyped using automated screening systems [26–29]. CAS ideally comprises a collection of sensors or sensing units to enable organ- to plant- to canopy-level sensing and measurement. Although such applications provide rapid measurements with affordable solutions, they provide limited physiological information, involve complex data reconstruction and extraction methods, and are also limited to specific illumination requirements besides the effects of spatial heterogeneity (due to changing gradients of environmental factors). The HTP advances have also benefited root trait studies through phenotyping platforms as well as sensing and imaging technologies [30]. These complex datastreams (spatial and temporal) require ML- and **computer vision (CV)**-based advanced information processing methods that constitute a crucial part of the sensing components in CAS.

Role of computer vision and machine learning

With the rapid rise in deep learning (DL) applications [31], many trait-specific pipelines or architectures have been developed [32–37]. There are numerous examples of the use of image-based phenotyping aided by computer vision and/or ML to study root traits [38–47], which aid mostly semi-automated analysis of root morphogeometric parameters, although end-to-end phenotyping pipelines have been developed [48,49]. Nodule features were studied and counted using a soybean nodule acquisition pipeline (SNAP) system that combines two **convolutional neural network (CNN)** models for nodule segmentation [50]. Similarly, published studies that leverage ML for phenotyping plant traits are rapidly accumulating. These include plant segmentation and image analysis to automate the temporal mapping of plant parameters [51], an image segmentation-oriented HTP system for temporal analysis of projected leaf area using distributed learning to train the CNN model [52], a leaf-tracking algorithm for motion estimation from time-lapse images to compared drought-tolerant and wild-type plants [53], compression of very deep CNN for easy in-field deployment that allows pixel-wise segmentation of plants into multiple classes [54], a 3D sensing-based stereo-imaging system to measure plant stem diameter [55], plant organ-level point cloud segmentation [56], and deep multiview image fusion for yield estimation and prediction [57], and prescriptive breeding [58,59].

Multimodal data assimilation

In many CAS instances, sensing involves multiple modalities in which a variety of traits are measured and then leveraged to estimate the derived features. The incorporation of multiple modalities often adds complexity to the reasoning process, and requires updating the single-modality models with multimodal measurements to estimate the CAS state variables. Furthermore, these measurements could be performed at different scales of environmental conditions and plant physiology that very likely require dealing with degraded sensing environments. However, the fusion process needs to be task-driven because different cross-modal features could be more informative for different decision objectives [60,61]. Hence, robust ML approaches will be necessary for feature extraction and fusion of multiscale, multimodal data to update the models. The schematic of such a framework is compared to a single modality in Figure 2A. One of the earliest applications of sensor fusion in this area can be traced to [62] in which plant diseases were detected using a fusion of hyperspectral images by Kohonen maps. Several other works [63–66] primarily consider sensor fusion using IR thermography, chlorophyll fluorescence, hyperspectral imagery, light detection and ranging (LiDAR), among others, for several types of plant disease detection and vegetation monitoring.

One of the earliest scalable multimodal open-source frameworks, namely the integrated analysis platform (IAP), handles different image sources and organizes phenotypic data by maintaining the metadata from the input in the result data [67]. On a smaller field scale, the field scanalyzer[i] gantry system is an advanced three-axis sensor-to-plant phenotyping system designed with a rail-based *x* axis, customizable widths for the *y* axis, and precise vertical movement capability in the *z* axis, enabling sub-centimeter precision during scheduled measurements. A multimodal sensor suite and data analysis pipeline for field phenotyping has also been implemented using unpiloted aircraft systems (UAS) [68–71]. GPhenoVision [72] is another notable multimodal system, comprising a high-clearance tractor and sensing and electrical systems, that substantially employs image-segmentation and point cloud reconstruction algorithms for deriving multiple phenotypic estimates. The modalities of its sensing system include a distributed structure that integrates environmental sensors, real-time GPS, and multi-imaging sensors such as RGB-D, thermal, and hyperspectral cameras. Similarly, NU-Spidercam [73] was also proposed as a large-scale and automated sensing/robotics system that integrates various sensor modules for field phenotyping. This system enabled the extraction of time-series canopy temperature and spectral induced fluorescence (SIF) traits. Thus, fundamentally, CAS is a leap towards realizing large-scale, ultra-precision agriculture and smart agriculture that intricately rely on sensing and advanced information processing.

