Perspective

DeCASA in AgriVerse: Parallel Agriculture for Smart Villages in Metaverses

Xiujuan Wang, Mengzhen Kang, Hequan Sun, Philippe de Reffye, Fei-Yue Wang, *Fellow, IEEE*

***Briefing*:** The demand for food is tremendously increasing with the growth of the world population, which necessitates the development of sustainable agriculture under the impact of various factors, such as climate change. To fulfill this challenge, we are developing Metaverses for agriculture, referred to as AgriVerse, under our Decentralized Complex Adaptive Systems in Agriculture (DeCASA) project, which is a digital world of smart villages created alongside the development of Decentralized Sciences (DeSci) and Decentralized Autonomous Organizations (DAO) for Cyber-Physical-Social Systems (CPSSs). Additionally, we provide the architectures, operating modes and major applications of DeCASA in AgriVerse. For achieving sustainable agriculture, a foundation model based on ACP theory and federated intelligence is envisaged. Finally, we discuss the challenges and opportunities.

***Keywords*:** Parallel Agriculture Management and Control, AgriVerse, Agriculture CPSS, ACP, DAO-Based Platform, Precision Agriculture.

I. Introduction

ACCORDING to the United Nations report, the global human population will increase by approximately 25% by 2050, reaching nearly 10 billion [1]. As a result, the demand for food will increase massively. Food security, known as availability, access, stability and use of food, is likely to deteriorate along with the negative impact of other factors such as climate change. For example, the global surface temperature will increase by 1.5 °C by 2050, which can dramatically reduce crop yields [2]. This has caused severe problems for human survival and development. To ensure food security, we must make every effort to prevent climate change and develop sustainable agriculture.

With the development of the fourth industrial revolution (Industry 4.0), Agriculture 4.0 is coming up, which is more autonomous and intelligent by integrating the emerging technologies such as the Internet of Things (IoT), robotics, big data and artificial intelligence (AI) into agriculture [3]. However, with the advancement of information and communications technologies, the effects of human behavior have been progressively integrated into agricultural management and control. Agriculture 4.0 is no longer adequate to address human and social factors in systems [4], [5]. As a result, smart agriculture has been converted from Cyber-Physical-System (CPS) to Cyber-Physical-Social Systems (CPSSs), where society will step toward to the fifth industrial revolution (or Industries 5.0). In Industries 5.0, biotechnology, information technology (IT), artificial intelligence (AI) are deeply integrated with the principles of human centrality, sustainability, and resiliency. This lays the foundation for revolutionizing agriculture by systematically linking the microworld, where gene expression, regulation and interaction can be deciphered at the molecular level, with the macroworld, where crop phenotyping, growth modeling, natural/social plant-growth environment monitoring, human intervention and management are carried out systematically [6]. Specifically, crop phenotyping, i.e., the process of measuring the quantity, quality, photosynthesis, development, architecture, growth or biomass productivity of crop plants, has become feasible in a high-throughput manner with intelligent robotics that are developed with techniques in computer vision, pattern recognition and AI. More generally, comprehensive spatial and ground information in agricultural production that influences the survival and development of crops will cover agricultural stages, including preproduction (scheduling, market and demand analysis, plant optimization, etc.), interproduction (planting task management, environmental control, soil analysis, fertilization, spraying, irrigation, usage of pesticide and herbicide, etc.) and postproduction (harvest, storage, processing, transportation and sales, logistics scheduling, etc.).

With the large agricultural data at the terabyte level, there are great challenges for data storage, transfer and sharing. Emerging technologies have shown the potential to address these challenges, such as edge computing and Decentralized

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X. Wang is with The State Key Laboratory for Management and Control of Complex Systems, Chinese Academy of Sciences, Beijing 100190, and also with the Beijing Engineering Research Center of Intelligent Systems and Technology, Beijing 100190, China (e-mail: xiujuan.wang@ia.ac.cn).

M. Kang is with The State Key Laboratory for Management and Control of Complex Systems, Chinese Academy of Sciences, Beijing 100190, and also with the School of Artificial Intelligence, University of Chinese Academy of Sciences, Beijing 100049, China (e-mail: mengzhen.kang@ia.ac.cn).

H. Sun is with Department of Chromosome Biology, Max Planck Institute for Plant Breeding Research, Carl-von-Linné-Weg 10, Cologne D-50829, and also with Faculty of Biology, LMU Munich, Großhaderner Str. 2, Planegg-Martinsried D-82152, Germany (e-mail: sun@mpipz.mpg.de).

P. de Reffye is with AMAP, Univ Montpellier, CIRAD, CNRS, INRAE, IRD, Montpellier F-34398, France (e-mail: ph.dereffye@gmail.com).

F.-Y. Wang is with The State Key Laboratory for Management and Control of Complex Systems, Chinese Academy of Sciences, Beijing 100190, and also with the Macao Institute of Systems Engineering, Macau University of Science and Technology, Macao 999078, China (e-mail: feiyue.wang@ia.ac.cn).

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Autonomous Organizations (DAO) [7], which leverage technologies such as blockchains to allocate resources, coordinate activities, and make decisions without centralized control or third-party intervention [8]. Another challenge is to integrate and analyse data on different dimensions and scales. Models have been developed on a broad scale from the diagnosis of crop disease to yield prediction [9]. However, as a biological entity, crops and their diseases exhibit dynamic behaviors, and continuous monitoring can be prohibitively expensive and thus impossible to apply. Mechanistic models are able to compensate for empty sites and create links among different data. In this regard, extensive studies have been conducted over the last century, including mathematical modeling of the production and allocation of biomass in relation to the shape, structure and ontogenesis of plants.

