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Digital Twins in agriculture: challenges and opportunities for environmental sustainability

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Food security, land degradation, climate change, and a growing population are interconnected challenges and key issues for sustainable agriculture. In this context, the Digital Twin (DT) is uniquely positioned to overcome these challenges and support the goals of sustainability. Through the use of state-of-the-art technologies, increased information availability can empower stakeholders to pursue sustainable objectives and production methods. However, if these benefits are to be fully leveraged, the potential negative technical and social–ecological effects of the technology must be assessed and mitigated. Therefore, an exploratory review is conducted, outlining the progress of current examples toward the aims of sustainable agriculture. Additionally, the social–ecological and technological dangers of the concept are investigated, culminating in a high-level roadmap that highlights necessary milestones required to support the open and sustainable development of DTs in agriculture.

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Introduction

As agriculture is a significant contributor to global greenhouse gas emissions, acidification, eutrophication, land-use conflicts, and general social welfare [1–4], its sustainable development is critical to meet the various political declarations and societal goals (e.g. Green Deal, Paris Agreement, SDGs, Farm to Fork Strategy, etc.) [5,6]. Digitization efforts in agriculture, such as Smart Farming, Precision Livestock Farming, and now the Digital Twin (DT), can assist stakeholders in tackling the aforementioned challenges while ensuring productivity goals by using advanced technologies to enable real-time monitoring, simulation, and automation through high-fidelity models and a bidirectional information flow [7,8]. Without careful consideration of social–ecological effects of the technological use cases, automation processes through DTs have the potential to increase systemic instability and further aggravate the vulnerability of agricultural sites to external stressors such as climatic change. Furthermore, DTs have enabled increased value and knowledge extraction across a variety of domains (e.g. manufacturing, logistics, smart city, etc.).

Introduced in 2003 by Dr. Michael Grieves, the DT concept focused predominantly on the concept of virtual replicates in manufacturing [9]. The DT has come to be defined as a dynamic approximation of an entity in virtual space, continuously updated through the collection of data, models, and what-if simulation. In the majority of applications found in current research, agricultural DTs form a simplified or functionally reduced view of the observed entity or system, as cost, complexity, and goals are balanced with functionality and replication correctness requirements, as guided by the functional requirements of the intended application [7,10]. This context provides an extendable framework for the design requirement approach and practical application to achieve the goals of digitalization in agricultural settings [11,12].

State-of-the-art literature on the topic shows that current advancements and proliferation of the concept has been primarily driven by breakthroughs in the domains of Internet-of-Things and Artificial Intelligence (AI) [13,14]. The extended data availability, including structured and unstructured information, has provided the necessary technological conditions for the (near) real-time replication to be successful [7]. The ability of the DT to provide usable, actionable, and on-demand information provides the foundational components for robust high-fidelity replication of complex entities and their environment across an expanding variety of applications [12]. Consequentially, DTs support stakeholders to efficiently utilize available resources and infrastructure through monitoring activities of livestock, optimization of inputs to crops, and also the reduction of emissions to air, soil, and water [1,15]. Additionally, the extended data availability provided by the DT creates novel assessment possibilities, allowing the investigation of social consumption, life-cycle assessment, and supply chain tracking, with the availability of information and increased transparency presenting exponentially more opportunities to initiate corrective measures that restore and enhance the social and environmental sustainability goals and the overall production of the agricultural sector [1,16,17]. The underlying information collected, processed, and modeled can be utilized and repurposed to fulfill multiple use cases. Through the use of what-if simulation, a key characteristic of the DT concept, a virtual laboratory can be constructed, empowering users of the twin to evaluate and predict the impact of entity alterations and tackle operational challenges through data integration (business, environmental, social, etc.) and computer modeling. The combination of diverse data and simulation assessment cannot be understated as it provides a novel solution to assess complex questions without the cost, risks, or disruptions associated with physical experimentation [10,18].