Modeling and reasoning

Upon gathering heterogeneous information from multiple CAS sensing units, computational modeling and reasoning frameworks are necessary to make optimized farm management or crop breeding decisions. This section highlights some of the key aspects of CAS modeling and reasoning strategies.

Computational modeling of crop systems

Crop modeling is a mature field of research that has produced several biophysical process-based models for various types of decision making. An incomplete list of well-used models includes APSIM [74], DSSAT [75], and MLCan [76]. However, in the context of CAS, computational modeling frameworks ideally need to include both data-driven and process-based models for reliable biophysical characterization of the plants, trait prediction (for instance, yield, phenology, stress response), and decision support – in both short(er)-term (production application) and longer-term (prescriptive breeding) applications. Although process-based models are useful, they suffer from crucial deficiencies necessitating this complementary (data + process) strategy for CAS applications. Key deficiencies include (i) incomplete knowledge of all the mechanisms impacting the quality of the modeled states, (ii) incorporation of latent variables that are often difficult to directly measure or are only empirically estimated, making transferability and personalization of process models very challenging, (iii) numerical and representational 'brittleness' due to mismatch between the length- and time-scales of parameters input to the submodels, their calibration with averaged properties, and their subjectivity. These deficiencies reduce the utility of any ensuing management decision and limit any decision necessarily to a coarse scale.

On the other hand, data-driven approaches have begun to show promise in various crop modeling applications. For example, early works in this field relied on utilizing a single data modality for crop yield prediction [77–80], disease identification [81], and irrigation optimization [82,83]. Even natural language processing and network theory have been proposed to compute phenotypic descriptions for novel candidate gene prediction [84]. However, with the advent of **internet of things (IoT)** devices in data collection from multiple modalities, decision making has distanced itself from previous single-mode ML approaches. For example, the authors of [85] have shown that publicly available weather and soil data can be relatively effective in county-level corn yield prediction for the US Midwestern region. Similarly, DL models have been developed to integrate genotype and environmental variables for crop yield prediction [86–88]. Whereas traditional DL models tend to be 'black box' (i.e., models without clear understanding of the inner workings) in nature, explainable DL models have been shown to uncover useful insights about important predictors in yield prediction problems [89]. However, purely data-driven models often fail miserably to provide meaningful outcomes even slightly outside their training data support. Carefully incorporating biophysical knowledge may alleviate such issues while also potentially reducing the need for extremely large amounts of data for training.

Therefore, several ML-based studies have begun to work towards assimilating data from high-throughput imaging/sensing platforms to rapidly, precisely, and accurately model plant traits at different growth stages, and integrate these data with (incomplete) knowledge models to create flexible, hybrid AI representations. For example, a knowledge-guided ML model for rice growth simulation has been proposed recently [90]. Similarly, coupling of ML and crop modeling was shown to improve crop yield prediction in the US Corn Belt [91]. Thus, the availability of hybrid data–biophysics models has the potential to transform plot-, field-, and region-level models from *ad hoc* calibration to a more principled CPS approach [92,93]. However, this remains a nascent area of research and there is no consensus yet in the community regarding the most effective ways to integrate knowledge and ML for modeling crop growth and production.

Reasoning frameworks for crop management

With a computational model in place that can simulate crop growth and production under various environmental conditions, as well as management inputs, reasoning and decision-making tools can leverage that model to generate optimized crop management prescriptions, as shown in Figure 2B. There have been several attempts to build such decision-making frameworks in the context of CAS. Among various techniques, **reinforcement learning (RL)**-based frameworks for planning and supervisory decision making have emerged as a popular choice [94], primarily driven by the popularity of advanced deep RL tools in various application sectors. Examples include control crop irrigation [95–97] and crop yield prediction [98]. The objective of an RL agent is to learn a policy for dictating a sequence of optimal actions that maximize the cumulative rewards over a particular time horizon [99]. The application of RL (specifically deep RL) in CAS is an active research area, especially for engineering a proper representation of the environment states, actions, and rewards.

Ideally, an RL agent should directly interact with the real physical system to arrive at an optimal policy, but it typically has a very large sample complexity – it needs many iterations of interactions with the underlying system to obtain an optimal policy. On top of that, during such a training process, utterly suboptimal actions can be taken by the RL agent that may be completely unacceptable for an actual crop farm. Therefore, a standard practice is to build reliable simulated environments (that can leverage the computational models, as described before) to train RL policies, followed by fine-tuning the policies to effectively transfer them from simulation to real (Sim2Real) environments. In the RL literature, these simulation platforms are referred to as gym environments, and these have also started emerging for CAS. For example, CropGym was proposed as a RL environment for crop management [95].