The origin of our agricultural related work can be traced back to the PhD of de Reffye in 1970s [10], who draw the first 2D plant of a coffee tree in Africa. In 1990s, Wang et al. built "virtual or shadow plant" on a computer by monitoring plants with a camera based on a project granted by the University of Arizona, Tucson, Arizona and Biosphere 2, Oro Valley, Arizona. Around the year 2000, the GreenLab model, a mathematical model describing the development and growth of plants, was developed through Sino-French cooperation [11]. In 2005, the work of Complex Adaptive Systems for Smart Agriculture (CASA) characterized by the parallel intelligence was initiated [12] as the integration of the above works. Subsequently, at the system level, we proposed a framework, called DiCASA for distributed CASA for parallel agriculture [6] following the ACP theory [13] for CPSSs, where 'A' refers to an artificial system, 'C' refers to computational experiments and 'P' refers to parallel execution. In recent years, Metaverse has emerged as a collective virtual space with decentralized and collaborative features where people will conduct activities associated with education, sales, entertainment, etc. Along the lines of Metaverses and parallel intelligence, we are building Metaverses for agriculture, referred to as DeCASA in AgriVerse since 2021 [14], designed along with the development of DeSci [7] and DAO for CPSS. With social information such as market demand and prices, DeCASA in AgriVerse can provide decision support for agricultural systems in reality via in-depth computational experiments in the corresponding virtual system [4]. In short, the development of technologies and theories in biology, computer science, control, communication, AI and DAO make it possible to improve agriculture by harmoniously joining the biological, physical and digital worlds. The challenges, opportunities and future direction of AgriVerse are discussed.

II. DEFINITION OF AGRIVERSE

AgriVerse is composed of smart villages and farms that are characterized by automation, digitalization, computerization and intellectualization. The design of the AgriVerse platform is based on the DAO principle [15] and the ACP methodology [6], as defined in [14]. Similar to the Metaverse, the common technologies used in the AgriVerse also embodies a convergence of web technologies, the internet, virtual reality (VR), augmented virtual (AR), mixed reality (MR), and extended reality (XR), cloud computing, edge computing, blockchain, AI and other technology [16]. The difference in technology between AgriVerse and Metaverse lies in the use of various agricultural models regarding the environment, crops and farmers.

In AgriVerse, the real and virtual systems interactively run in parallel, and any agriculture-relevant information can be perceived, recorded and analyzed automatically, intelligently and systematically to provide optimal solutions or decision-making guidelines for the management and control of practical agricultural production. Fig. 1 shows the conceptual framework of DeCASA in AgriVerse based on CPSS. The basis is the interaction between the real and artificial agricultural systems (AASs) and their corresponding management centers. AASs simulate and optimize the dynamic processes related to agricultural production, the environment, and management activities around the production chain.

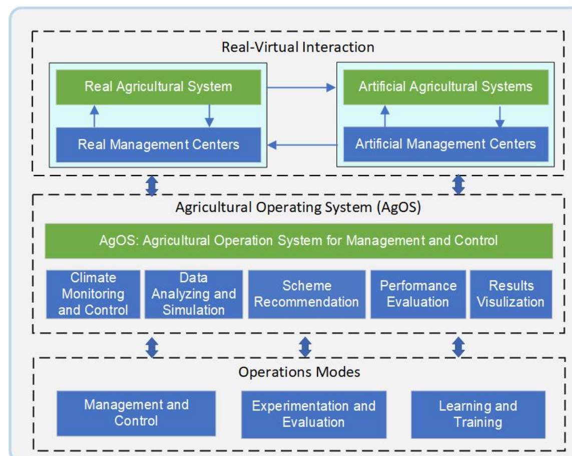

Fig. 1. DeCASA in AgriVerse based on CPSS.

The agricultural operating system (AgOS) is an extensive platform that addresses the management and control of agricultural facilities and software for various tasks through the interaction between the real agricultural system and its corresponding AASs. Applications for various purposes, such as climate monitoring and control [17], data analysis and simulation, scheme recommendation [4], performance evaluation, and visualization of results, can be integrated into AgOS. For example, information on topography and crop planting distribution can be displayed with the platform (Fig. 2(a)), the monitored data of the environment and crop growth status during different growth stages can also be analyzed (Fig. 2(b)), and the 3D architectures of the plant can be displayed using Qingyuan (Figs. 2(c) and 2(d)) [18]. In addition, IoT-based hardware can be managed (e.g., add, remove, rename) and controlled (e.g., switch on/off) remotely. Based on the analysis of data and forecasts of agricultural commodity prices [19], crop phenology [20] and yield [21], optimized crop planting schemes [22] will be recommended. Plant growth can be simulated under a variety of environmental conditions and management operations. It also supports performance evaluation of both real and artificial systems. With the ACP features, AgOS supports three operating modes for different purposes, described below.

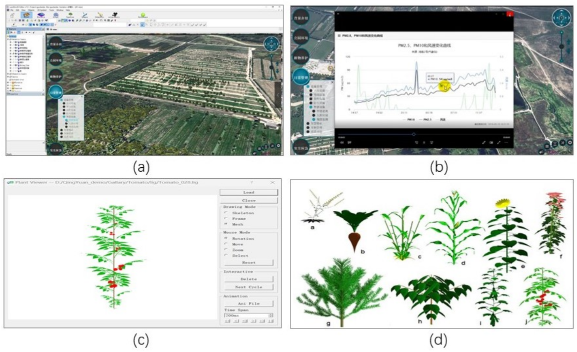

Fig. 2. System interface of agricultural management and control platform. (a) A topography image of a farm. (b) An analysis display of environment monitoring. (c) 3D visualization of tomato plant simulated in Qingyuan. (d) Plant library based on the GreenLab model.