Given the promised benefits of the DT as a real-time replicated experimentation sandbox along with its growing application across a wide variety of agricultural use cases, this paper explores and summarizes the progress of current research on the DT toward the goals of sustainable farming, as well as outlining the sociotechnological–ecological obstacles and potentials of its application. By leveraging these insights, this paper forms a roadmap that seeks to achieve key milestones of the concept's development while mitigating identified pitfalls.

Assessment of exemplary Digital Twin use cases in agriculture

The DT has gained increasing traction in both agricultural research and commercial applications, highlighted by the rapid growth in available examples [7,19,20]. However, a majority of agriculture applications have yet to emerge past lab-scale implementations, where most have focused primarily on the integration of computational intelligence and remote sensing devices for specific system optimization and informed management tasks [7]. In specific scenarios, these new implementations have demonstrated an ability to provide robust and accurate measurements of enterprise-specific key performance indicators, allowing informed optimization, decision support, and automation of production processes to take place [7,10]. Therefore, the following section seeks to summarize current developments of DTs in agriculture, classifying current research within exemplary applications. Additionally, an overview of DT investigated can be found in the Appendix section.

Land cultivation

Crop and land cultivation accounts for the largest use of arable land globally and currently boasts the largest concentration of DTs in agriculture [7]. Owing to the resource-intensive nature of crop cultivation (e.g. fertilizer, seed, labor, fuel, water, etc.), use cases have focused primarily on resource optimization and growth forecasting, with the goal of improving stakeholder profitability while reducing waste [21,22]. Utilizing a combination of Internet-of-Things, Cyber-physical systems, mechanistic modeling, and increasingly Machine Learning, the DT has found success across a variety of applications, including yield forecasting, water use optimization, machine calibration, and environmental transparency [23–26]. Current European research projects in this field include the DT development for individual crops and their biophysiological environment, as can be seen at the University of Natural Resources and Life Sciences (digital.twin.plant) or at the University Wageningen (Digital Future Farm, Virtual Tomato Crops). While machine learning has enabled many state-of-the-art developments, the long-term operational quality of these systems has yet to be determined [27]. A key concern of these applications is the lack of clear conceptual modeling of the underlying systems, something which could become an issue in the context of increasing pressures such as soil degeneration, loss of biodiversity, or climate change, where climate patterns are expected to diverge from historical expectations [28]. Given these circumstances, design principles and validation frameworks that ensure the fidelity, interpretability, and resilience of developed models are fundamental to guaranteeing that the underlying dynamic processes and complex entity interactions are correctly replicated within the DT [21,29]. First approaches in this direction should include use-case-specific alignment of DT goals and functionality that also includes technological design requirements to support transparency and model validation processes (see *Roadmap for sustainable Digital Twins in agriculture*).

Livestock farming

Livestock farming has been marked as a substantial contributor to global warming [30], with animal emissions being a key contributor to greenhouse gases. While applications of the DT in livestock farming are relatively limited when compared with other domains, welfare improvement, labor reduction, decision support, and supply chain transparency are the primary areas of concern [31–33]. However, other use cases have included optimization of environmental conditions and energy consumption, which are key to achieving the goals of improved sustainability and quality standards in the livestock industry [34,35]. DTs in the livestock domain have built on similar efforts found in Precision Livestock Farming research, utilizing a combination of Internet-of-Things, Cyber-physical systems, and primarily Machine

Learning, with some examples of mathematical models in supply chain optimization being documented [36]. Here, the principles of Precision Livestock Farming and the application of the DT concept closely align in their goals, demonstrating the DT ability to supplement and improve digitization efforts [20].

Controlled Environment Farming

The concept of Controlled Environment Farming is nothing new, but this approach to food production has seen a significant reemergence in recent years, gaining popularity from both the research and industrial communities alike [37]. The DT in particular has found a large and diverse range of applications in this use case, with the principles of self-contained and self-regulating systems being ideally suited to its strengths [38]. The DT could be even seen as an enabling technology, given the high level of automation and tight integration required to sustain such systems. To achieve this level of integration, DT should be developed during the design stage, allowing system optimization and mitigation of potential risks to be evaluated before physical system implementation [39]. The flexibility of the DT concept in Controlled Environment Farming applications has allowed the issues of urban farming to be tackled directly [40]. However, the ability of the DT to provide optimization and informational insights across the entire life cycle of Controlled Environment Farming installations has led to examples being found in vertical farming, aquaponics, hydroponic, urban beekeeping, and greenhouses. Utilizing an array of technologies, the mentioned examples are composed primarily of Internet-of-Things sensors, Machine Learning, and robust simulation models [18,41,42].

