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Introducing digital twins to agriculture

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ABSTRACT

Digital twins are being adopted by increasingly more industries, transforming them and bringing new opportunities. Digital twins provide previously unheard levels of control over physical entities and help to manage complex systems by integrating an array of technologies. Recently, agriculture has seen several technological advancements, but it is still unclear if this community is making an effort to adopt digital twins in its operations. In this work, we employ a mixed-method approach to investigate the added-value of digital twins for agriculture. We examine the extent of digital twin adoption in agriculture, shed light on the concept and the benefits it brings, and provide an application-based roadmap for a more extended adoption. We report a literature review of digital twins in agriculture, covering years 2017-2020. We identify 28 use cases, and compare them with use cases in other disciplines. We compare reported benefits, service categories, and technology readiness levels to assess the level of digital twin adoption in agriculture. We distill the digital twin characteristics that can provide added-value to agriculture from the examined digital twin applications in agriculture and in other disciplines. Then, inspired by digital twin applications in other disciplines, we propose a roadmap for digital twins in agriculture, consisting of examples of growing complexity. We conclude this paper by identifying the distinctive characteristics of agricultural digital twins.

1. Introduction

Digital twins (DT) are being increasingly adopted by several disciplines, including the manufacturing (Kritzinger et al., 2018), automotive (Caputo et al., 2019) and energy (Sivalingam et al., 2018) sectors, for addressing multidisciplinary problems. DT are digital replicas of actual physical systems (living or not), interweaving solutions of complex systems analysis, decision support and technology integration. DT have gained prominence, partially due to the uptake of Internet of Things technologies, that allow for the monitoring of physical twins at high spatial resolutions, almost in real-time, through both miniature devices and remote sensing, that produce ever-increasing data streams. DT have been useful for converging the physical and virtual spaces (Tao et al., 2018), guaranteeing information continuity through the system lifecycle (Haag and Anderl, 2018), system development and validation through simulation (Boschert and Rosen, 2016), and preventing undesirable system states (Grieves and Vickers, 2017).

The DT concept was coined by M. Grieves in a white paper (Grieves, 2014), as a unification of virtual and physical assets in product lifecycle management. Since then, several disciplines have adopted DT, each providing their own definition as there is no generally accepted definition of DT. A working definition for this study considers DT as "*a dynamic virtual representation of a physical object or system, usually across multiple stages of its lifecycle, that uses real-world data, simulation, or machine learning models combined with data analysis to enable understanding, learning, and reasoning. DT can be used to answer what-if questions and should be able to present insights in an intuitive way*" (Clark et al., 2019).

The benefits of DT applications include reduced production times and costs, hiding the complexity of integrating heterogeneous technologies, creating safer working environments and establishing more environmentally sustainable operations. DT are utilized by several leading companies and organizations, including Siemens (Negri et al., 2017), General Electric, NASA, US Airforce (Mukherjee and DebRoy, 2019), Oracle, ANSYS, SAP, and Altair (Qi et al., 2018). Furthermore,

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the recent availability of commercial software tools to develop DT, like Predix[1] and Simcenter 3d[2] (Negri et al., 2017), is an evidence in itself of increased interest in DT applications.

Information and communication technologies can be leveraged to design and implement the next generation of data, models, and decision support tools for agricultural production systems (Janssen et al., 2017). Today, technologies like artificial intelligence (Patricio and Rieder, 2018), big data (Wolfert et al., 2017) and Internet of Things (Elijah et al., 2018) find their way in practice, and start to converge. Benefits of this convergence have been demonstrated in DT applications in other disciplines. However, DT are hardly utilized in agricultural applications, and their added value has not yet been discussed extensively. As a result, questions emerge regarding the benefits of DT for agriculture, the characteristics that differentiate them from current practices, and their design and implementation.

The purpose of this work is to investigate the potential added-value of DT in agriculture. To achieve this goal, we will first research the extent to which DT have already been explicitly adopted in agricultural applications, and investigate their reported benefits. Second, we examine the similarities between DT applications in agriculture and other disciplines, to identify opportunities of potential added-value for agricultural DT. Our research questions are formulated as:

- RQ1: To what extent have digital twins been applied in agriculture?
- RQ2: What is a potential application-based roadmap for the adoption of digital twins in agriculture?

To address these questions, we employed a mixed-method approach, as exploratory research suggested DT have not been extensively used in agriculture. Thus, a literature review alone would not suffice due to the limited number of reported cases in the literature. Our approach consists of a literature review of existing DT in agriculture, and a survey of case studies in other domains, the latter added to compare with the DT adoption level in agriculture and investigate potential future applications. We searched for DT use cases in agriculture, as well as in other disciplines to see how they employ DT. Note that we did not focus on identifying specific DT applications, rather we aimed at generalizing them into abstract, representative use cases. For the use cases identified, we explored the dimensions of maturity, service types and benefits offered. Our methodology is described in detail in Section 2 and the results are presented in Section 3. In Section 4, we discuss our findings concerning the current state of DT in agriculture, the added-value of DT, and we potential areas for future research. Section 5 concludes this work.

2. Methodology

To answer '*RQ1: To what extent have digital twins been applied in agriculture?*', we identified existing DT use cases in agriculture and extracted attributes which helped us assess how advanced these applications were. To identify use cases, we performed a literature review for DT in agriculture and extracted indicators of maturity, service type and benefits. Maturity captures the development stage of the application (e.g., idea, lab, production). Limited use cases of production level DT is an indicator of less widespread use of DT. On the other hand, increased research and deployed applications indicate that DT are still finding their way into agriculture. To describe the purpose of DT on an operational level, we extracted the service type attribute. These services indicate the broader set of operations that DT perform. From the service type, we can understand the complexity of the DT operations, with higher complexity meaning potentially higher added value for the application domain. Also, the service category of DT in agriculture was compared with the service categories found in other disciplines to examine how advanced agricultural DT operations are. Next, to show what is the added-value of DT based on existing applications, we extracted the benefits attribute. Less materialized benefits from the applications indicate limitations for adoption. Below we describe step-by-step how the literature review was performed.

First, we searched in scientific databases and subsequently extended our search to grey literature. We included grey literature because a pre-literature search showed that the peer-reviewed corpus covering DT in agriculture is rather limited. By including grey literature, we also cover work in progress and commercial applications that have not been published in scientific literature.

Second, we checked the corpus for relevance. In scientific publications, we read the abstracts to verify that the topic was about agriculture with references to DT. For the grey literature, we scanned the entire articles to see whether they connect DT to agriculture.

Third, we read all the selected articles and extracted use cases of DT applications. References to similar DT applications between multiple articles were considered only once to avoid redundance. We identified each use case with a number, summarized it in a single paragraph describing its functionality, and extracted the reported benefits.

Fourth, we identified the services offered by each DT use case. We used the service classification initially proposed in (Tao et al., 2018), and subsequently aggregated in (Cimino et al., 2019). The categories we used for classifying the use cases are presented in Table 1. We categorized the use cases in this way to identify the complexity of operations that DT performed as operation complexity is an indicator of the advancement of DT in agriculture. Also, this categorization helped us compare the types of operation offered by DT in agriculture and other disciplines, and determine any potential gaps to further assess their adoption in agriculture.

Fifth, we categorized the use cases based on their technology readiness level (TRL) to examine whether they are in experimental stage, or if they have been used in production. We partitioned the European Union's TRL scale (European Commission, 2014) into three generic levels shown in Table 2, and used them to tag the use cases. The first level represents DT which were still in a conceptual phase, the second consists of DT that had a working prototype even without the complete planned functionality, and the third level covers mature DT deployments in production.

Sixth, we identified the physical twin, i.e. the physical system that was twinned in each use case. We classified them in the following categories: living plants or trees, animals, agricultural products, i.e. harvested fruits; agricultural fields, farms, landscapes, farm buildings, as barns, greenhouses or other agricultural buildings, agricultural machinery, including equipment and tractor appliances, and food supply chains and logistics.

Finally, we summarized in a table all the identified use cases, their respective descriptions and the extracted three dimensions - service categories, TRL, and physical twin - to depict the breadth of the application of DT in agriculture. Fig. 1 summarizes the methodology for answering RQ1.

To answer the second research question, '*RQ2: What is a potential application-based roadmap for the adoption of digital twins in agriculture?*', we searched in literature for use cases aiming to identify the ways in which DT have been successfully applied in other disciplines. Again we aimed at identifying use cases, and extracted indicators of benefits, maturity, discipline, and service type to understand the operations in which DT are most effective and what problems they can solve. First, we searched for peer-reviewed review papers of general DT applications.

[1] Predix is a software platform that facilitates data collection, processing and analytics for industrial applications. The product description can be found in https://www.predix.io/.

[2] Simcenter 3d is a software environment that integrates 3d modeling, simulation and data management. It includes modules to capture the dynamics of fluids, composites, acoustics and others. The product description can be found in https://www.plm.automation.siemens.com/global/en/products/simcenter/simcenter-3d.html.