A. Experimentation and Evaluation

In this mode, the various agricultural models supporting AASs are used for various simulations and predictions [23], as described in Fig. 3. AgOS monitors and obtains various data and stores all the information in data centers, including climatic data and crop phenotyping information, social and economic information, etc., and those from expert knowledge. In the experimental design, computational experiments can be set up to generate various agricultural scenarios using supporting models, including climate models, agricultural price models, crop growth models, and farmer behavior models. As a CPSS, predicting agricultural commodity prices [19] can help farmers adjust their harvest time and thus improve their profits by integrating a profit model [22]. For example, crop phenology and yield can be simulated and predicted under various experimental conditions using statistical models or process-based models such as 'GreenLab' [24]. In the performance evaluation, the result of computational experiments can be analyzed; emerging properties can appear and bring new knowledge which is hard to find in the real world. The results can be displayed in the graphs for numeric data or in 3D for crop architectures that clearly show the results of computational experiments. In the decision generation, the planting scheme recommendation can be given according to the simulation and prediction results, such as when to plant, how many to plant and how to plant during the agricultural production process. In addition, by interacting with actual situations, AgOS could optimize and evaluate the performance of recommended strategies. Evaluation results are stored in data centers to help farmers and farm administrators make decisions.

B. Management and Control

In this mode, three layers are involved, namely, the coordination layer, the execution layer and the organization layer (Fig. 4) [25]. The coordination layer organizes the interactions and actions of the real system and AAAs. According to the analysis results obtained through simulations and predictions, the planting scheme can be given; for example, an environment control prescription can be set according to the current environment and plant demand [17]. As a result, AgOS can send a message to the control facilities in the execution layer to adjust the installations and thus control the environmental conditions. The organization layer manages all the resources in the system, including all the agricultural planting technologies, the stakeholder's database, and the typical agricultural scene tests. In the performance evaluation module, the strategies can be tested in actual agricultural scenes; then, by interacting with agricultural experts, the planting technologies stored in the database can be optimized and updated. The same processes can also be used in agricultural machinery management and control. The tasks of machinery, including irrigation, fertilization and harvesting, can be distributed in real-time.

C. Learning and Training

In this mode, with the help of virtual reality and human-computer interaction technologies, users could interact with different agricultural learning and training modules, which enables farmers and administrators to quickly grasp planting technologies and management and control methods during the agricultural production process. Trained farmers would be able to monitor and evaluate the performance of recommendation systems, performing a "human-in-the-loop" control. In turn, feedback from farmers and agricultural experts will help AgOS improve and strengthen agricultural management and control intelligence.

III. INTELLIGENT DECISION SUPPORT BY AGRIVERSE

The core of AgriVerse is an accurate decision support for agriculture-related planning, management and control, based on the perception and analysis of various agricultural data. Greenhouse management and control is a typical scenario for applying AgOS. We have developed a parallel agricultural system based on ACP theory, JJfarmer, which has been named after "Awakening of Insects (Jing Zhe, one of the 24 solar terms used in China for agricultural planning)" [4]. Fig. 5 shows the architecture of JJfarmer. Information perception includes climate conditions (temperature, humidity and light, etc.) and crop growth status during crop growth, the status of greenhouse facilities (on/off), and social information includes the product price (reflecting the balance of product supply and demand), growers' abilities, etc.

Intelligent decision support can provide services covering the entire pre-inter-post agricultural production process. Firstly, suggestions are made according to prior knowledge. Secondly, decisions need to be updated based on the actual environment and management during actual agricultural production. For such a complex farming system, ACP theory can be applied to descriptive, predictive, and prescriptive learning [6]. The objectives of decision support include crop planning,

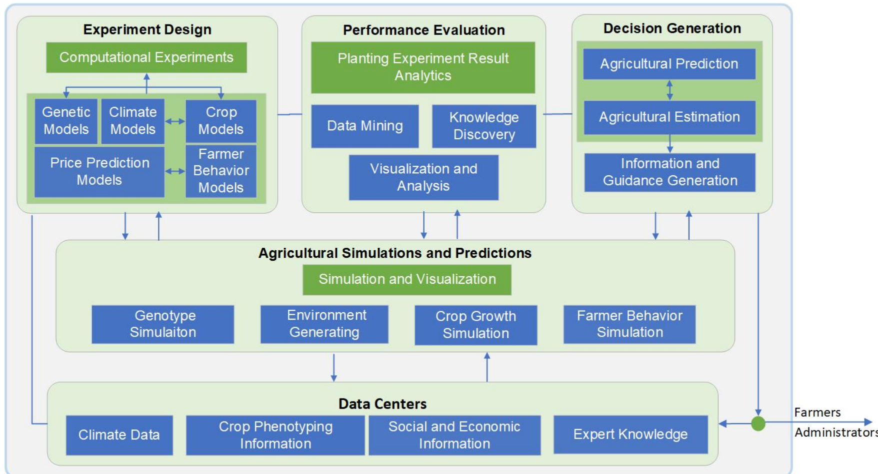

Fig. 3. Agricultural Operations System for Management and Control (AgOS) in Experimentation and Evaluation Mode.

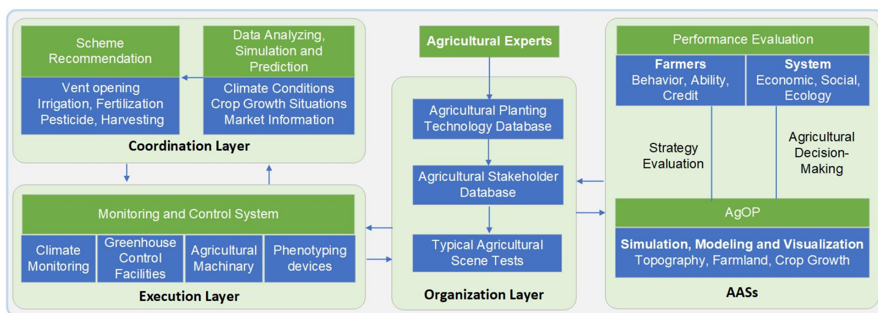

Fig. 4. Agricultural Operations System for Management and Control (AgOS). AASs represents Artificial Agricultural Systems.