Actuation and in-field Intelligence

In the CAS setting for crop production, actuation refers to the use of mechanical and electrical systems to control and automate various processes in farming to optimize agricultural goals [100]. In plant breeding and crop improvement, actuation refers to decision making following sensing and modeling to decide the outcome of tested varieties – whether it will be culled or retained for further testing or release to farmers.

Advanced robotic actuation in CAS

Agricultural robots can be divided into a few categories based on their characteristics. According to their working environment, agricultural robots are divided into indoor and outdoor robots [101]. Indoor robots are mainly utilized in greenhouses and indoor settings, such as for indoor harvesting, flower cutting, fruit and vegetable grasping, and greenhouse automation control systems [102–104]. Outdoor robots such as spraying robots, weeding robots, nursery robots, tractors, and fruit-harvesting robots [69,105–109], on the other hand, are used in large-scale farmland, pasture, and other outdoor environments. These include both aerial robots, such as unpiloted aerial vehicles (UAVs), and ground robots, such as unpiloted ground vehicles (UGVs), based on their operational domain. In addition, they also can be classified into robots for seeding, planting, harvesting, weeding, and pesticide application [102,110–112]. Regarding agricultural management approaches, actuators can be categorized into soil management robots, field mapping robots, irrigation management robots, harvesting management robots, and weather tracking and forecasting platforms [100,113–115]. Moreover, from the mechanical point of view, agricultural robots have an actuation system as the key component which, depending on their specific use, can be one or a combination of electric, piezoelectric, hydraulic, and pneumatic systems [116–120].

The CAS vision is to have teams of semi- or fully autonomous mobile robots that can provide *avant-garde* actuation options to farmers that improve the production efficiency and quality of agricultural products [121–123]. Such teams can scale from a small group of robots or UAVs to a large swarm depending on the scale of operation, the size and capability of the platforms, and cost. Technical and digital advances in crop production, sensing, and phenotyping include an interest in automating in-field actions using robots and drones (e.g., the 'see and spray' technology) [124]. To execute diverse in-field actions, the robot/UAV teams can be composed of homogeneous (i.e., similar capability, performing similar tasks) and heterogeneous (i.e., different capability, performing different tasks) platforms. To enable autonomous fleets of robots in agriculture with minimal human intervention, it is imperative to build scalable electrified agricultural systems and use energy optimally. The authors of [125] perform a cost analysis considering battery charge and health behavior for autonomous electric field tractors. The works presented in [126–128] also offer valuable insights into power management, life maximization, and battery balancing strategies related to agricultural applications. However, further research in this area will be necessary to realize the potential of electrification in promoting sustainable agriculture, including power optimization in scalable and connected electric-powered agriculture. For instance, although teams of mobile robots equipped with plant manipulation systems could help to alleviate the acute labor shortage in agriculture [129], it is also crucial to consider optimizing the power management of this robot network for sustained, autonomous operation.

In-field intelligence

ML has greatly enhanced the capabilities of agriculture robots of all categories, particularly those designed for sensing and actuation. These intelligent robots range from small robots in greenhouses to UAVs and tractors in the outside field, which are equipped with ML algorithms to analyze vast amounts of data collected by sensors/cameras to identify agricultural data patterns and make decisions. For instance, UAVs equipped with high-resolution cameras and sensors can be used to monitor crop health and growth patterns, and identify any potential issues such as pests, diseases, or irrigation problems [22,130–132]. Recently, the use of ML algorithms with multiple connected drones in agriculture has enhanced field mapping, thus providing a more comprehensive view of the farmland, which leads to improving the land management practices [133,134]. Similarly, automatic navigation of tractors using machine vision algorithms (e.g., object detection, segmentation) enhances accuracy by mapping the crop lines and navigation routes in real time to improve efficiency in agriculture operations [135–137]. A key challenge in enabling envisaged CPS for large-scale row-crops is long-duration reliable autonomy in harsh and changing field environments at low cost. One way to achieve this is to use intelligent software that makes the most out of cheaper sensors. For example, low-cost LiDARs with inertial sensors and encoders could enable robust row-following [138,139], and vision sensors can be used to replace LiDAR sensors which are comparatively more expensive [140]. However, it is relatively challenging to reduce the cost and effort required for programming robot tasks while still reaching high accuracy in the perception process to avoid wrong actions in the field.