Table 1
The digital twin service categories used to classify the use cases identified by the literature review. The column *Typical components* lists the components that are usually needed to implement the corresponding services.

Service Categories	Definition	Typical components					
		Monitoring	Simulation	User interface	Learning	Actuator	Analytics
Real-time monitoring	Monitor and log the status of a system	x		x			
Energy consumption analysis	Analyze the energy consumption of the physical system and find ways to minimize it	x	x	x			x
System failure analysis and prediction	Analyze the data coming from a system to identify the source of failure or when the system is going to need maintenance	x	x	x	x		x
Optimization/update	Find the optimal parameters for the operation of a system and update it to run with those parameters	x	x	x	x	x	x
Behaviour analysis/ user operation guide	Analyze human made operations and provide feedback	x		x			x
Technology integration	Bring together different already deployed technologies under the same umbrella to control and visualize operations more easily	x	x	x	x	x	x
Virtual maintenance	Allow users to virtually test different maintenance strategies to find the least intrusive one		x	x			x

Table 2
The European union TRL grouped into three general levels. Concept level includes European TRL 1–2, Prototype includes levels 3–6 and Deployed includes levels 7–9.

Aggregated level	European Union technology readiness levels
concept	1 Basic principles observed
	2 Technology concept formulated
prototype	3 Experimental proof of concept
	4 Technology validated in lab
	5 Technology validated in relevant environment
	6 Technology demonstrated in relevant environment
deployed	7 System prototype demonstration in operational environment
	8 System complete and qualified
	9 Actual system proven in operational environment

Second, we scanned the full texts for occurrences of the string 'digital twin', to check if the reviews were related to DT. If DT were briefly mentioned and not the main point of the review paper, we considered the reference irrelevant. Third, the remaining articles were examined in alphabetical order based on their title to extract use cases. Repeated mentions of similar use cases were not considered. Fourth, we extracted a short summary of the use cases, the reported benefits that they offered, the discipline, maturity and service categories using the same framework as for research question 1, and the publication and application years. Fifth, we proposed areas of potential application in agriculture, and identified potential benefits based on the use cases in other disciplines. Fig. 2 illustrates the methodology for answering RQ2.

3. Results

3.1. Literature review of digital twins in agriculture

For the literature review of DT in agriculture, we first searched in Web of Science (Web of Science) using the query `"digital twin*" AND (agri* OR crop* OR farm* OR aqua* OR animal*)`. This query returned results which contain DT and derivatives of `agri`, `crop`, `farm`, `aqua`, or `animal`, to capture cases of DT in subfields of agriculture. The query returned seven results. After the relevance scan the results were reduced to four (Smith, 2018; Tagliavini et al., 2019; Paraforos et al., 2019; Tsolakis et al., 2019). We then extended the search to Google Scholar (Google Scholar) using the query `"digital twin" agriculture`. The query returned 947 results. We examined them until five consecutive results were irrelevant (24 results examined), and checked for duplicate results from the previous search in Web of Science, thus reducing the number of results to nine (Tan et al., 1094; Jo et al., 2018; Kampker et al., 2019; Moghadam et al., 2020; Qi et al., 2019; Machl et al., 2019; Verdouw and Kruize, 2017; Gomes Alves et al., 2019; Delgado et al., 2019). Extending to the Google search engine (Google), we used the query `"digital twin" agriculture` which returned 143.000 results. We examined them until five consecutive results were

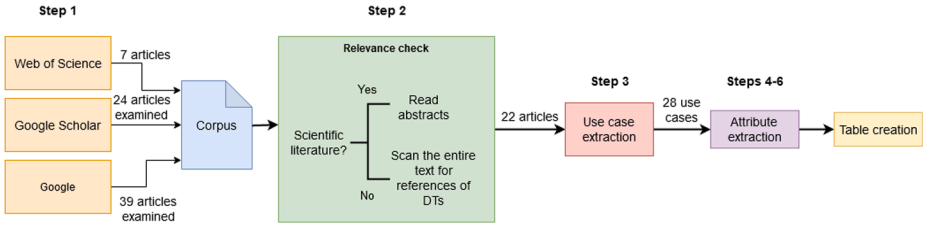

Fig. 1. The steps followed to search for use cases of digital twins in agriculture.

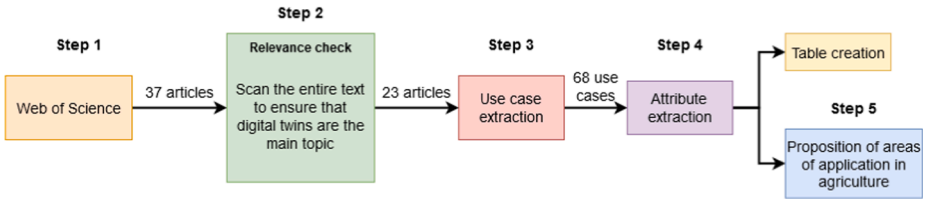

Fig. 2. The steps we followed to find digital twin use cases in other disciplines so as to answer the second research question.

irrelevant or referring to previously found applications (38 results examined). We then checked the extracted results for duplicates from our searches in Web of Science and Google Scholar, eventually reducing the results to nine (Monteiro et al., 2018; IBM Research, 2018; R&D WORLD, 2019; Collins, 2019; Barnard, 2019; Chiu et al., 2019; Mokal and Sharma, 2020; Ohnemus, 2020; Wageningen University & Research, 2020). In total our search yielded 22 sources for DT applications in agriculture. From this result-set, we identified 28 use cases. Following the methodology described in Section 2, we summarized each use case and extracted data about the expected benefits, TRL, physical twin, and service category. The results are reported in Table 3.

Our search yielded 14 scientific articles. Nine of which were published in journals and five in conference proceedings. Additionally, we identified eight website articles from the grey literature search. Publication outlets, titles and year of publication are summarized in Table 4. We observe that the first published references to DT in agriculture date back to 2017, and most of our sources are from 2019 onward.

The use cases reside in different sub-fields of agriculture: In dairy farming we found DT for the detection of mastitis in cows. Related to apiculture, we found a DT of bee colonies aiming to control their welfare and honey production. In plant production, a DT of tomato crops in a greenhouse aimed to control the growing environment. In agricultural machinery, a DT of tractors was used to emulate their performance prior to purchasing. Other DT included orchards, pig farms and aquaponics production units. We noticed that DT of animals and fields, farms and landscapes are reported with less technical detail. In contrast, DT of agricultural machinery and food supply chains and logistics were often described with more details about their design and operation.

The reported benefits varied, depending on the physical twins. For twins of living systems, like plants and animals, the benefits included early disease identification, production optimization and identification of factors that could degrade their welfare. For agricultural products the benefits were cost savings and improved product quality. Support in crop management decisions allowing for faster action was reported for agricultural fields and farms. Twins of agricultural buildings reported benefits related to growing conditions management and production increase. Lastly, DT in agricultural supply chains and logistics reported benefits included cost savings and more environmentally friendly operations (Table 3).

Physical twins include both non-living subjects, like farm buildings such as farm bins or livestock barns, and living subjects, such as arable farms or individual animals. Most of the DT were found for physical twins of agricultural fields, farms, landscapes and buildings. Fewer were found for living plants and animals or agricultural products and the food supply chain. Fig. 3 illustrates the types of physical twins identified together with the maturity of the use cases as TRL level.

Regarding the TRL, most DT identified in this study were on the conceptual level. In Fig. 3 we observe that DT of agricultural fields, farms and landscapes are mostly on the concept level. We also notice that DT in the food supply chain and agricultural machinery have surpassed the concept level stage. Besides, none of the identified agricultural products DT have reached the deployment stage.

Regarding the service categories, the identified use cases of agricultural DT perform energy consumption analysis, real-time monitoring, system failure analysis and prediction, optimization/update, and technology integration. The majority of the DT perform monitoring and optimization operations (Fig. 4). We do not observe any pattern of the TRL levels across the service categories.

3.2. Digital twins in other disciplines

For the examination of DT in other disciplines we searched in Web of Science using the query `TS="digital twin*" AND ALL=review`. This query returned results that had DT mentioned in the title, abstract, or keywords and had the word *review* mentioned somewhere in the text. Instead of filtering the type of results to reviews only, we chose to search for the word review because some review papers are not always not explicitly tagged as such in Web of Science, or sometimes they miss the word review from their title. The query returned 37 results. After scanning the articles for relevance, the results were reduced to 23 (Kaewunruen et al., 2018; Patterson and Whelan, 2017; Fraga-Lamas and Fernández-Caramés, 2019; Zheng et al., 2019; Tilbury, 2019; Dewitt et al., 2018; Bolton et al., 2018; Dong et al., 2019; Cohen et al., 2019; Tomiyama et al., 2019; Qi and Tao, 2018; Tao et al., 2019; Lu et al., 2020; Raman and Hassanaly, 2019; Yi Wang et al., 2019; Paraforos et al., 2019; Pizzolato et al., 2019; Mabkhot et al., 2018; Cimino et al., 2019; Gupta and Basu, 2019; Ghobakhloo, 2018; Kim and Kim, 2017; Longo et al., 2019). Following the methodology of Section 2, we identified 68 use cases, and extracted a short summary, benefits, maturity level, discipline, service categories, year of publication and year of application for each case, reported in Table 5.