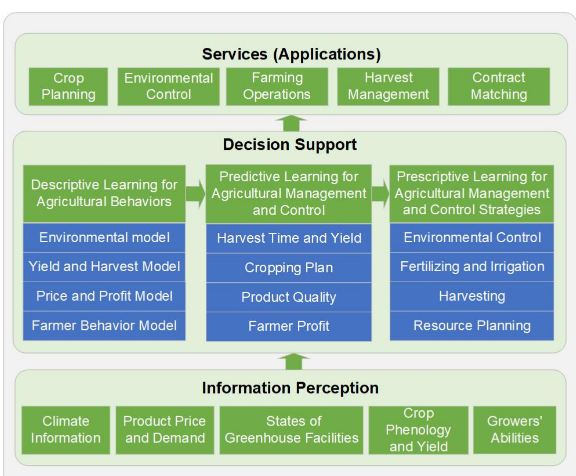

Fig. 5. *JJfarmer* system for environmental monitoring and control, as well as production management during the entire process of the pre-inter-post agricultural production.

environmental monitoring and control, facility control, harvest management, contract matching, etc.

Decision support from this system for monitoring and controlling the environment of a solar greenhouse has been successfully implemented in Changping District, Beijing. In general, JJfarmer achieves real-time control in three steps: 1) producing virtual greenhouse data using a greenhouse climate model; 2) pretraining the greenhouse climate model according to the produced virtual data and calibrating it using the historical climate data collected from inside and outside this greenhouse [17]; 3) transferring the model to the real greenhouse, or learning the knowledge and experience of the farmers from the real greenhouse system, and finally giving the real-time control strategy recommendation. In this greenhouse, the environmental monitoring facilities measure air and soil temperature and humidity using low-cost sensors for smallholders. Control facilities can adjust the size of the vent opening according to the calculation results based on the monitored data.

At the modeling stage, the greenhouse environment and crop growth status can be modeled using the monitored data and climate models. The real greenhouse and virtual systems could operate and be adjusted simultaneously (Fig. 6). In the real target greenhouse, the observed data are obtained for model calibration. With greenhouse sensors gathering real-time data, the climate model of the greenhouse could be refined. Finally, the training model generates a unique solution for each specific planting condition, which is stored in the recommendation system. The modeling processes are demonstrated in Fig. 6, which consists of two basic modules, the real greenhouse system and the virtual greenhouse systems. In a real greenhouse system, farmers adjust the control system, taking into account the actual situation and the historical experience of greenhouse management systems. Farmer control strategies can be derived from monitored data [26], which can be the starting point for an standalone system.

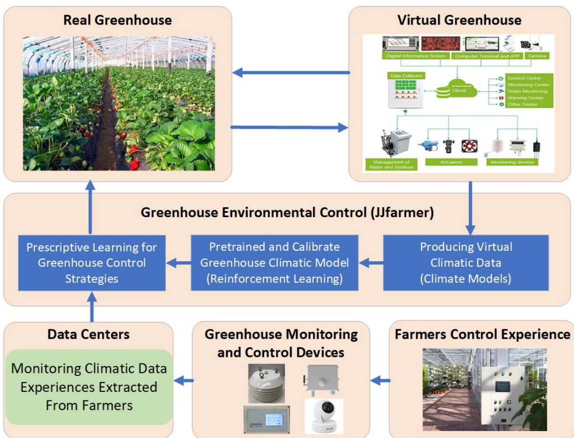

Fig. 6. The facilities, system and application scenarios of greenhouse environment control.

At the recommendation stage, an appropriate control strategy can be recommended for an real greenhouse system depending on the current climate and crop growth states. In addition, the climate control model can also be used to test the effect of a greenhouse climate control algorithm, which provides feedback to the control system, forming a closed loop. The algorithm sends the control strategy to the greenhouse actuators and automatically triggers the execution. The greenhouse climate model and control algorithm will be updated regularly to maintain synchronization with the real greenhouse. In parallel control, operations of actual control strategies will be progressively enhanced by comparison, evaluation, and interaction with virtual control algorithms [27]–[29]. With this framework, it is able to control the indoors climate in an optimal way and minimize the need for human intervention and specialized knowledge.

IV. FOUNDATION MODEL FOR AGRIVERSE

With the development of technologies in big data and IoT, etc., a large amount of data has been obtained [30], where AI technology can be used to perform data mining and combine expert experience and more domain knowledge to provide decision-making support for agriculture [31]. Although it becomes possible to collect agricultural data at multiple scales, dimensions and modalities even with the help of AI-powered robots, intelligent computational methods for analyzing such big data are still not sufficient. Given the heterogeneity of the circumstances, it is difficult to obtain comprehensive, accurate and up-to-date agricultural information or knowledge. In addition, existing predictive models tend to be overflow and cannot be used under different climatic conditions and fields with regional, seasonal and cyclical characteristics during agricultural production. These facts restrict the power of AgriVerse to support decisions.

To empower AgriVerse and improve its function in agricultural management and control in an intelligent and automatic way, by integrating parallel learning theory [32], [33] and federated intelligence [34], we propose an Agricultural Foundation Model for it, as shown in Fig. 7. It should be noted that this is very comparable to the Transportation Foundation Model designed for the transportation system in 'TransVerse', as described in [35].

In its data perception stage, the development of novel technologies in sensors, remote sensing, cameras and UAVs provides the efficient infrastructure in this framework for collecting data [30], including agricultural domain knowledge and rules, monitored environmental data, crop growth status and market prices, etc., as well as data produced from other production management platforms, from the microworld where molecular interactions take place to the macroworld where crop plants grow and enter human society. Data types include text, imagery, audio and video. Recently, technologies developed in information and biology, in particular genome/transcriptome sequencing, phenotyping, and knowledge automation, have become indispensable in the production and processing of data.