In addition, an active area of work includes automatic detection of traversable regions through improved robot mission programming [141–145]. Such intelligent coordination of agricultural robot teams enables mechanical tasks such as weed removal using planning algorithms [146–148], speeding of route schedules on the aisles for complex tasks such as harvesting in vineyards and pruning trees in orchards [105], and dexterity for tasks such as harvesting and grasping. These tasks require actuation components such as drive systems, controllers, robotic arms, end-effectors, and environmental perception components such as radar and cameras with DL-based detection algorithms [149–153]. Figure 2C showcases that agricultural robots need to be dexterous (to achieve human level performance) but must be able to scale up to millions of acres of farming. This means that plant manipulation needs to be robust, reliable, and fast. This is, of course, highly challenging owing to clutter, occlusion, and the soft nature of fruits and other plant organs. Adding to this is the challenge that the robots must be cost-effective, precluding the use of expensive industrial rigid arms and expensive sensors. There is considerable promise in soft-robots [154], but the underlying control and sensing challenges require further work.

Digital twins

Building on the three technical modules of a CAS, as described above, the concept of agricultural DT has recently started to emerge. The notion of a DT brings together the sensing, modeling, control, and actuation aspects of the CPS under a single conceptual umbrella. DTs have found extensive utility in engineered systems [155,156] as well as in logistics and supply chains [157]. Plant sciences and agriculture are ripe for the development and deployment of DTs across the spectrum of applications from basic research [158] to breeding [159] to precision agriculture [160,161] to policy [162]. The basic idea of a DT in agriculture is a data and software framework that serves as a digital replica of the agricultural physical system [163]. That is, the DT mirrors the behavior of the physical object over its lifetime. This includes mimicking the physiological state, growth, and development of a plant (in case of a plant DT), or of a field (in case of a field DT), as illustrated in Figure 3A. Building the DT starts with identifying the states that are most important, the measurements that are being made, and the management decisions (formally, control inputs). We note that the definition of DTs (i.e., their digital states) will be highly context-specific, and depend on the key properties of interest and the associated rewards.

As discussed earlier, crop models play a crucial role in understanding plant physiology, growth, development, and management. However, it is useful to distinguish between such agricultural