We observed that DT in other disciplines performed energy consumption analysis, real-time monitoring, system failure analysis and prediction, optimization/update, technology integration and virtual maintenance. Most of them performed monitoring and system failure analysis operations (Fig. 5). The TRL varied by the year. The earliest documented DT application (2011) was that of an aircraft, which was used in production. From 2011 to 2016, new use cases were scarce. After 2016, many DT applications emerged at the concept and prototype levels, as well as some deployed ones. Applications in the concept stage were more frequent than the ones at the prototype and deployed stages. The reported benefits included cost reductions, energy savings, reduced equipment downtime, quantification of system reliability and safer working environments for personnel.

3.3. Threats to validity

The results of the literature review for DT in agriculture showed that there are only a few DT use cases reported in scientific literature. Moreover, 13 *(Table 3, uc. 11–16, 20–26)* out of 28 DT use cases were used in the commercial sector and 7 *(Table 3, uc. 20–26)* out of those 13 were documented only in non-scientific literature. This may imply that the industry is ahead of academia in the development of DT.

Also, we limited our search to Google Scholar and Google to applications up to 5 consecutive irrelevant or duplicate results. More DT could potentially be found if we examined more results or additional sources.

Another factor that the literature review of this work does not consider is the existence of agricultural applications which are not defined as DT in literature. There are potentially applications that are used as DT but for unknown reasons they were not tagged as such and as a result they were not included in our results.

Besides, in our literature review we included conceptual level DT applications, which means that they are not established applications, but work in progress.

4. Discussion

4.1. Current state of DT in agriculture

In this section, we investigate the state of DT in agriculture by comparing it to the state of DT in other disciplines. The results of the literature review in agriculture show that the available literature is limited. Considering the year of publication, DT have been discussed in other disciplines since 2011 (Table 5, *uc. 54*), while in agriculture the first references occurred in 2017. Our interpretation for this delay to investigate DT, is that agricultural researchers are more risk-averse than in other disciplines. A reason may be that in agricultural applications, firms are often small and medium farms. Such farms can bear less risk than bigger companies in other industries, who can afford to experiment and innovate, and thus pioneered DT. Also, DT in other domains are mostly concerned with non-living physical twins, as complex industrial

Table 3
The use cases of agricultural DT. Use cases are referred as "uc" and their corresponding numbers in the text. The numbering of the use cases continues for the use cases in other disciplines.

Use case No.	A digital twin:	Benefits	Physical twin	Technology readiness level	Service category					Citation
					Real-time monitoring	System failure analysis	Optimization / update	Technology integration tool	Energy consumption analysis	
1	of a cow having access to historical and real-time data, able to predict the probability of developing mastitis as a function of various management and treatment decisions.	a data organization system for each entity individually which is also queryable and identifies the best response to each query	animal	concept	x	x				Smith (2018)
2	of picked mango fruit that captures its temperature variability and biochemical response throughout the cold chain, to evaluate quality losses along the cold chain like firmness and vitamin content.	insight into the remaining quality attributes of picked mango fruit	agricultural product	concept	x	x				Tagliavini et al. (2019)
3	of a field using data coming from ISOBUS sensors, other field related data, human expertise and machine learning to provide better field prognostics and act faster in the presence of predicted deviations.	continuous detailed crop and soil information that allows for faster actions when anomalies occur	agricultural field, farm, landscape	concept	x	x				Paraforos et al. (2019)
4	to emulate the use of unmanned ground vehicles in fields. It accepts the actual landscape of a field as input by utilizing digital elevation models retrieved from Open Street Maps. It recreates the 3D model of the field along with possible additions like trees and static objects. It contains a predefined selection of commercially available unmanned ground vehicles which a farmer can test on the virtual field to find the most efficient for their case.	economic and environmental benefits for the farmers since they can choose the optimal machine for their specific field	agricultural machinery	prototype			x	x		Tsolakis et al. (2019)
5	of a self-contained aquaponics production unit. The purpose of this digital twin is to balance the fish	production maximization, waste minimization, water	agricultural building/ agricultural machinery	prototype	x	x	x		x	Tan et al. (1094)

(*continued on next page*)

Table 3 (*continued*)

Use case No.	A digital twin:	Benefits	Physical twin	Technology readiness level	Service category: Real-time monitoring	System failure analysis	Optimization / update	Technology integration tool	Energy consumption analysis	Citation
	stock and plants in the unit by monitoring them and controlling the unit automatically. The digital twin uses temperature, light intensity, water flow, pH and dissolved salts sensed data. The virtual unit performs simulations of fish feed, fish weight gain, pH, nitrates and plant growth as what if scenarios to find optimizations on the behavior of the whole system. It does this for production maximization, waste minimization, water conservation, meet quality standards and other production goals.	conservation, quality standards								
6	of a pig farm to monitor pig health status and prevent diseases. The digital twin operates by deciding which of the sensed data are useful, performing simulation to find the optimal working conditions of the farm, a control system gets the results of the simulations to apply them to the physical system. The digital twin consists of a layer handling the connectivity between the sensors and their configuration, and a layer analyzing the given conditions in the farm, performing simulations, data handling and visualization. The analysis includes machine/ deep learning methods, the results of the simulations are used to control the farm and are presented in an intuitive interface.	improved animal welfare, disease cost reduction	animal/ agricultural building	concept	x	x				Jo et al. (2018)

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Table 3 (*continued*)

Use case No.	A digital twin:	Benefits	Physical twin	Technology readiness level	Service category					Citation
					Real-time monitoring	System failure analysis	Optimization / update	Technology integration tool	Energy consumption analysis	
7	of a harvested potato to gain insight into harvester damage to potatoes. During harvesting shocks have the greatest economic impact and potential damage to potatoes. The digital twin of the potato is a plastic object with the weight and size of a real potato, equipped with sensors to detect impacts and rotations. The data is analysed in real time on the harvester and presented to the machine user.	less damage to potatoes and higher profits for the farmers	agricultural product	prototype	x					Kampker et al. (2019)
8	of a tree and its surrounding in an orchard. The authors created a system that can create a digital twin for every tree in an orchard by using spinning 3D cameras. These cameras monitor the condition of every plant in 3D by capturing indicators that show their health, structure, and fruit quality among others. These digital twins allow the continuous monitoring of orchard production systems to predict stress, disease and crop losses, and develop a self-learning system. This self-learning system can be queried automatically to analyse varying scenarios based on environmental and management parameters.	discovery of higher orchard density layouts, detection of plant degrading indicators	living plant or tree	prototype	x		x			Moghadam et al. (2020)
9	of any agricultural entity, using holographic devices, augmenting the world with camera-based imaging, placing 2D or 3D content in the real world, simulating	enables the users to see the complete picture of a system leading in improved decision making	agricultural field, farm, landscape	concept	x	x	x	x	x	Qi et al. (2019)

(*continued on next page*)

Table 3 (*continued*)

Use case No.	A digital twin:	Benefits	Physical twin	Technology readiness level	Service category					Citation
					Real-time monitoring	System failure analysis	Optimization / update	Technology integration tool	Energy consumption analysis	
	them, and creating logs and maintenance events.									
10	of the cultivated landscape for supporting planners in designing agricultural road networks. The digital twin finds the road network segments with high relevance for agricultural transportation helping planners to modernize these segments according to the agricultural needs. The digital twin creates an information model (described as a UML class) by coupling spatiotemporal information of the cultivated landscape with complex analytical methods.	optimal agricultural road planning, a landscape representation model of high quality that can be reused for other causes	food supply chain and logistics	prototype		x	x	x		Machl et al. (2019)
11	of a cow that makes predictions for heat, estrus and health according to its behaviour. It is working based on data from a pedometer attached to the cow as well as company provided location services that accurately detect the cow's movement.	animal health analysis and prevention of diseases	animal	deployed	x	x				Kruize (2018)
12	of feed silos for livestock to monitor their status. It works by placing an IoT device on top of the silos and a cloud platform that allows the stakeholders to access the silo's status through various apps. When the silo stock reaches a certain threshold an alarm is send to the stakeholders phones. It also provides the ability to organize the stock	supply replenishment optimization, cost saving by reducing labour and transport costs, reduction of CO2 from transport emissions by 25%	food supply chain and logistics	deployed	x		x			Kruize (2018)

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Table 3 (*continued*)