For a better description, agricultural simulation and predictive models should also take into account the relationship between the environment, crops and farmers. Models can be grouped into three categories: data-driven, knowledge-driven, and data/knowledge-driven. The data-driven models can learn from data without using any domain knowledge, such as support vector machines, random forests, and artificial neural networks, which can be used to predict the climate of crop growth or the market price of crops, to identify the pest, and to diagnose the disease of crops. The knowledge-driven models are derived from domain knowledge, including crop phenology and growth models, which can be used to simulate crop growth and development. With the development of AI, IoT and big data, studies on integrating these two types of modeling approaches have been conducted to take advantage of both knowledge and data-driven models to reduce the demand for the mass of data and improve the training efficiency, leading to so-called knowledge- and data-driven models, such as those used in [21] to predict crop yield and in [36] to incorporate human domain knowledge into the neural network model in semantic segmentation.

All the monitored data, domain knowledge, rules and models are crucial to building the Agricultural Foundation Model underlying AgriVerse. First, the transformer architecture [37] is introduced to integrate deeper bidirectional encoders and to evolve towards larger models and data sets, as explained in [35]. To train the Agricultural Foundation Model to achieve proper operating processes through the collected data, in the multimodal feature extraction module, the self-attention mechanism [38], [39] is used, which can capture long-term dependencies with higher performance. Second, federated intelligence is incorporated to ensure autonomous management of the DAO-based agricultural system. Within this system, agricultural data is securely stored, maintained, updated, shared and exchanged among stakeholders, including agricultural input suppliers, farmers, machinery suppliers,

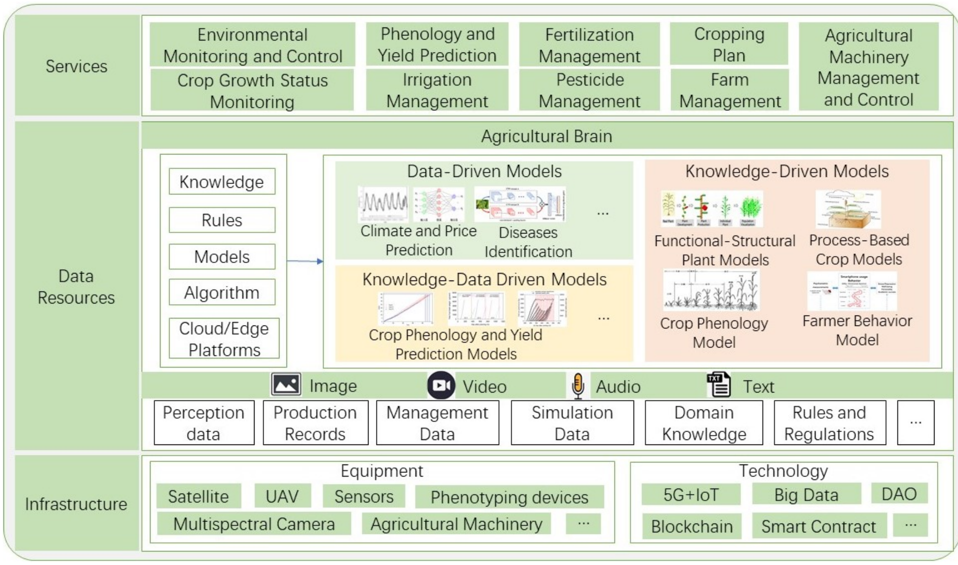

Fig. 7. Future AgriVerse with Agricultural Foundation Model.

financial service providers, consumers, and farm administrators. In AgriVerse, all the processes related to agriculture are to be virtually achieved, including planning, planting, processing, packaging, storing, distribution, resale, preparation and consumption along the agri-food chain until the food arrives on our plates in reality [40]. Such an environment can also be a useful sandbox for testing AI techniques to bring about a responsible AI for agriculture [41]. Therefore, ideally, through computational learning from substantial practical data, AgriVerse would behave automatically and intelligently by taking specific information as input and calculating optimal solutions at any stage of the agricultural production process. Therefore, we can assist farmers and agricultural sectors make agricultural management and control decisions. In addition, the AgriVerse platform can adjust previous solutions for real-time situations as it is based on parallel learning theory and federal intelligence. Thus, the AgriVerse platform can be applied to education, farming training and government management, etc. for example, it is possible to use the AgriVerse to train farmers on farming skills or to remotely control robots conducting harvesting tasks.

V. CHALLENGES AND PERSPECTIVES

Major technology developments in the past couple of decades, particularly in the areas of telecommunications, computing and AI, focused on the development of urban areas, where the concept of smart cities evolved. The level of computerization in rural areas is far behind, leading to what is known as the "urban–rural divide".

To alleviate this issue, it has been recommended to develop smart villages to provide a bundle of services which are delivered to its residents and businesses in an efficient and effective manner [42]. Smart villages are expected to bridge the urban–rural divide. The smart village can be implemented using modern digital technologies, modern management techniques and current social sensibilities [43]. As the economic engine of most rural communities is agriculture, the development of smart villages must include a roadmap to promote agricultural methods, optimize agricultural human resources, and introduce new technologies and processes. As a result, there is an increasingly diverse and complex demand for intelligent agricultural services that must be addressed. 'Agricultural Brain' has been put forward in many provinces of China and is regarded as a significant means for the management and control of agricultural production as well as a new paradigm for achieving sustainable rural development.

In fact, agriculture has faced many complex challenges, including climate change, environmental pollution, food scarcity and waste, natural resources constraints, and uncertainties in agricultural productivity [44]. Although large-scale research on intelligent agricultural techniques is underway and several applications are available, the wide utilization is still insufficient, e.g., the identification of pests, disease detection, yield prediction, and the planning of fertilizer and pesticide use [45]. When it comes to addressing real-world issues and solving them through autonomous decisions and predictive solutions, modern precision agriculture is still in its infancy.