Social–ecological impact and potential threats of radical digitization

Digitization, in the form of smart farming, Precision Livestock Farming, and the DT provides exciting opportunities to achieve a more efficient, economical, and climate-robust agricultural sector [43]. However, if implemented incorrectly, these technologies could have wide-sweeping, detrimental, and unforeseen social–ecological consequences, with the potential to reinforce existing unsustainable systemic effects. Therefore, the following chapter looks to summarize potential key issues by highlighting contributing factors and considerations of DT implementation [7,44,45].

Social impacts

As many design aspects of the DT are driven by individual economic incentives, the deployment of larger and more complex DTs has the potential to accelerate prominent issues facing the wider global community, for example, wealth inequality and market centralization [46]. Agricultural holdings are often small scale or even family-run enterprises. In this context, automation-focused technologies such as the DT have the potential to drastically change the economics of existing agricultural market structures, allowing large volumes of agricultural goods to be produced while decreasing labor [9,46]. If these technologies are not developed in an open and socially mindful way, unforeseen and unwanted systemic effects that ultimately hinder sustainable farming may be introduced, including monopolization of agricultural production, decreased robustness due to centralized single points of failure, increased external dependencies, and loss of industry knowledge [45].

Ecological impacts

The DT drives optimization through the management and monitoring of replicated real-world entities, based on predefined goals and metrics. As the DT is inherently linked with its physical entity, it is vital that the criteria of these optimizations are evaluated in the context of their ecological impacts [47]. This challenge gets amplified by unknown and hidden biophysical feedback processes or redeployment of DT modules in different environmental settings [48]. Failure to align the goals with ecological dependencies can lead to negative ecological feedback loops and unwanted emergent effects, reducing the long-term sustainability of replicated systems. Therefore, it is absolutely necessary that the ecological compatibility of the internal decision-making processes is ensured, both at the system and algorithm design level, with a focus on developing clear operational limits that follow transparently defined metrics [49].

Technological considerations

Design goals of current DTs focus nearly singularly on the automation of information flow, data processing, and decision-making [45], with applications increasingly leveraging machine learning models to accomplish these tasks. However, an unfit design might incorporate unknown biases that can reinforce unwanted effects of agricultural production through algorithmic feedback loops. This situation can be further aggravated through the combination of multiple and codepended machine learning models that focus on individual but interconnected aspects of the replicated entity and its environment [50]. The consequent dependency of different black-box algorithms further aggravates the lack of transparency of data flows and decision-making processes [51], which renders the importance of correct and comparable model evaluation even more important in the DT context. Failure to do so can lead to unwanted behavior emergence, single points of failures, difficulties in maintenance, or in severe cases, cascading error propagation that leads to anomalous operation, culminating in detrimental effects on entity, environmental, and social sustainability [48,52].

Roadmap for sustainable Digital Twins in agriculture

To support future research on the topic of Agricultural DTs, social–ecological concerns have to be observed and formulated as design requirements for sustainable DT development. The following high-level roadmap in the form of core milestones, as first introduced in [48], is outlined:

Milestone one

The realization of a DT often requires use-case-specific adaptations, constraints, and operational limitations that are unique to a given context. While a significant overlap in technology and attributes can exist between DTs, the architectural design methodology employed is often bespoke [7,19,20]. To ensure the benefits and sustainability of agricultural DTs, a robust set of design guidelines and standards will need to be established, guaranteeing the alignment of goals and functionality. These design principles should not only support the rapid development of DTs in novel applications through the incorporation of design principles such as the FAIR framework (findable, accessible, interoperable, reusable), but also aim to support the integration and evaluation of experimental technologies in an open and equitable way [53,54].