Use case No.	A digital twin:	Benefits	Physical twin	Technology readiness level	Service category					Citation
					Real-time monitoring	System failure analysis	Optimization / update	Technology integration tool	Energy consumption analysis	
	replenishment with a simple action.									
13	that allows users to identify pest and diseases in plants. It is based on a mobile app with an on-the-field and on-the-fly systems for fast identification. The user takes photos of the plant and describes the problem, those two constitute the digital twin of the plant. Based on this digital twin a community of experts supports with their opinions to help identify the disease.	fast identification of pest and diseases in plants based on expert opinions	living plant or tree	deployed	x					Kruize (2018)
14	of a field and its machinery. It provides online visualization of the current position of any machine in the field along with historical movement data. It allows the real-time monitoring of machines and their energy consumption and evaluation of the economic efficiency of the crop management treatment.	insight into how the use of machinery for cropping affects a farmer's economics	agricultural field, farm, machinery/ agricultural machinery	deployed	x		x		x	Kruize (2018)
15	of olive trees to monitor olive fly occurrence. The digital twin is accompanied by an application which uses automated real-time imaging to capture images of pest traps that are then transferred to the digital twin twin. Olive growers can monitor the crop status remotely through the application.	allows for timely reactions to save the crop and product quality, reduce pesticide and labour cost	living plant or tree	deployed	x					Kruize (2018)
16	of bee colonies. The digital twin is created based on a GPS tracking system along with sensors for humidity, exterior & interior apiary temperature, brood temperature and weight. It provides	maintain healthy bee colony population, prevent pests, nectar flow monitoring	animal/ agricultural building	deployed	x	x	x			Kruize (2018)

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Table 3 (*continued*)

Use case No.	A digital twin:	Benefits	Physical twin	Technology readiness level	Service category: Real-time monitoring	System failure analysis	Optimization / update	Technology integration tool	Energy consumption analysis	Citation
	real-time continuous apiary monitoring that enables beekeepers to remotely control them and make management decision that interact with the bees as little as possible. It allows the beekeepers to manage the food storage reserves, to identify disease and pest infections, to inspect if queenless and swarming states exist, it provides an anti-theft mechanism, and insight into the colony status and hygiene.									
17	of a smart farm. The digital twin is built around small services and connects them together. These services provide information of particular systems such as the irrigation and seeding systems. The services use sensed data from soil probes, weather stations, irrigation systems and equipment analyzing and storing them using cloud services. The digital twin then uses these data for visualizations and for decision making actions which are then applied to the physical system through programmable logic controllers (PLAs).	sustainable development, insight into farm operations	agricultural field, farm, landscape	concept	x		x			Gomes Alves et al. (2019)
18	of the globe's agricultural systems using the WebGIS framework as an organizing principle that connects local, site-specific data generators to a regional and global view of agriculture using technologies like AI, IoT, drones, robots and Big Data, to aid in the	supports agricultural industry and government policy makers, increases incomes and global sustainability of agricultural systems	agricultural field, farm, landscape	concept	x		x	x	x	Delgado et al. (2019)

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Table 3 (*continued*)

Use case No.	A digital twin:	Benefits	Physical twin	Technology readiness level	Service category: Real-time monitoring	System failure analysis	Optimization / update	Technology integration tool	Energy consumption analysis	Citation
	development of site-specific conservation and management practices.									
19	of a vertical farm. The virtual and physical components are interconnected through sensors embedded in the materials of the farm structure that monitor temperature, humidity, luminosity and CO2. Embedding the sensors to the materials allows the digital twin to weight the data closest to the point of interest and establish an ideal value and variations for it. If the measured value is not in the expected range the digital twin controls actuators like air conditioning, air extraction, lighting and misting system. The data gathered by the sensors are analysed in the cloud and provide recommendations to producers to improve their production process.	structure sustainability, decision support, more profitable vertical farming	agricultural building	prototype	x	x	x		x	Monteiro et al. (2018)
20	of the world's agricultural resources. The digital twin will give instant access to critical data on the world's farmland. It will allow to share insights, materials and connection with the food supply chain.	data democratization, more equitable farming economy, more food at lower cost	agricultural field, farm, landscape	prototype			x	x		IBM Research (2018)
21	of a greenhouse which aids in decision making. It monitors the status of the greenhouse's fans, windows, sprayers and shading net as well as environmental factors like CO2, temperature, pH and solar radiation to analyze them	decision support	agricultural building	concept	x		x			R&D WORLD (2019)

(*continued on next page*)

Table 3 (*continued*)

Use case No.	A digital twin:	Benefits	Physical twin	Technology readiness level	Service category					Citation
					Real-time monitoring	System failure analysis	Optimization / update	Technology integration tool	Energy consumption analysis	
	and simulate different scenarios of decisions. It then visualizes the results to help the user take the optimal decision.									
22	of a parch of land. It makes multiple high resolution simulations of the cultivation procedure in parallel, taking into account information from many different sources. It does that continuously to account for several inputs, actions and stresses.	best response identification	agricultural field, farm, landscape	concept	x		x			Collins (2019)
23	of an indoor garden that calculates the ideal conditions for plants to grow. It uses the data gathered by a gardening robot such as humidity and nutrient content of the soil as well as simulations to determine what the robot has to do to ensure that each plant gets exactly the right quantity of nutrients and water it needs for ideal growth. The data gathered, the algorithms and the digital twin itself are saved in the cloud.	ideal plant growing conditions	agricultural building	prototype	x		x			Barnard (2019)
24	for aquaculture combining human intelligence and artificial intelligence to help fishermen develop accurate digital decision-making process for production management.	productivity increase, cost reductions	agricultural building	prototype	x		x	x		Chiu et al. (2019)
25	for livestock that uses a computer vision system installed on the dairy farm along with deep learning to monitor animal behavior and farm operations. It monitors the cows 24/7, sends notifications to the farmer's phone about event in the	constant cattle monitoring, shows where there is room for improvement, improved milk production and animal well-being	animal/ agricultural building	deployed	x		x	x		Mokal and Sharma (2020)

(*continued on next page*)

Table 3 (*continued*)

Use case No.	A digital twin:	Benefits	Physical twin	Technology readiness level	Service category: Real-time monitoring	System failure analysis	Optimization / update	Technology integration tool	Energy consumption analysis	Citation
	farm, and provides interpretations using analytic techniques to point which operations can be optimized.									
26	of tractors. Tractors are fitted with IoT sensors that monitor how they operate in real-time and proactively prevent malfunctions.	prevent equipment malfunctions, improve asset uptime	agricultural machinery	deployed	x		x	x		Ohnemus (2020)
27	of tomato crops. The digital twin consists of a 3D simulation model fed with real-time sensor data from a greenhouse. The interactions of the crop variety, the environmental factors and crop management are simulated in the virtual model.	prediction refinement to make better choices for the real crop	living plant or tree	concept	x		x			Wageningen University & Research (2020)
28	of an arable or dairy farm to monitor the existing nitrogen cycle. The digital twin consists of crop growth models, soil models and business management systems which are linked with a variety of data like company, weather and sensor data.	improved decisions on whether to supplement nitrogen or to prevent losses	agricultural field, farm, landscape	concept	x	x	x	x		Wageningen University & Research (2020)

and manufacturing applications. In agriculture, even the non-living physical twins, as those of agricultural buildings, still indirectly interact with plants or animals. The direct or indirect interactions with living systems introduce more challenges for DT in agriculture.

We identified only two overlapping use cases between our searches for agricultural DT, and DT in other disciplines. Use cases (*uc. 83, 84*) correspond to (*uc. 6, 3*). We expected a larger number of overlapping use cases, especially as our search of DT in other disciplines did not exclude agriculture-related use cases. This may be an indication that agricultural DT have not been adopted extensively, as they are not selected as representative use cases in DT reviews.

The benefits of the applications mentioned in the agricultural use cases include cost reductions (*uc. 6*), more detailed information (*uc. 3*), catastrophe prevention (*uc. 15*), positive economic impacts (*uc. 7*), aid in decision making (*uc. 4*) and more efficient management operations (*uc. 12*). Looking at the benefits of DT in other disciplines, we observe that they have a broader range. They also include safer human-machine interaction (*uc. 58*), building cost and energy efficiency estimation (*uc. 35*), and insights into complex multidisciplinary systems (*uc. 94*). DT in agriculture have not yet reached the point to demonstrate similar benefits.

Regarding the TRL, we were initially surprised to see that all levels are approximately equally represented. This large number of field-deployed or production-level DT could indicate a high adoption level in agriculture. However, upon closer inspection, we noticed that 6 out of 8 deployed DT were extracted from a single article (Verdouw and Kruize, 2017), reporting on the results of the FIWARE Accelerator Programme (FIWARE Foundation, 2020), whose purpose was to create applications using the FIWARE platform.[3] Apart from the DT deployed by the FIWARE program, we observe that there has been little progress in advancing DT beyond the concept and prototype levels to the production level, where they can be used in real-world conditions. A reason for this may be that in other disciplines there are greater financial incentives, and larger research capacity to try out new technologies, or report their findings at earlier stages. Also, some applications on the conceptual level were described abstractly without any detailed technical design reporting, i.e. *uc. 1, 3, 9*. To our knowledge, Wageningen University and Research has recently introduced an investment theme on Digital Twins, developing twins of tomato crops and arable and dairy farms, but they are still on a conceptual stage (*uc. 27, 28*).