DeCASA in AgriVerse offers a solution to this end; however, the construction of AgriVerse is also only in its infancy. Firstly, since VR and AR information is primarily visual, the foundations are not established in the provision of agricultural production, which need the use of all five senses, including touch [16]. Secondly, many agricultural management and control systems are at the research stage, which is still difficult to apply in real agricultural production and for different field areas. Current agricultural models are mainly dedicated to specific scenarios that cannot be dynamically adapted and are difficult to implement in practice. There is a serious information imbalance between supply and demand in practice; for example, farmers face a digital divide in agricultural productivity and economic and social integration. Information asymmetry (between supply and demand) and lack of knowledge have resulted in soil pollution, unmarketable products, and economic losses [4]. Furthermore, collecting, processing and using agricultural productivity data also face a broad range of challenges. For example, farmers are facing data security and privacy challenges in the information age. In addition, data availability and quality issues are often encountered in agricultural information systems [46].

To address these challenges, emerging technologies have recently led to exciting innovations in agriculture, offering unprecedented opportunities to build an intelligent agricultural system. Research in intelligent agriculture is rapidly developing with advances of deep learning techniques and their various variants [45]. The advancement of blockchain, smart contracts, DAOs and Web 3.0 creates a solid data and trust foundation for future smart villages characterized by human–machine integration [47] and virtual-real interaction [48]. Going forward, it is expected that the above issues can be addressed through the Agricultural Foundation Model for AgriVerse.

The goal of AgriVerse is to achieve food security through precision agriculture with accurate resource planning and agricultural production in a safe, cost-effective and environmentally friendly way. The development of agriculture is inseparable from those involved in agriculture and village conditions. The connotation of rural revitalization includes the habitability of the village. It is expected that in the future, on the basis of Web3 and DAO, AgriVerse will transform smart villages into "6S" societies with "6I", that is, Safe in the physical world, Secure in the cyber world, Sustainable in the ecological world, Sensitive to individual needs, Serves for all, and Smart in all, with cognitive intelligence and parallel intelligence for intelligent science and technology, crypto intelligence and federated intelligence for intelligent operations and management, and social intelligence and ecological intelligence for smart development and sustainability [49].

VI. Conclusion

In this paper, we present AgriVerse, a DAO-based smart virtual digital world, as a specific implementation of the CPSS. The construction of DeCASA in AgriVerse builds on our research work on parallel agriculture since the beginning of the 21st century, from plant modeling to agricultural management and control. The goal of DeCASA is to provide accurate decision support for sustainable agriculture. We presented the architectures, operating modes and major applications of DeCASA in AgriVerse. An Agriculture Foundation Model based on parallel learning and federated intelligence is given as a potential solution to cope with challenging tasks of data analysis and decision support, which paves the way to the agricultural brain and smart village.

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References

[1] United Nations Department of Economic and Social Affairs, Population Division, "World population prospects 2022: Summary of results," Report, 2022.

[2] S. Vermeulen, P. Aggarwal, B. Campbell, E. Davey, E. Grainger-Jones, and X. Yao, "Climate change, food security and small-scale producers: Analysis of findings of the fifth assessment report (AR5) of the intergovernmental panel on climate change (IPCC)," 2014.

[3] T. Wang, Y. Liu, M. Wang, Q. Fan, H. Tian, X. Qiao, and Y. Li, "Applications of UAS in crop biomass monitoring: A review," *Frontiers in Plant Science*, vol. 12, p. 616689, 2021.

[4] M. Kang, X.-R. Fan, J. Hua, H. Wang, X. Wang, and F.-Y. Wang, "Managing traditional solar greenhouse with cpss: A just-for-fit philosophy," *IEEE Transactions on Cybernetics*, vol. 48, no. 12, pp. 3371–3380, 2018.

[5] M. Kang, X. Wang, J. Hua, H. Wang, and F.-Y. Wang, "Parallel agriculture: intelligent technology toward smart agriculture," *Chinese Journal of Intelligent Science and Technology*, vol. 1, no. 2, pp. 107–117, 2019.

[6] M. Kang and F.-Y. Wang, "From parallel plants to smart plants: Intelligent control and management for plant growth," *IEEE/CAA Journal of Automatica Sinica*, vol. 4, no. 2, pp. 161–166, 2017.

[7] F.-Y. Wang, W. Ding, X. Wang, J. Garibaldi, S. Teng, R. Imre, and C. Olaverri-Monreal, "The DAO to DeSci: AI for free, fair, and responsibility sensitive sciences," *IEEE Intelligent Systems*, vol. 37, no. 2, pp. 16–22, 2022.

[8] F.-Y. Wang, "The DAO to MetaControl for MetaSystems in Metaverses: The system of parallel control systems for knowledge automation and control intelligence in CPSS," *IEEE/CAA Journal of Automatica Sinica*, vol. 9, no. 11, pp. 1899–1908, 2022.

[9] L. C. Ngugi, M. Abelwahab, and M. Abo-Zahhad, "Recent advances in image processing techniques for automated leaf pest and disease recognition – a review," *Information Processing in Agriculture*, vol. 8, no. 1, pp. 27–51, 2021.

[10] P. de Reffye, "Modelisation de l'architecture des arbres par des processus stochastiques. simulation spatiale des modeles tropicaux sous l'effet de la pesanteur. application au coffea robusta," Thesis, 1979.

[11] B.-G. Hu, P. de Reffye, X. Zhao, H. Yan, and M. Kang, "Greenlab: A new methodology towards plant functional-structural model-structural part," in *PMA03: The First International Symposium on Plant Growth Modeling, Simulation, Visualization and their Applications*. Tsinghua University Press, Springer, 2003, Conference Proceedings, pp. 21–35.