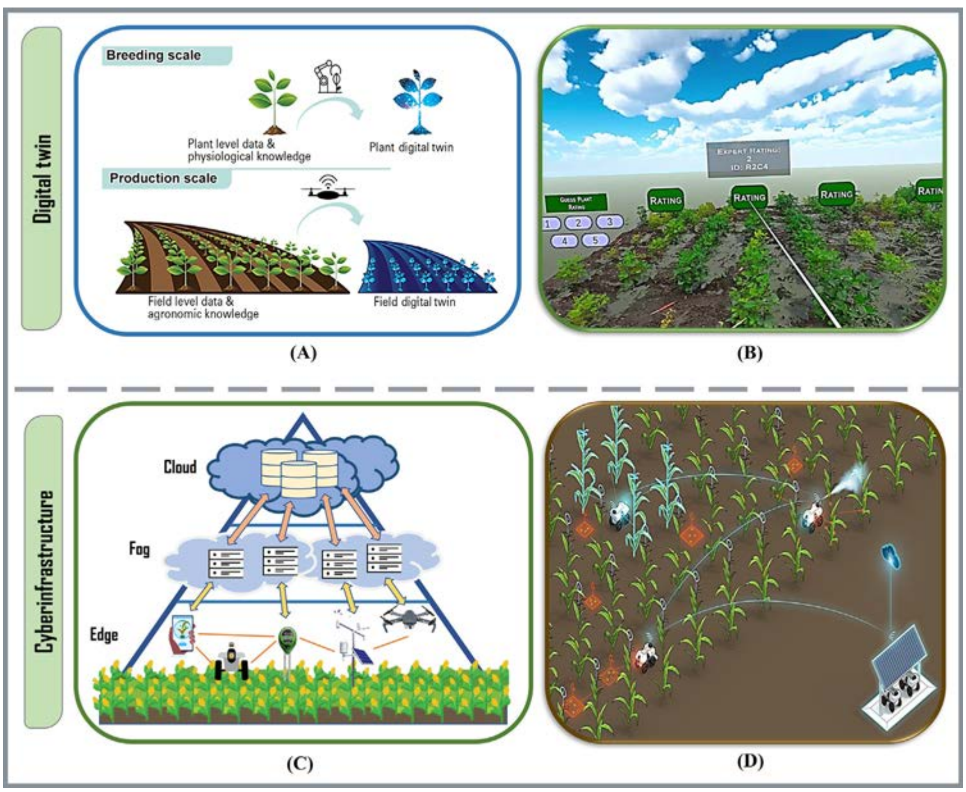

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Figure 3. Cyber-agricultural system (CAS) digital twins (DTs). (A) Illustration of plant- and field-level DTs for breeding and production scales, respectively. (B) Example of remote scouting of soybean plants using virtual reality (VR) and CAS cyberinfrastructure. (C) Distributed CAS computing framework at the edge, fog, and cloud layers hierarchically. (D) Conceptual illustration of a CAS with a team of robots working together to maximize productivity and profitability by using fundamentally more sustainable actuation options, including see-and-spray, mechanical weeding, and cover-crop planting. Reliable data travel and networking solutions are a key enabler of such a vision.

simulators (or crop models) and a DT [158]. A primary difference is that a DT must – by definition – be able to update its digital state continuously (or periodically) using measurements made on its physical counterpart. This includes both physical state measurements (phenotyping, physiological measurements, etc.) as well as environmental measurements (soil, weather, and management) that impact on its state. In addition, the DT (in its various formulations) provides a principled approach to account for known dynamics (as encoded in a crop model) with unknown dynamics (as encoded in physical measurements). This is especially important in biological DT because no complete first-principle models exist (unlike engineered systems where models can completely describe behavior with no tunable parameters). Finally, a desirable property of a DT is its ability to be transferable to different scenarios. This is particularly useful to evaluate various what-if scenarios to identify the best control action. Another exciting technological option for CAS and DT is **augmented reality (AR)** and **virtual reality (VR)** which were earlier proposed for precision farming [164]. AR and VR can play an important role in sensing, reasoning, and future actuation applications via remote robotic manipulation. Utilization of AR and VR allows researchers and (in future) farmers to conduct various experiments and operations (e.g., remote scouting, as illustrated in Figure 3B) with significantly less effort. For example, through VR simulations, researchers can gain insights into how robots navigate, interact with crops, and execute specific tasks, thus facilitating the identification of potential improvements and optimizations in their behavior. Furthermore, virtual experiment runs using VR allow researchers to collect valuable data on robot performance, thereby enabling them to refine algorithms, adjust parameters, and enhance the overall efficiency and effectiveness of agricultural robots before deploying them in real-world scenarios.

DT concepts have recently been used in a variety of contexts in agriculture. They have been used across species, with applications to row crops, orchards, viticulture, gardens, and horticulture. DTs can also be defined, constructed, and deployed at different length scales, and recent studies have been performed at the organ, plant, field, and farm/greenhouse scales [165–167]. Finally, DTs can be deployed for a variety of end-goals ranging from monitoring and real-time diagnosis to maximizing yield and/or profitability [161,168–170], breeding decision support, and autonomous field operations. The next goal for research in DT would be to successfully create an 'intelligent digital twin' (IDT) [168], which means a DT that can self-learn and decide what is best for the farm. ML methods can be used for adding intelligence to DT, as discussed in [168]. A few more studies have explored IDT, mostly utilizing generative models as the basis of DTs [171,172]. These intelligent twins can self-learn with different levels of data integration. Therefore, the integration of ML and large-scale sensing with autonomous systems provides significant opportunities to build DT for CASs.

Cyberinfrastructure

Although sensing, modeling, and actuation are the technical pillars of a CPS, scalable and robust CI is a key enabler of such a framework. In this section we discuss some of the major components of CAS CI.

Data management

Data management in a CI framework substantially differs from traditional data representations that are not suitable for large-scale, real-time analysis, visualization, and information dissemination for complex dynamic phenomena. By contrast, CAS platforms need to offer access to suitable software and hardware that can handle various data types and scale computations. This entails having access to a shared data storage system that can efficiently and securely transfer large datasets, connections to the proper computational hardware such as high-memory computers and virtual machines for analysis, the ability to label and retrieve data using descriptive metadata, and identity management systems for secure data sharing with reliable entities [173].