Another interesting finding from Fig. 3 was that the supply chain and logistics and agricultural machinery twins were the only ones that did

[3] A framework of open source components to develop applications for the Internet of Things.

Table 4
The source, article type and publication year of the use cases for the literature review in agriculture.

Citation	Use case No.	Source	Article type	Year	Title
Smith (2018)	1	Web of Science	journal	2018	Getting value from artificial intelligence in agriculture
Tagliavini et al. (2019)	2	Web of Science	journal	2019	Multiphysics modeling of convective cooling of non-spherical, multi-material fruit to unveil its quality evolution throughout the cold chain
Paraforos et al. (2019)	3	Web of Science	journal	2019	ISO 11783-compatible industrial sensor and control systems and related research: A review
Tsolakis et al. (2019)	4	Web of Science	journal	2019	AgROS: A Robot Operating System Based Emulation Tool for Agricultural Robotics
Tan et al. (1094)	5	Google Scholar	journal	2019	Digital Twin Technology for Aquaponics: Towards Optimizing Food Production with Dynamic Data Driven Application Systems
Jo et al. (2018)	6	Google Scholar	conference	2018	Smart Livestock Farms Using Digital Twin: Feasibility Study
Kampker et al. (2019)	7	Google Scholar	conference	2019	Business Models for Industrial Smart Services - The Example of a Digital Twin for a Product-Service-System for Potato Harvesting
Moghadam et al. (2020)	8	Google Scholar	journal	2020	Digital Twin for the Future of Orchard Production Systems
Qi et al. (2019)	9	Google Scholar	journal	2019	Enabling technologies and tools for digital twin
Machl et al. (2019)	10	Google Scholar	journal	2019	Planning Agricultural Core Road Networks Based on a Digital Twin of the Cultivated Landscape
Kruize (2018)	[11–16]	Google Scholar	conference	2017	Digital twins in farm management: illustrations from the FIWARE accelerators
Gomes Alves et al. (2019)	17	Google Scholar	conference	2019	SmartAgriFood and Fractals A digital twin for smart farming
Delgado et al. (2019)	18	Google Scholar	journal	2019	Big Data Analysis for sustainable Agriculture on a Geospatial Cloud Framework
Monteiro et al. (2018)	19	Google	conference	2018	Towards Sustainable Digital Twins for Vertical Farming
IBM Research (2018)	20	Google	website	2018	#twinning: Farming's digital doubles will help feed a growing population using less resources
R&D WORLD (2019)	21	Google	website	2019	Digital Twin Solutions for Smart Farming
Collins (2019)	22	Google	website	2019	Agility in Digital Farming
Barnard (2019)	23	Google	website	2019	In the digital indoor garden
Chiu et al. (2019)	24	Google	website	2019	"Digital Twin Solutions for Smart Farming", the III Development AI + HI Total Solution, Awarded R&D 100.
Mokal and Sharma (2020)	25	Google	website	2020	Use Cases: Digital Twin in Livestock Farming
Ohnemus (2020)	26	Google	website	2018	Digital Twin Excellence: Two Shining Examples
Wageningen University & Research (2020)	27, 28	Google	website	2020	WUR is working on Digital Twins for tomatoes, food and farming

not have any use cases on the conceptual level. While this could be circumstantial, it may also indicate that agricultural DT targeting these sectors are more mature than others. As DT of agricultural supply chains and logistics build upon relatively similar deployments in other supply chains and manufacturing, this could explain their relatively higher level of maturity. However, we did not check thoroughly to what extent DT of agricultural supply chains are concerned with perishables. This argument also pinpoints a significant challenge of DT in agriculture: Most agricultural operations have to do with living subjects, like animals and plants or perishable products, and creating DT for such systems is harder than for non-living human-made systems.

Another reason why most DT are on concept and prototype level might be that agriculture is a slow adopter of technology, partly due to the growing complexity of information technology (Delgado et al., 2019). To successfully develop DT, the community must become familiar with a variety of related technologies including Internet of Things, machine learning and big data. Most of these technologies are still considered new fields of experimentation in agriculture (Basso and Antle, 2020), and once the community gains confidence around them and adopt best practices for their application, we are likely to see more DT emerging in prototype and deployed levels.

Considering the service categories, most of the agricultural DT offer monitoring and optimization services. Other service categories reported

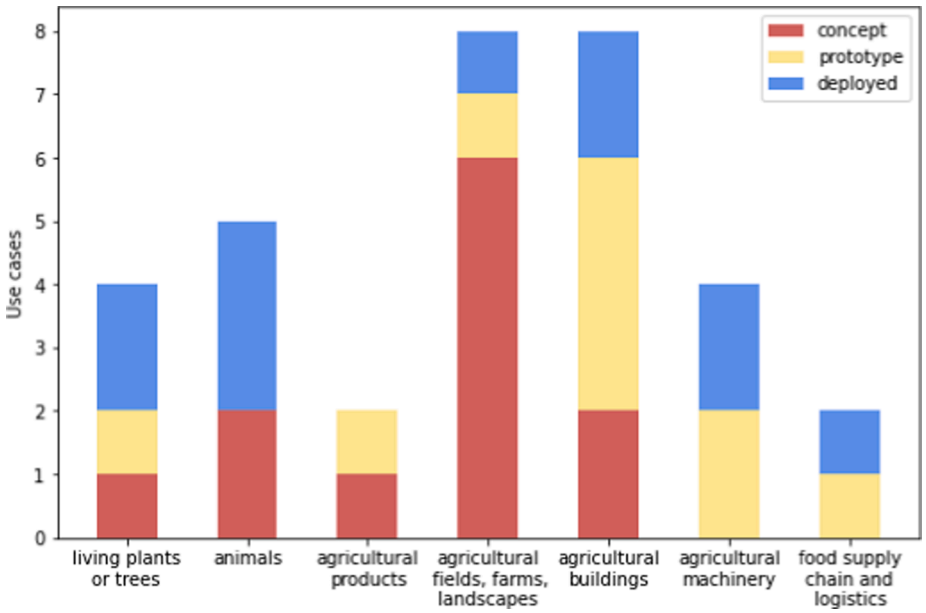

Fig. 3. Classification of physical twins in agriculture. The colors indicate the maturity level of the DT.

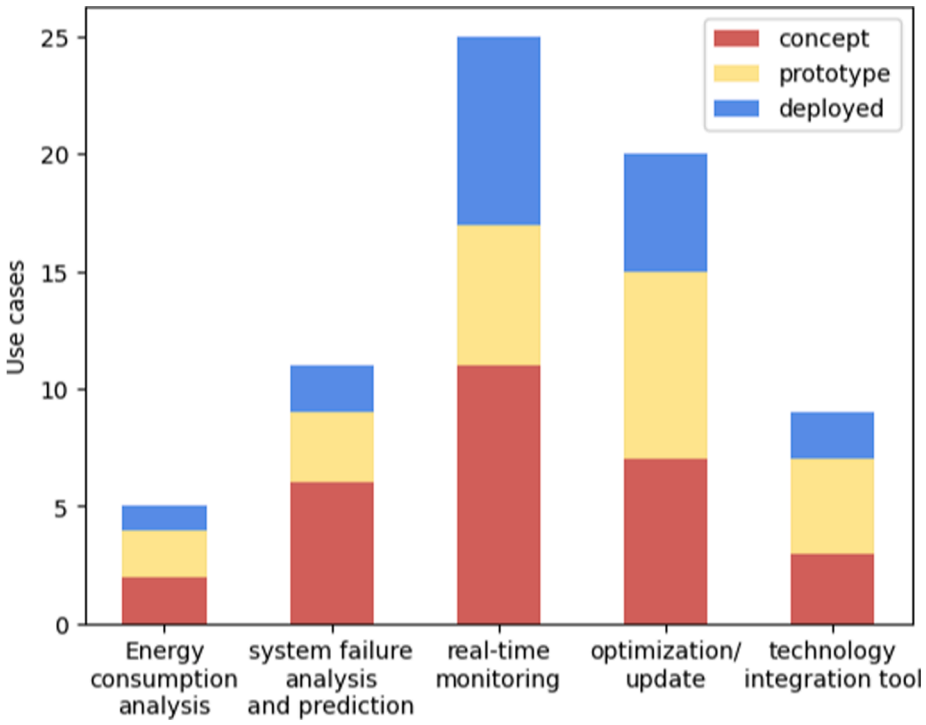

Fig. 4. Service categories of DT use cases in agriculture. The colors show the maturity level based on TRL.

were related to energy consumption analysis, and a few of the DT acted as technology integration tools. In other disciplines, we also came across the *virtual maintenance* category which was absent in agricultural DT. A reason for this gap could be that implementing an advanced technology like DT with more complex operations can be expensive (Delgado et al., 2019), at least in the early experimental phase of its adoption. Applications of DT performing virtual maintenance could be useful for determining the optimal repair/maintenance strategy of agricultural machinery before laying hands on it, similar to repairing subsea equipment in (*uc. 75*).