[12] F.-Y. Wang, "Digital agriculture and parallel intelligence: Towards complex adaptive systems for smart agriculture," CASIA, CASKL-CSIS Tech Report, October 2005.

[13] F.-Y. Wang, "On the modeling, analysis, control and management of complex systems," *Complex Systems and Complexity Science*, vol. 3, no. 2, pp. 26–34, 2006.

[14] X. Wang, M. Kang, J. Hua, H. Wang, and F.-Y. Wang, "AgriVerse: Application of Metaverses in agriculture based on CPSS," *International Journal of Intelligent Control and Systems*, vol. 2, no. 1, pp. 1–6, 2022.

[15] S. Wang, W. Ding, J. Li, Y. Yuan, L. Ouyang, and F.-Y. Wang, "Decentralized autonomous organizations: Concept, model, and applications," *IEEE Transactions on Computational Social Systems*, vol. 6, no. 5, pp. 870–878, 2019.

[16] K. Bhugaonkar, R. Bhugaonkar, and N. Masne, "The trend of Metaverse and augmented & virtual reality extending to the healthcare system," *Cureus*, vol. 14, no. 9, p. e29071, 2022.

[17] Y. Weng, X. Wang, J. Hua, H. Wang, and M. Kang, "Greenhouse environment control based on computational experiments," in *Proceedings of the 2020 3rd International Conference on Big Data and Artificial Intelligence*, ser. HPCCT BDAI '20. New York, NY, USA: Association for Computing Machinery, 2020, p. 238–245.

[18] J. Hua, M. Kang, and P. de Reffye, "An interactive plant pruning system based on greenlab model: Implementation and case study," in *IEEE International Conference on Computer Science and Automation Engineering*, vol. 4, 2011, Conference Proceedings, pp. 185–188.

[19] Y. Weng, X. Wang, J. Hua, H. Wang, M. Kang, and F.-Y. Wang, "Forecasting horticultural products price using arima model and neural network based on a large-scale data set collected by web crawler," *IEEE Transactions on Computational Social Systems*, vol. 6, no. 3, pp. 547–553, 2019.

[20] J. Hua, X. Wang, H. Wang, X.-R. Fan, and M. Kang, "Prediction of crop phenology — a component of parallel agriculture management," in *Chinese Automation Congress (CAC)*, 2017, Conference Proceedings, pp. 7704–7708.
[21] X.-R. Fan, M. Kang, E. Heuvelink, P. de Reffye, and B.-G. Hu, "A knowledge-and-data-driven modeling approach for simulating plant growth: A case study on tomato growth," *Ecological Modelling*, vol. 312, pp. 363–373, 2015.
[22] M. Fan, M. Kang, X. Wang, J. Hua, C. He, and F.-Y. Wang, "Parallel crop planning based on price forecast," *International Journal of Intelligent Systems*, vol. 37, no. 8, pp. 4772–4793, 2022.
[23] X. Wang, J. Hua, H. Wang, M. Kang, and F.-Y. Wang, "CASA: Complex adaptation system for agriculture based on computational experiments," *Journal of Intelligent Science and Technology*, vol. 1, no. 1, pp. 14–20, 2021.
[24] P. de Reffye, B.-G. Hu, M. Kang, V. Letort, and M. Jaeger, "Two decades of research with the greenlab model in agronomy," vol. 127, no. 3, pp. 281–295, 2021.
[25] M. Kang, H. Wang, J. Hua, X. Wang, and F.-Y. Wang, "DeCASA: Decentralized intelligent management and control for agriculture," *Journal of Intelligent Science and Technology*, vol. 2, no. 2, pp. 30–35, 2022.
[26] X. Zhao, H. Wang, X. Wang, U. Lewlomphaisarl, J. Hua, and M. Kang, "Learning greenhouse climate control policy from monitored data," *Chinese Automation Congrass (CAC)*, p. In Press, 2022.
[27] Q. Wei, H. Li, and F.-Y. Wang, "Parallel control for continuous-time linear systems: A case study," *IEEE/CAA Journal of Automatica Sinica*, vol. 7, no. 4, pp. 919–928, 2020.
[28] G. Xiong, X. Dong, H. Lu, and D. Shen, "Research progress of parallel control and management," *IEEE/CAA Journal of Automatica Sinica*, vol. 7, no. 2, pp. 355–367, 2020.
[29] J. Lu, Q. Wei, and F.-Y. Wang, "Parallel control for optimal tracking via adaptive dynamic programming," *IEEE/CAA Journal of Automatica Sinica*, vol. 7, no. 6, pp. 1662–1674, 2020.
[30] A. Kamilaris, A. Kartakoullis, and F. X. Prenafeta-Boldú, "A review on the practice of big data analysis in agriculture," *Computers and Electronics in Agriculture*, vol. 143, pp. 23–37, 2017.
[31] O. Friha, M. A. Ferrag, L. Shu, L. Maglaras, and X. Wang, "Internet of things for the future of smart agriculture: A comprehensive survey of emerging technologies," *IEEE/CAA Journal of Automatica Sinica*, vol. 8, no. 4, pp. 718–752, 2021.
[32] L. Li, Y. Lin, N. Zheng, and F.-Y. Wang, "Parallel learning: a perspective and a framework," *IEEE/CAA Journal of Automatica Sinica*, vol. 4, no. 3, pp. 389–395, 2017.
[33] L. Li, Y. Lin, D. Cao, N. Zheng, and F.-Y. Wang, "Parallel learning-a new framework for machine learning," *Acta Automatica Sinica*, vol. 45, no. 1, pp. 1–8, 2017.
[34] F.-Y. Wang, R. Qin, J. Li, X. Wang, H. Qi, X. Jia, and B. Hu, "Federated management: Toward federated services and federated security in federated ecology," *IEEE Transactions on Computational Social Systems*, vol. 8, no. 6, pp. 1283–1290, 2021.
[35] C. Zhao, Y. Lv, J. Jin, Y. Tian, J. Wang, and F.-Y. Wang, "DeCAST in transverse for parallel intelligent transportation systems and smart cities: Three decades and beyonds," *IEEE Intelligent Transportation Systems Magazine*, pp. 2–13, 2022.
[36] J. Mei and H. Zhao, "Incorporating human domain knowledge in 3-D LiDAR-based semantic segmentation," *IEEE Transactions on Intelligent Vehicles*, vol. 5, no. 2, pp. 2379–8858, 2020.
[37] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, and L. Jones, "Attention is all you need," *International Conference on Neural Information Processing Systems (NIPS)*, pp. 5998–6008, 2017.
[38] P. Liu, Y. Zhou, D. Peng, and D. Wu, "Global-attention-based neural networks for vision language intelligence," *IEEE/CAA Journal of Automatica Sinica*, vol. 8, no. 7, pp. 1243–1252, 2021.
[39] Y. Zhang, B. Xu, and T. Zhao, "Convolutional multi-head self-attention on memory for aspect sentiment classification," *IEEE/CAA Journal of Automatica Sinica*, vol. 7, no. 4, pp. 1038–1044, 2020.
[40] M. C. Rillig, A. Lehmann, J. Lehmann, T. Camenzind, and C. Rauh, "Soil biodiversity effects from field to fork," *Trends in Plant Science*, vol. 23, no. 1, pp. 17–24, 2018.
[41] T. Asaf, D. Medha, K. Brian, A. Shahar, and H. Seán, "Responsible artificial intelligence in agriculture requires systemic understanding of risks and externalities," *Nature Machine Intelligence*, vol. 4, no. 2, 2022.
[42] N. Viswanadham and S. Kameshwaran, *Smart Villages and Cities*. World Scientific Publishing Co. Pte. Ltd., 2013, pp. 175–192.
[43] V. I. Lakshmanan, A. Chockalingam, V. Kumar Murty, and S. Kalyanasundaram, *Smart Villages: Bridging the Global Urban-Rural Divide*. Springer Nature Switzerland AG, 2020.
[44] N. Trendov, S. Varas, and M. Zeng, *Digital Technologies in Agriculture and Rural Areas Status Report*. FAO, 2018.
[45] T. Ayoub Shaikh, T. Rasool, and F. Rasheed Lone, "Towards leveraging the role of machine learning and artificial intelligence in precision agriculture and smart farming," *Computers and Electronics in Agriculture*, vol. 198, p. 107119, 2022.
[46] X. Yang, L. Shu, J. Chen, M. A. Ferrag, J. Wu, E. Nurellari, and K. Huang, "A survey on smart agriculture: Development modes, technologies, and security and privacy challenges," *IEEE/CAA Journal of Automatica Sinica*, vol. 8, no. 2, pp. 273–302, 2021.
[47] Z. Shen, A. Elibol, and N. Y. Chong, "Understanding nonverbal communication cues of human personality traits in human-robot interaction," *IEEE/CAA Journal of Automatica Sinica*, vol. 7, no. 6, pp. 1465–1477, 2020.
[48] L. Li, X. Wang, K. Wang, and Y. Lin, "Parallel testing of vehicle intelligence via virtual-real interaction," *Science Robotics*, vol. 4, no. 28, p. eaaw4106., 2019.
[49] F.-Y. Wang, "Parallel intelligence in Metaverses: Welcome to Hanoi!" *IEEE Intelligent Systems*, vol. 37, no. 1, pp. 16–20, 2022.