Hence, with rapid development of sensor networks, IoT systems, hardware-accelerated graphic cards, and computer vision, CI data are distributed in cyberspace [174]. These sensor observation data are multivariate, space/time-sensitive, and are found in different types, formats, dimensions, sources, and structures [175]. In distributed CAS, different observation sites or nodes sense/observe different sets of variables, mostly collected at different frequencies, resulting in streaming of heterogeneous data. Such data require complex data structures for storing, representation, and management techniques involving cloud computing infrastructure.

In CAS, the IoT is a vital component because it involves the deployment of IoT devices such as Raspberry Pi cameras, irrigation sensors, and geographic information systems (GISs) in farms to gather data from the fields. These data are then transmitted to the server (computer unit) for further processing and analysis. With a distributed framework, these sensing units hierarchically operate at the edge, **fog computing**, and cloud layers. The data feed is ideally scheduled such that historical field data serve as input iteratively for informed and improved decision making. In addition, there is the option of smart warehousing, which makes use of these data to improve post-harvest storage and enable big data-enabled warehousing. This assists farmers in making decisions about how much produce to store and sell [176]. Some instances of data management systems and CI-enabled consortiums are iRODS [177], IBP[ii], NEVP[iii], and SERNEC[iv] [173,178,179] that assist with data analysis and sharing.

Computing

Li *et al.* [174] highlight the difficulties involved in managing multivariate data collected across modalities from a distributed sensor network, which is commonly observed in CAS. The study suggests that, to address those challenges and improve online interactive visual analysis, conventional data integration methods must be revamped to support more efficient, scalable, and collaborative visual analysis. Hence, multimodal data fusion that has already proved to be very efficient in improving accuracy and robustness by combining learning over multiple modalities is integral to computing in a CI [180,181].

For computational efficiency, it is imperative to learn from a compressed representative set of the overall sensor data that can also be converted to human-interpretable actionable insights. These computations are generally scheduled and performed in a central computing unit or in distributed units that are connected to the cloud [182,183]. These computations make decisions based on area-specific knowledge as well as business intelligence. As a result, CAS can also function as a decision support system (DSS) for users (e.g., farmers). The decisions made can be sent to the end-users through WiFi-enabled smartphones or computers that act as an interface to enable the user to control all the activities taking place in the field from their computer or smartphone; it therefore enables a service platform for the end-user [176].

Edge, fog, and cloud computing

Despite the advantages of IoT, it is challenging to transmit a large amount of sensory data from agricultural fields to the back-end servers, whether they are in the cloud or in data centers. Such communication requires significant energy, causes delays in communication, and generates substantial network traffic. For example, reliable communication between coordinated robots in an intelligent system is crucial; however, low-range (LoRa) high-bandwidth wireless connectivity (in the 2.5–5 GHz range) and larger power-demand make it challenging. Figure 3D depicts an example CPS where multiple robots work together through reliable communication to enable fundamentally more sustainable actuation for agriculture. There are multiple technology options for communication, such as 5G and MIoTy [184]. However, in many rural areas, broadband technologies such as 5G may not be available. LoRA communication and other lowbandwidth options could help, but significant edge computing is required so that only essential messages need to be exchanged [185]. Another challenge here is in creating reliable predictive models and keeping their prediction on track using feedback-like mechanisms [186]. Edge computing refers to the process of locally storing and processing data near end devices or users [187,188]. This reduces the energy consumption and communication delay required to transmit the collected data. Recent advances in compression/decompression methods using ML models have further helped to decrease the data size at edge/local devices [189–192]. However, edge devices (e.g., sensors) have limited resources and cannot efficiently execute DL. To address this, a recent approach has been proposed that utilizes efficient online computation offloading through deep RL for extensive mobile edge computing [193].