Regarding the variety of the applications, from Fig. 3 we observe that a variety of applications like livestock farming (*uc. 6*), cropping (*uc. 4*) and apiculture (*uc. 16*) are encompassed. Yet, we believe that there is more room for DT to grow in each subfield. In our view, one of the reasons for not having a wider range of applications is the added complexity of the systems that DT pursuit to digitize, especially as this domain is lagging in digitization. Many agricultural systems are living systems, comprising of complex processes, which are harder to model than DT of products or human-made systems. This is in agreement with our findings related to DT in healthcare, another domain that also has to do with living physical twins: Only two use cases were identified related to healthcare (*uc. 22, 46*). Challenges related to living physical twins include capturing underlying processes that are still not well-understood, and accurately monitoring certain processes, for example

Table 5
The use cases of DT in all disciplines. Use cases are referred as "uc" and their corresponding numbers in the text. The numbering of the use cases continues from the use cases in agriculture.

Use case No.	A digital twin:	Benefits	Technology readiness level	Discipline	Service category						Citation	Publication year	Application Year
					Real-time monitoring	System failure analysis and prediction	Optimization / update	Technology integration tool	Energy consumption analysis	Virtual maintenance			
29	as an installer base management system to manage machines	assist in data structuring and management of machines	prototype	manufacturing	x	x	x				Cimino et al. (2019)	2019	2019
30	for the organization of the production line	handle flexibility of production system	prototype	manufacturing	x		x				Cimino et al. (2019)	2019	2018
31	for machine reconditioning	machine reconditioning	prototype	manufacturing	x	x					Cimino et al. (2019)	2019	2018
32	performing machine optimization in the design phase	–	prototype	manufacturing			x				Cimino et al. (2019)	2020	2018
33	monitoring the interaction of humans and machines to prevent accidents	human safety in workplace	prototype	manufacturing			x				Cimino et al. (2019)	2019	2019
34	for workplace redesign	improved working conditions, improved productivity	prototype	industry			x				Cimino et al. (2019)	2019	2019
35	of a building providing ways to make it more energy efficient	building cost and energy consumption estimation, discovery of technical issues that may arise	prototype	construction					x		Kaewunruen et al. (2018)	2018	2018
36	simulating different scenarios of a biology model to verify its credibility	provide a traceable route to model credibility and acceptance	concept	biology				x			Patterson and Whelan (2017)	2017	2017
37	of a vehicle providing historical information and recreating past states and estimating future states	monitor current state, recreate past and future	prototype	automotive industry	x	x					Fraga-Lamas and Fernández-Caramés (2019)	2019	2017
38	for the optimal organization of a shop floor	improved resource management	concept	manufacturing			x				Zheng et al. (2019)	2019	2017
39	of the production process performing simulations to find the optimal parameters of the production process	trace process performance, find potential improvement	concept	manufacturing			x				Zheng et al. (2019)	2019	2017
40	for product service systems calculating the optimal	autonomous interaction and further	concept	business			x				Zheng et al. (2019)	2019	2018

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Table 5 (*continued*)

Use case No.	A digital twin:	Benefits	Technology readiness level	Discipline	Service category						Citation	Publication year	Application Year
					Real-time monitoring	System failure analysis and prediction	Optimization / update	Technology integration tool	Energy consumption analysis	Virtual maintenance			
	parameters for the system	optimization of the components											
41	for the monitoring of a shop floor and the identification of anomalies	improve visibility of real-time operations, faster and more accurate identification of anomalies	deployed	manufacturing	x	x					Tilbury (2019)	2019	2017
42	calculating optimal assembly schedules	optimal assembly schedules	concept	manufacturing	x		x				Tilbury (2019)	2019	2018
43	for the product design stage	–	prototype	manufacturing			x				Tilbury (2019)	2019	2017
44	for 3D printing monoliths	insight into heat and mass transfer during solidification	concept	biomolecular engineering	x						Dewitt et al. (2018)	2018	2017
45	of a ship that allows for the assessment of the vessel before its construction	virtually assess the safety and performance of vessels	concept	shipping			x			x	Bolton et al. (2018)	2018	2017
46	of a country that helps bring together different aspects of management and take optimal decisions	–	concept	management	x		x				Bolton et al. (2018)	2018	2017
47	of a mobile network that finds the optimal parameters to reduce energy consumption	lower power consumption	prototype	telecommunications					x		Dong et al. (2019)	2019	2019
48	of a manufactured product detecting surface anomalies	improved detection surface anomalies	concept	manufacturing	x						Cohen et al. (2019)	2019	2019
49	of a smart product monitoring its status	monitoring through product lifecycle, aid in decision making for maintenance and end of product life	concept	manufacturing	x	x	x				Tomiyama et al. (2019)	2019	2019
50	to represent an array of contributors and verify the reliability of their operations	reliability verification	concept	manufacturing	x						Tomiyama et al. (2019)	2019	2019
51			concept	manufacturing		x						2018	2017

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Table 5 (*continued*)

Use case No.	A digital twin:	Benefits	Technology readiness level	Discipline	Service category						Citation	Publication year	Application Year
					Real-time monitoring	System failure analysis and prediction	Optimization / update	Technology integration tool	Energy consumption analysis	Virtual maintenance			
	for the product design phase that helps tot optimize product parameters and identify potential flaws	optimize design scheme, forecast and verify product functions									Qi and Tao (2018)		
52	for the monitoring of a manufactured product for the assessment of its performance and identification of flaws	predict lifetime, performance, faults	concept	manufacturing	x	x					Qi and Tao (2018)	2018	2017
53	to proactively maintain aircraft structure and virtually diagnose problems	reduce cost, improve reliability	prototype	aerospace engineering	x	x					Qi and Tao (2018)	2018	2012
54	for the monitoring of the aircraft structure and the prediction of its service life	facilitate the management of aircraft service life	deployed	aerospace engineering	x	x					Tao et al. (2019)	2019	2011
55	for monitoring the degradation of machine equipment	monitor machine operation and predict surface roughness	prototype	manufacturing	x	x					Tao et al. (2019)	2019	2017
56	for the organization of the production line	more reliable, flexible, predictable production process	concept	manufacturing			x				Tao et al. (2019)	2019	2016
57	analyzing aircraft wing structural damage	predict fatigue cracks in wings	prototype	aerospace engineering	x	x					Tao et al. (2019)	2019	2015
58	bringing many aspects of the manufacturing process under the same umbrella for optimization	smooth interactions among human, machine, product	concept	manufacturing			x				Tao et al. (2019)	2019	2017
59	optimizing parameters for a magnet insertion process	production optimization	prototype	manufacturing			x				Tao et al. (2019)	2019	2017
60	for geometry assurance of manufactured products	–	concept	manufacturing	x	x					Tao et al. (2019)	2019	2017
61	to reduce material waste and prolong machine lifetime	reduce material waste, prolong machine lifetime	concept	manufacturing	x	x					Tao et al. (2019)	2019	2017
62	monitoring the operational state of wings		prototype	aerospace engineering	x	x					Tao et al. (2019)	2019	2017

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Table 5 (*continued*)

Use case No.	A digital twin:	Benefits	Technology readiness level	Discipline	Service category						Citation	Publication year	Application Year
					Real-time monitoring	System failure analysis and prediction	Optimization / update	Technology integration tool	Energy consumption analysis	Virtual maintenance			
63	predicting the time of failure for aircraft tires	improved prediction of probability of failure of tire	prototype	aerospace engineering	x	x					Tao et al. (2019)	2019	2017
64	for predicting manufacturing parameters	more accurate predictions than classic models	deployed	additive manufacturing			x				Tao et al. (2019)	2019	2017
65	for a driver assistance system	reduce complexity, increase flexibility	concept	automotive industry			x				Tao et al. (2019)	2019	2017
66	a system to control multiple digital twins of wind turbines	–	concept	renewable energy	x						Tao et al. (2019)	2019	2018
67	to control the cooling of a power system	–	prototype	renewable energy	x		x				Tao et al. (2019)	2019	2018
68	simulating different scenarios for the construction of a power system	automation, data visualization, decision making	deployed	power systems	x		x				Tao et al. (2019)	2019	2017
69	for the monitoring and energy efficient use of the pipes of a wastewater treatment plant	energy saving, forecast faults	deployed	wastewater plant	x				x		Tao et al. (2019)	2019	2018
70	optimizing the operations of a wind farm	operation efficiency increase by 20%	prototype	renewable energy			x				Tao et al. (2019)	2019	–
71	of a locomotive form its design to its end of life for monitoring and optimization of its parameters	timely operation optimization	deployed	rail industry	x	x	x				Tao et al. (2019)	2019	2016
72	of a hospital used for bed planning and work allocation	–	deployed	healthcare			x				Tao et al. (2019)	2019	–
73	for maintaining oil/ gas facilities in remote areas	improve reliability of oil facility	deployed	oil industry	x	x					Tao et al. (2019)	2019	2018
74	for the optimization of an aircraft assembly line	optimize operation efficiency	concept	manufacturing			x				Tao et al. (2019)	2019	2017
75	producing prognostics for subsea equipment	cost effectiveness, security of equipment	concept	subsea cable						x	Tao et al. (2019)	2019	2017
76			prototype	automotive industry	x	x	x					2019	–