Xiujuan Wang received her Ph.D. degree in applied mathematics from Ecole Central Paris, France, and in soil resource use from China Agricultural University, Beijing, China, in 2011. She is currently an Associate Professor with the State Key Laboratory of Management and Control for Complex Systems, Chinese Academy of Sciences, Beijing. Her current research interests include plant growth modeling and parallel agriculture.

Mengzhen Kang (M'16) received her Ph.D. degree in pattern recognition and intelligent systems from the Institution of Automation, Chinese Academy of Sciences, Beijing, China, in 2003. She is an Associate Professor with the State Key Laboratory of Management and Control for Complex Systems, Chinese Academy of Sciences. Her current research interests include parallel agriculture and computational plants.

Hequan Sun received his Ph.D. degree in computer engineering from Nanyang Technological University (Singapore) in 2014. Currently, he is working as a bioinformatician at the Max Planck Institute for Plant Breeding Research (Cologne, Germany) and Ludwig Maximilian University of Munich (Germany). His research focuses on crop genomics and, more specifically, developing computational methods for deciphering crop biology in the context of next/third generation sequencing and genetics.

Philippe de Reffye received his Ph.D. degree in agricultural engineering from Université Paris-Sud/Orsay - Paris/France, in 1979. He was a Senior Professor with the Plant Modeling Unit: AMAP Montpellier, CIRAD, France. He was Head of the GreenLab project in LIAMA, CASIA (1998-2010). He was awarded the outstanding foreign expert by the Chinese government in 2006 and the Outstanding Contribution Award of Chinese and French Scientists by the French government in 2017. His current research interests include plant growth modeling and visualization.

Fei-Yue Wang (S'87–M'89–SM'94–F'03) received his Ph.D. degree in computer and systems engineering from Rensselaer Polytechnic Institute, Troy, NY, USA, in 1990. His current research focuses on methods and applications for parallel systems, social computing, and knowledge automation. He received IEEE ITS Outstanding Application and Research Awards in 2009, 2011 and 2015, and the IEEE SMC Norbert Wiener Award in 2014.In 2021, he became the IFAC Pavel J. Nowacki Distinguished Lecturer. He is a fellow of the International Council on Systems Engineering; International Federation of Automatic Control (IFAC); American Society of Mechanical Engineers; and American Association for the Advancement of Science.