To address the computing limitation of edge devices, an edge–fog architecture is introduced to process IoT data in an efficient way while avoiding the communication delay that occurs in cloud computing [194]. As argued in [195], the three layers (edge, fog, and cloud) architecture in smart agriculture, as shown in Figure 3C, would reduce energy consumption, network traffic, and communication delay. Moreover, a state-of-the-art survey on fog computing for IoT was proposed in [196]. Fog devices (e.g., laptops or low- end computing machines) are usually equipped with more resources than edge devices, and are mostly located at closer communication distance than the cloud. DL with light configuration (few layers and neurons) may be executed efficiently in the fog. Specifically, energy-aware fog-based frameworks were recently studied for mobile crowdsensing, where farmers use smartphones to supply high-quality information [197,198]. However, edge computing is not a replacement for the cloud, and thus the cloud services are still preferable for performing heavy computational tasks in IoT-based farming; for instance, big data analysis and execution of resource-intensive DL models (e.g., ResNet [199]) for real-time crop monitoring.

Data travel and networking

The objective of any CPS is to connect embedded systems with the help of worldwide networks and to enable communication as well as back-coupling between the digital and the physical worlds [200]. Ideally, a CPS comprises several interconnected layers that facilitate secure data travel (between the end users and the cloud) from the physical layer to the IoT layer. The data captured in the IoT layer is moved to the cyber layer, which is enabled with a DT that allows the experts to study system behavior virtually and observe the analytical outcomes by iteratively predicting, modeling, analyzing, and actuating on the cyber platform [201]. The cyber layer connects the edge tier to the data analytics platform tier, followed by the enterprise layer that accounts for business intelligence and decision making. Finally, the cloud tier stores and handles the big data and connects to the application tier forming the service platform for the farmers/stakeholders [176]. However, this data travel requires a cybersecurity strategy to guarantee that sensitive information is only accessed by authenticated entities [202,203]. In addition, meeting the time requirements for such data transfer between and within the layers is extremely crucial [200]. Hence, the identification and tracking technologies, and the networking and communication technologies, play a key role in making the whole integration functional. The most common identification and tracking technologies include radio-frequency identification devices (RFIDs) and intelligent sensors [204]. For interconnecting the sensors and actuators, the prevalent wireless network protocols used in CPS typically include Bluetooth, WirelessHART, ZigBee, and WiFi [203]. With a goal to provide internet access to rural areas, existing solutions utilize either short-range technologies (e.g., WiFi, and Bluetooth) or long-range solutions (e.g., 3G/4G/5G, WiMax, LTE/LTE-A) or a combination thereof. The long-range wide area network (LoRaWAN) has recently been suggested as a solution to meet the needs of providing connectivity in agricultural environments owing to its scalable network architecture and straightforward access method, thus enabling long-range communication with low energy consumption [205]. Although LoRaWAN provides promising applications in the agricultural domain, it's very limited data rates prohibit the adoption of many broadband solutions in a rural context. As an example, transferring large hyperspectral images collected by a drone would be infeasible with a low data rate technology such as LoRaWAN [206,207].

Concluding remarks and future perspectives

Bringing CPS concepts to agriculture, both for crop breeding and production, has enormous potential to enhance productivity, profitability, and resiliency while lowering the environmental footprint. This review article presents the current state of CAS development as well as the trends of innovation that will determine the near and distant future of CAS. CAS tools are at various levels of technology readiness and market adoption. Given the enormous uncertainties stemming from many confounding factors such as disruptive innovations (e.g., generative AI), manufacturing and supply chain issues, market economy, labor market situation, and environmental regulations, it is difficult to forecast precise future trends and timelines. However, we provide a broad discussion here based on our views and understanding (also see Outstanding questions). We summarize the main takeaways from the paper in Box 1 and suggest some best practices for future research in Box 2.

In the context of CAS sensing tools, many high-throughput phenotyping tools are available and deployable today. Although the commercially available tools primarily enable extraction of relatively simpler traits (e.g., plant height, canopy volume, detection and counting of fruits, and estimation of yield), capabilities to extract more complex traits (e.g., identification, classification, and quantification of biotic and abiotic stresses, pests) will also be starting to roll out soon. Research and development in this area can specifically benefit from data sharing and open innovations. Although the CAS community has made many datasets publicly available as benchmarks, data sharing needs to be further incentivized to trigger widespread open innovation. Widely collected citizen science data can also be extremely useful in this regard [208]. Data annotation (especially by experts) is still a major bottleneck to train ML models in this regard. However, the rise of foundation models in ML is helping to address this issue at least partially [209].

Outstanding questions

How can we ensure a high degree of reliability of a CAS 'in the wild' that would guarantee performance under environmental uncertainties, system faults, and natural edge cases?

How can we build and maintain reliable 4D (3D + time) in-field (as opposed to controlled environment) DT models from plant to plot to field scale?