Milestone two

Assessment of model fidelity and behavior in adverse conditions is often complex and nontrivial [55]. Expert validation, although adequate for proof-of-concept and research-scale applications, can become a constraint as the DT continues to grow into ever-diverse domains [55]. The lack of an analytical benchmark by which to compare DTs makes the quantification of model fidelity, both in unknown and adverse conditions, increasingly difficult to determine [7,19,20,56]. To overcome these issues, methodological protocols, key performance metrics, and domain-specific benchmarks must be developed in strategic application areas.

Milestone three

To support open, equitable, and sustainable development of the DT in agriculture, a set of open-source gold standard implementations should be made available across a set of strategic applications. As high investment costs, technological robustness, and trust are one of the key barriers of smart farming technology adoption [57–60], prevalidated modularized and stand-alone (i.e. single use-case) models could support adoption. Consequently, validated and scalable modular applications can support sustainable development while ensuring that social–ecological concerns are observed, providing the stakeholder with measured and known failure modes and expected behavior. This would enable DTs to be developed safely and quickly for new applications, without the need to undertake cumbersome validation processes for every deployment [17,61,62].

Conclusion

The DT is a powerful technology, demonstrating its potential to accomplish digitization and replication of complex systems across a variety of domains in agriculture. However, its key role in enabling sustainability in agriculture is often absent in research. Nevertheless, the goals of the DT and with those of general Sustainability are heavily interlinked, both in terms of reduction of greenhouse gases and resource, economic, and production optimization, with the concept supporting the development of new and sustainable methods of agricultural production. If these benefits are to be fully leveraged, potential negative technical and social–ecological effects of the technology must be incorporated into design requirements at an early stage. Therefore, a high-level roadmap has been included next to the state-of-the-art, outlining key milestones necessary to manage systemic dependencies and lay the foundations for sustainable digitization development in agriculture. First, the alignment of goals and functionality of DT farming use cases, requirements, and technology. Second, the identification of standardized criteria for the development and validation of integrated models within DTs. Finally, the creation of validated and scalable modular applications driven by design frameworks that enable model validation and promote DT accessibility.

Data Availability

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

Declaration of Competing Interest

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

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Appendix

Table A1.

Table A1

An overview of key DT applications.

Paper	Area	Goal
Laryukhin et al. [21]	A Farm DT	Replicate complex systems through emergent behavior to improve general farm management
Skobelev et al. [22,24]	A DTs of Wheat	Smart decision-support and effective forecasting of wheat growth in the context of climate change
Angin et al. [23]	A Farmland DT	To utilize LoRaWAN and drone imagery, to model plants for disease and weed detection.
Tsolakis et al. [26]	A DT of Agricultural Machinery	To virtually evaluate system behavior under real-world field conditions.
Moghadam et al. [29]	An Orchard DT	To reduce labor requirements through real-time condition monitoring and decision support.
Jo et al. [34,35]	A Pigsty DT	To determine optimal layouts and system configurations of pigsties through simulation.
Keates [36]	A Livestock Value Chain DT	To evaluate key metrics against a reference model, allowing better understanding of the supply chains.
Monteiro et al. [39]	A Vertical Farm DT	A focus on creating resilient and adaptable automation.
Ghandar et al. [40]	An Aquaponic System DT	To better manage and integrate multiple urban farms within a geographical area.
Johannsen et al. [41]	A Bee Hive DT	To improve management of beehives in urban settings, through agent-based entity modeling.
Jans-Singh et al. [18]	An Urban Farm DT	To enable remote monitoring, decision-making support, forecasting, and optimization.
Chaux et al. [38]	A DT for Controlled Environment Agriculture	To optimize controlled environment productivity.
Akroyd et al. [25]	A Universal DT for land use	To combine land-use data geospatial analysis of scenarios for energy provision, and analysis of flood risk.
Raba et al. [32]	A DT for Livestock Feeding	Investigation of business processes between farmers and animal feed producers, in order to control and optimize the feed delivery supply chain.
Evert et al. [33]	A DT for arable and dairy farming	General farm optimization through a large-scale simulation framework, to investigate wide-ranging farm processes.

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