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Table 5 (*continued*)

Use case No.	A digital twin:	Benefits	Technology readiness level	Discipline	Service category						Citation	Publication year	Application Year
					Real-time monitoring	System failure analysis and prediction	Optimization / update	Technology integration tool	Energy consumption analysis	Virtual maintenance			
	to analyze engine speed, oil pressure and other parameters to prevent vehicle breakdowns	prevent breakdowns, more efficient engine development									Tao et al. (2019)		
77	to monitor equipment status	enhance operation resilience and flexibility	concept	manufacturing	x	x					Lu et al. (2020)	2020	2020
78	of human workers to monitor their health and working conditions and provide productivity optimizations	worker health, production performance	concept	manufacturing			x				Lu et al. (2020)	2020	2020
79	of a factory	creation of self organizing factories, with complete operational visibility, flexibility	concept	manufacturing			x				Lu et al. (2020)	2020	2020
80	providing insight into production network operations	unprecedented visibility into operation performance, predict future needs in the network	concept	manufacturing			x				Lu et al. (2020)	2020	2020
81	to monitor a gas turbine, detect anomalies and perform what-if scenarios	real-time monitoring, in-depth analysis of deviation, scenario assessment	concept	chemical engineering	x	x	x				Raman and Hassanaly (2019)	2019	2019
82	for material fabrication	growth of material knowledge	concept	material science				x			Yi Wang et al. (2019)	2019	2019
83	to monitor pig health and prevent diseases	reduced animal disease costs	concept	agriculture	x	x					Paraforos et al. (2019)	2019	2018
84	using ISOBUS sensors to provide better field prognostics	continuous detailed crop and soil information	concept	agriculture	x	x					Paraforos et al. (2019)	2019	2018
85	of a neuromusculoskeletal system to estimate optimal muscle activation patterns	estimate optimal muscle activation patterns	concept	neurorobotics			x				Pizzolato et al. (2019)	2019	2019
86	to easily reconfigure production lines	–	concept	manufacturing	x		x				Mabkhot et al. (2018)	2018	2017

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Table 5 (*continued*)

Use case No.	A digital twin:	Benefits	Technology readiness level	Discipline	Service category						Citation	Publication year	Application Year
					Real-time monitoring	System failure analysis and prediction	Optimization / update	Technology integration tool	Energy consumption analysis	Virtual maintenance			
87	as a test bench for a benching beam	–	prototype	manufacturing			x				Mabkhot et al. (2018)	2018	2018
88	to monitor the production line	trace process performance, find potential improvement	prototype	manufacturing			x				Mabkhot et al. (2018)	2018	2017
89	to easily reconfigure production lines	trace process performance, find potential improvement	prototype	manufacturing			x				Mabkhot et al. (2018)	2018	2018
90	of a vertical milling machine monitoring its health status	avoid sudden downtime	prototype	manufacturing	x	x					Mabkhot et al. (2018)	2018	2017
91	of an aluminium smelter	energy reduction, insight into performance and deviations from target	prototype	manufacturing			x		x		Gupta and Basu (2019)	2019	2019
92	for the optimization of the production line	optimize production line functionality	concept	manufacturing			x				Ghobakhloo (2018)	2018	2018
93	for the monitoring and evaluation of a product during its lifetime	status of product through its lifecycle for consumers. Evaluation of product for companies	concept	manufacturing	x						Ghobakhloo (2018)	2018	2018
94	of a city to manage it based on lifestyle and prevent disasters	forecast issues related to lifestyle and disasters	concept	management			x				Kim and Kim (2017)	2017	2017
95	of tourism destinations to assess different parameters	assess positive and negative impact of tourism, also in sustainability	concept	management	x						Kim and Kim (2017)	2017	2017
96	serving detailed information about the whole production process	reduced downtime, reduced maintenance costs, machine setup time reduction	prototype	manufacturing			x				Longo et al. (2019)	2019	2019

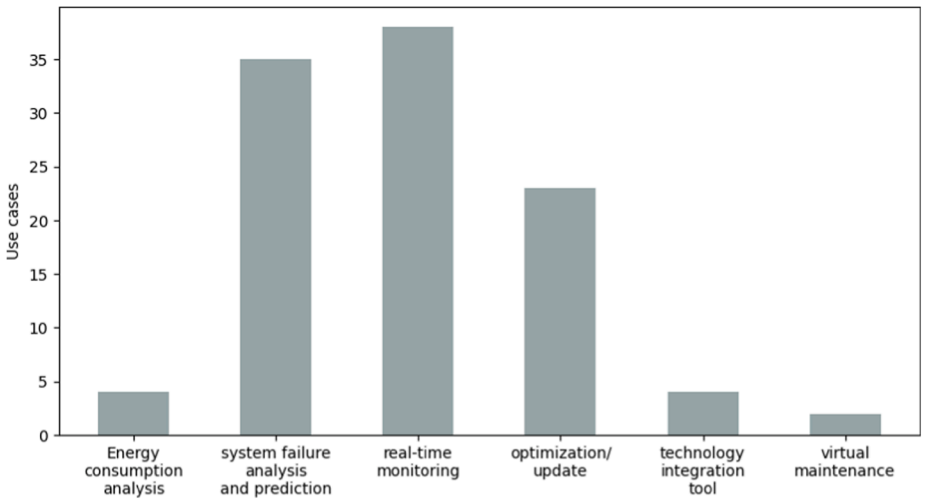

Fig. 5. The DT service categories for DT in other disciplines. The majority of the proposed DT perform monitoring, optimization and system failure analysis operations.

nitrogen leaching in crop systems. In agricultural systems, it is also common that certain processes are not digitized because there are no financial incentives for doing so.

Another aspect affecting the adoption of DT in agriculture is that the community has to build trust in the interplay of the DT components for its correctness. This trust is essential to create DT that can accurately represent the inner workings of a system, propose maintenance strategies and alternative ways of management. Yet, building this trust in agriculture is difficult, because many decisions affect living systems where, unlike in other disciplines, consequences can be hard to reverse.

The lack of data culture also slows the adoption of DT in agriculture. DT require large amounts of data to operate, and the expected benefits are not eminent in small-scale deployments. In this respect, the lack of a data culture (Jones et al., 2017) and compartmentalization of agricultural systems understanding inhibits DT development and decreases potential for adoption. As a last note, integrating DT components and updating them in real-time can be daunting. For a community that is highly interdisciplinary and less information technology-oriented (Brown et al., 2019), this is a major turnoff.

4.2. The added-value of digital twins

This review identified few applications of DT in agriculture, with several of them being only superficially described in the corresponding articles. This suggests that DT benefits have not been clearly communicated to the agricultural community yet. Consequently, the community has not yet had the chance to investigate how they could utilize them and include them in their current practices. In this section, we pinpoint in the form of characteristics the benefits that DT can bring to agriculture. The characteristics can be seen in Fig. 6.

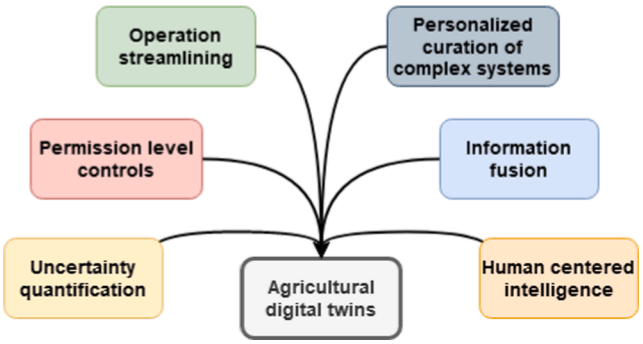

Fig. 6. The characteristics of DT that can benefit agricultural applications.

The vision behind DT is to offer **personalized curation of complex systems**. This means that DT can account for local system idiosyncrasies, that are often too complex to be accounted for in a generic model. DT adapt to local conditions in each individual physical twin, by fusing data and learning from them. DT are customized to mimic the individual characteristics of each system instance and deployment, and expose the system under different perspectives like system health, operation effectiveness, and profitability.

Streamlining of operations is another characteristic of DT. They offer an automated pipeline of operations like data acquisition from sensors, performing simulations, creating reports and controlling actuators. These operations are executed continuously, without requiring the attention, time and expertise of the users. DT bring together operations that previously were offered by a range of tools, hide their complexity, save time and remove context switching obstacles for the users. In this way, DT democratize technology and make it available to a wider range of stakeholders.

A key aspect of DT is **information fusion**, as they integrate and enrich information originating from several heterogeneous sources. DT observe physical twins from different perspectives by using multiple sources of data and assessing possible outcomes of actions. Information fusion combined with the continuous nature of operations depicts the complete picture of the past and current state of the system, and allows to estimate future states.