How can we achieve the 'economy of scale' for advanced CAS sensing and actuation solutions (i.e., to enable widespread adoption and reduce costs as well as barriers to entry)?

How can we build fully autonomous (i.e., level 5 autonomy which does not require human attention) platforms for CAS operations?

Box 1. Key take-away points for practitioners

CAS tools are at various levels of technology readiness. For example, many high- throughput phenotyping tools are available and deployable today; AI-driven farm management decision support tools will also be starting to roll out soon. However, fully autonomous robots running a farm may not become a reality immediately.

Designing a specific CAS framework, such as an appropriate choice of platform – drones, ground robots, traditional machinery, or static sensors – depends on the objective (e.g., stress identification and mitigation, or yield estimation), scale of application, cost, and resource availability.

A scalable cyberinfrastructure solution that is the backbone of a CAS should range from edge to fog to cloud computing.

Advanced wireless communication technology is another key enabler of a CAS, and improving rural connectivity will act as a catalyst for accelerated development and deployment of CAS technologies in farms.

Remark: despite excellent progress in the area of CAS research over the past few years, significant effort will still be required for a transition of many of these tools into practice. Although some CAS tools will be more readily adopted by the farming and research community, other aspects will need a more drastic overhaul of the system, and hence may take longer for market penetration. Different parts of the world may also see different trajectories for adoption, depending on various factors such as economic status, labor market situation, and environmental regulations. Therefore, it is imperative for CAS researchers to continuously consider any adoption issues alongside the challenges and advances of science, engineering, and technology.

Box 2. Best practices for using CAS tools

Multimodal, multiscale (spatial and spectral) data collection is crucial for greater effectiveness of CAS tools.

Hybrid modeling approaches that can seamlessly combine process models and data-driven models are more robust for in-field applications.

A scale-agnostic approach to actuation using collaborative teams of (autonomous) heterogeneous platforms will be a more sustainable solution for future agriculture with a low entry barrier.

Leveraging advanced data warehousing and machine learning operations (MLOps) to manage data and generate insights is an important design choice that streamlines the development, deployment, and maintenance of CAS tools.

AI-driven farm management decision support tools are next in line to be deployed commercially. Within the next 5–10 years, breeders and producers should have many technology options to turn their data into decisions using CAS modeling and reasoning tools for making optimal choices in choosing seeds, deciding planting dates, farm management (e.g., irrigation, applying fertilizers and pesticides) and scheduling harvest. In many cases, these products may be available as 'software as service', thus lowering the barrier to adoption by the farming community. However, the cost of sensing infrastructure and data privacy are common bottlenecks in this regard. Although 'economy of scale' can alleviate the cost issue in future, the research community and the AgTech industry need to engage with the farming community extensively to raise awareness about CAS capabilities for technology adoption.

In terms of actuation, design modification and retrofitting of large equipment (e.g., autonomous tractors) for increased levels of automation have already been commercialized. However, the vision of fleets of autonomous robots and drones running a farm with little human supervision may not become a reality immediately. Although there have been several successful proof-of-concept demonstrations of autonomous field robots performing several tasks such as planting, chemical spraying, and harvesting, fine manipulation and individual plant-level actuation remain challenging. In addition, the technology needs to be hardened further to handle the harsh agricultural environment. Apart from the technical issues, various social (e.g., uncertainty about the future of work and employment), legal (e.g., regulation, liability, certification), and economic (e.g., manufacturing cost) issues also remain in this regard. However, these problems can be very different in different parts of the world depending on the scale of farming, the type of crops, climate, communication infrastructure, economy, and cost of labor.

Finally, deployment of CPS tools at scale relies heavily on communication and computation infrastructure. However, high-quality broadband connectivity may still not be available in many rural areas, and this poses a significant challenge in deploying advanced CAS solutions in rural agriculture. Hence, the CAS research community has been focusing on developing edge computing solutions to reduce the need for extensive communication. With recent advances in both hardware and software for edge computing, hybrid edge–cloud solutions are becoming increasingly feasible and cost-effective for deploying CAS solutions.

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Declaration of interests

The authors declare no conflicts of interest.

Resources

[i]www.lemnatec.com/field-scanalyzer/

[ii]www.integratedbreeding.net/

[iii]http://nevp.org/

[iv]http://sernec.appstate.edu/

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