Uncertainty quantification is another characteristic of DT. DT can take into account the cumulative effect of the involved uncertainties since they observe systems from different angles. This information can then be customized and communicated to the stakeholders according to their expertise.

DT often embed **permission level controls**. The type of reports and controlling mechanisms can vary, based on the user of the application. This makes it possible to create different levels of transparency, depending on the sensitivity of the handled data and the importance of the operations taking place.

Finally, DT may demonstrate **human-centered intelligence** to control mechanisms for aspects that were neglected in the past, like human-machine interaction for safer working environments.

4.3. The future of digital twins in agriculture

The added value of DT has not yet materialized in agricultural applications. DT could be used pervasively, on different spatial and temporal scales and with varying levels of complexity, depending on their

components and the desired functionality. We expect that the future of DT will evolve from simpler cases, exhibiting fewer components, to more sophisticated ones. We propose a roadmap for the development of DT in agriculture, starting from simple DT applications, with fewer components and simpler functionality, gradually adding components and functionality, to demonstrate the full potential of DT.

On a fundamental level, a DT will include monitoring, user interface and analytic components. These components are the first step towards empowering a DT to monitor and analyze agricultural systems and offer a continuous stream of operations. An example DT with these components could be deployed to monitor the microclimate of a greenhouse and provide insights for its management. In this case, the DT would monitor environmental conditions, like solar radiation, humidity and CO_2, analyze them according to user-defined thresholds and report its findings, similar to the use case (*uc. 21*).

A slightly enhanced DT could include actuator components to control fans and windows in a greenhouse. The monitoring and control operations would be performed continuously, notifying different stakeholders with information that is relevant to them. For instance, in the case of consecutive stormy days, the DT would notify the farmer that it closed the windows because the temperature dropped, and notify the supply chain stakeholders that the production will be delayed because the plants cannot grow fast enough with the current weather. Also, the DT will report which indicators surpassed certain thresholds, thus taking specific actions using its actuators, and consequently assuring the stakeholders of its correct operation. Similar twins could be deployed to food silos (*uc. 12*) to keep track of their stock and autonomously organize their proactive replenishment, notifying the supply chain stakeholders and farmers respectively, and to livestock farms to keep track of environmental indicators that are known to affect animal welfare (*uc. 25*).

Further enhancing DT with simulation components is necessary for them to support decision-making based on past and future predicted states of the physical twin. A dairy farm DT could use simulation to forecast the occurrence of mastitis due to intensive milking for each individual cow. Utilizing this DT, a farmer could evaluate multiple milking scenarios and choose the one that strains the cow the least (*uc. 1*). Data analysis and simulation would happen in local or guaranteed cloud infrastructure to ensure data privacy. More advanced, simulations could investigate factors that have already lead to the appearance of mastitis, and result in improved breeding decisions. On an agricultural farm, DT of fields could use simulation to approximate the behavior of equipment in local conditions (*uc. 4*). Utilizing such a DT, a farmer could test a harvester, before purchasing it, on her local field with different weather scenarios to measure fuel consumption and plant damage.

Incorporating a learning component brings agricultural DT to the next level. A learning component may allow DT to assist in management operations for systems where the underlying mechanisms are unclear. In the case of a livestock farm, a DT with learning capabilities would be able to find patterns in real-time and in historical environmental data that could facilitate the onset and spread of diseases like swine fever. This would help stakeholders to take proactive measures to prevent not only the spread but also the appearance of diseases (*uc. 6*). Additionally, the DT would identify the most important variables shaping these patterns, estimate related risks, and clearly communicate the involved uncertainties, by presenting probability metrics for example.

Towards Digital Earth (Goodchild et al., 2012), a large-scale DT of an agricultural landscape, may consist of multiple DT of individual farms, each with several learning components. Such a DT will be able to consider the inter-field dynamics regarding water flow, fertilizer dispersion and nutrient leaching. It would provide variable fertilizer rates, based on site-specific intelligence, for example what amount can be absorbed by each field without being dispersed to other fields, and how much each field should be irrigated considering groundwater levels, and the availability of irrigation infrastructure. This would happen by learning from historical data about how the amount of fertilizer and irrigation affected the crop yield and depleted the nutrients of each field in the past. Ultimately, the DT would constantly improve itself in defining the acceptable fertilizer amounts and irrigation through continuous learning, also learning from the past decisions of the individual farmer. Besides, capitalizing on this information would lead to the creation of better cropping patterns, using different constraints like weather, profitability and field nutrient replenishment rate.

Further improving agricultural twins with a human-machine interface component would allow the establishment of safer working environments. A DT of a harvester with a human-machine interface component could trace the position of the workers and their actions to ensure that the machine is distant enough to avoid injuries (*uc. 33*). Also, a DT of grain bins could detect human presence inside the bin with cameras, and stop the procedures that cause grain movement to prevent entrapment. This is crucial as a large number of injuries occur every year with agricultural equipment due to the lack of safety measures (Jadhav et al., 2016).

Overall, DT can be applied to several agricultural subfields like plant and animal breeding, aquaponics, vertical farming, cropping systems and livestock farming. Adopting DT can start with simple setups, that can be gradually enhanced with more components to make them more intelligent and autonomous.

4.4. Considerations regarding the application of DT in agriculture

The application of DT in agriculture also involves potential pitfalls. As mentioned in (Smith, 2018), controlling physical twins through their virtual counterparts may lead to a lack of attention to the real-world systems. In agriculture, such neglect could cause irreversible damage, as DT are applied to living physical twins, among other things.

There are also cases where DT are not yet feasible, due to the large amount of resources they require to be developed, and the high complexity of the physical twins (West and Blackburn, 2017). This could be the case of some agricultural system interactions that cannot be accurately quantified yet. There are also concerns about the technology skills required to create DT (Lohtander et al., 2018). DT development requires specialized knowledge from several technology domains, which can be a serious threat in an already multidisciplinary domain like agriculture.

Synchronization between the physical and virtual twins is another target that is difficult to achieve (Talkhestani et al., 2018). In agriculture, human-made systems like agricultural equipment could be easier to synchronize with the virtual system, unlike natural systems such as animals or land parcels.

Also, the integration of DT components can be difficult (Kurth et al., 2019). In agriculture, this could be the case for combining the simulation and monitoring components for crops, as they rely on different infrastructures, software and end-users.

Last but not least, the widespread success of DT in agricultural applications does not only depend on technology, skills, or data infrastructures and availability but the involved business aspect. As with any new technology that is to be introduced in a farm, DT need to demonstrate their added value and the return on investment.

5. Conclusion

Returning to our first research question, we found that there are already a few applications of DT in agriculture. However, they are in primary stages and are not designed thoroughly enough to offer the benefits that other disciplines enjoy. Exceptions included some deployed applications that were part of a European Union-funded program. We believe that there is still a long way to go before the agricultural community can fully seize the benefits of DT. Agricultural researchers and stakeholders should make an effort to stay up-to-date with technological advancements and seek to find links between agricultural problems, and problems that are solved with DT in other disciplines.

Regarding the second research question, we proposed a roadmap of applications, starting from DT with simpler functionality, incrementally adding components to gradually demonstrate the benefits that are already present in other disciplines. As for the twins themselves, we foresee that there will be some confusion in the coming years about what a DT is and when a technology can be considered a DT. Research has been done to classify technologies based on how close they are to becoming DT (Kritzinger et al., 2018), but it is still difficult to identify when a system can be called a DT. For the needs of most agricultural applications, we suggest that a DT should have at least the monitoring, interface and analytic components.

We identified two distinctive characteristics of DT in agriculture while reviewing the use cases and proposing our application roadmap. The first difference is that many agricultural DT involve directly or indirectly living systems and perishable products. While DT are ideal to provide insights into such complex systems and incorporate non-deterministic processes, their integration with the physical twin can be difficult. This is further amplified due to the idiosyncrasies of living physical twins. The second difference lies in the spatio-temporal dimension of their operation. DT in other disciplines range between the size of an airplane to that of a factory. Agricultural DT range from individual plants and animals to twins of land parcels, farms, or regions. As such, one may need to consider effects across these scales. On the temporal dimension, agricultural DT differ due to the slower response rates of their physical twins. Agricultural processes like the growing of plants tend to evolve relatively slow, so at least initially there is no need for high-frequency interactions between physical and digital twins. These two characteristics of agricultural DT need to be considered when developing DT inspired by DT in other disciplines.

As a final note, given the potential for the adoption and the benefits of applying DT in agriculture, we strongly believe that they have the prospect to bring a technological breakthrough in the near future.

CRediT authorship contribution statement

Christos Pylianidis: Conceptualization, Methodology, Validation, Investigation, Data curation, Visualization, Writing - original draft, Writing - review & editing. **Sjoukje Osinga:** Conceptualization, Methodology, Validation, Writing - review & editing, Supervision. **Ioannis N. Athanasiadis:** Conceptualization, Methodology, Validation, Writing - review & editing, Supervision, Project administration, Funding acquisition.

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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