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Interoperable agricultural digital twins with reinforcement learning intelligence

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ABSTRACT

Digital twins and artificial intelligence are increasingly explored to support decision-making. In this work, we introduce a modular and interoperable architecture that combines digital twins with reinforcement learning for adaptive decision-making in complex environmental systems. We apply this approach to smart farming, where efficient resource use is critical to balance productivity with environmental impact. Our contributions are threefold: (a) the augmentation of agricultural models as digital twins—specifically the crop growth model WOFOST and the plant disease model A-scab—that assimilate field data to reflect current crop conditions; (b) the integration of reinforcement learning agents that generate recommendations for pesticide and fertilizer application—the first to demonstrate interoperable reinforcement learning-integrated digital twins in operational agriculture; and (c) the development of a FIWARE-based interoperability layer that integrates a diverse set of (edge) components. We demonstrate our approach in two pilot studies—apple scab management and nitrogen application in winter wheat—showcasing its potential for real-world application in diverse agricultural contexts and its transferability to other domains.

1. Introduction

The escalating consequences of environmental degradation and climate change are urging governments and industry to adapt their policies, adopt green practices, and enhance resilience. Addressing these challenges requires more advanced methods for understanding, predicting, and managing complex environmental systems. Digital twins, virtual representations of physical systems or processes, are emerging as evolutionary tools in environmental science, valued for their ability to simulate system dynamics and support informed decision-making [13,14,56].

Digital twins are being developed across a range of environmental applications, from large-scale ones like those focused on climate [66,42,95], ocean [91], and biodiversity [89], to more local scale systems, such as urban flood prevention [37] and farm management [74].

As digital twins evolve, their capabilities are increasingly enhanced through integration with artificial intelligence (AI) [59]. AI is used to enhance simulation capabilities (e.g., by emulating complex process-based models [49,85]), or to enhance decision making in operational conditions (e.g., by addressing issues related to data availability and resolution) [75]. Leveraging AI techniques allows for the development of sophisticated control strategies that are more adaptive than traditional rule-based approaches. Most current applications of AI in digital twins rely on supervised learning methods such as regression and classification. However, reinforcement learning (RL), a subfield of machine learning focused on sequential decision-making, offers a particularly promising, though less explored, alternative for optimization tasks [11,36,38,70]. Several barriers have impeded broader adoption of RL, most notably its data-intensive training requirements, the well-known sim-to-real gap—where differences between simulated and real-world states hinder direct applicability—and limited interpretability due to its black-box nature. In this work, we address these challenges by (1) leveraging RL agents pre-trained in a simulation environment that enables extensive training without real-world trials; (2) deploying them through a digital twin that continuously adapts to real-time data, thereby helping to bridge the sim-to-real gap; and (3) enhancing inter-

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pretability by using the digital twin to simulate what-if scenarios. This approach introduces a new blueprint for adaptive decision support and sustainable practices with digital twin intelligence.

One area where digital twins hold significant promise is in the transition towards sustainable agriculture. Policy frameworks such as the European Green Deal [31] accelerate the transition towards more environmentally responsible farming, particularly by encouraging reductions in pesticide and fertilizer use. Smart farming systems, which integrate advanced technologies such as smart sensors, data analytics, and robotics into agricultural practices, are seen as key enablers of more sustainable farming [23,54,79]. Digital twins within smart farming are dynamic models that evolve with real-time data from diverse sources, including IoT sensors and edge devices [93,74]. They provide tools for monitoring crops, simulating scenarios, forecasting various outcomes, and generating optimized action suggestions for farmers and autonomous systems.

The effective deployment of digital twins is significantly challenged by interoperability issues [77,55]. Data that feeds into digital twins is frequently generated by disparate digital systems with limited compatibility, hindering data exchange [25]. While numerous standards define specific approaches to data modeling, entity relationship specifications, and data exchange, interoperability at scale is impeded by the lack of coherent mappings between these standards. Successful implementation of these standards within the broader technological context of smart farming necessitates robust, practically validated processes. Therefore, to facilitate smooth and cost-effective standard compliance, a wider range of technological enablers is required for integrators. Guided by the principle of interoperability, we developed a blueprint that leverages the FIWARE framework—including the NGSI-LD standard [28]—best practices in data modeling, and a set of enabling tools for scalable implementation

In this paper, we present an integrated approach that combines digital twins, AI-based control strategies, and interoperable data infrastructure to support adaptive and sustainable agriculture. While digital twins and RL have each received growing attention in smart farming, their combined use—particularly in operational settings—remains underexplored. Our work addresses this methodological gap by demonstrating how digital twins and offline-trained RL agents can be brought together in an interoperable system for real-world agricultural applications.

We demonstrate our approach through two digital twins for smart spraying systems. Our contributions are threefold: (1) we augment agricultural models—specifically the crop growth model WOFOST and the plant disease model A-Scab—as digital twins that continuously assimilate field data to accurately represent current crop status; (2) we integrate reinforcement learning agents trained to provide optimized recommendations for pesticide and fertilizer use; and (3) we develop a FIWARE-based interoperability layer that enables seamless integration of heterogeneous (edge) components using NGSI-LD data models and APIs. Together, these contributions form a modular, standards-compliant platform that supports adaptive and interoperable smart farming applications and beyond.

This paper is structured as follows. Section 2 reviews related work in the areas of digital twins, artificial intelligence, and interoperability, in the context of smart farming. In Section 3, the system design is elaborated. Specifically, our digital twin catalog, the reinforcement learning approach, the smart data model, and the constituent components of our implementation. Section 4 presents the deployment in two pilot studies. Finally, Sections 5 and 6 provide a discussion of the findings and the concluding remarks, respectively.

2. Background and related work

2.1. Digital twins

Digital twins are emerging as a key technology within Smart Farming, offering virtual representations of agricultural assets and processes [93,74,65,18,30]. Implementations range from digital shadows—systems with unidirectional data flow that reflect sensor data and may include simulation and prediction—to true digital twins that enable two-way interaction, allowing not only virtual modeling but also (real-time) influence on the physical system. While often grouped under the same term, digital shadows lack the interactive feedback loop that defines true digital twins. Applications include modeling the impact of different irrigation strategies [4] and optimizing fertilization [75].

In agricultural digital twins, the core often consists of an agricultural model that simulates elements of the farming system. The complexity of such a model can vary widely, ranging from simple statistical models to sophisticated process-based crop growth models. For instance, a basic statistical model might predict end of season yield based on historical weather and fertilizer data. At the other end of the spectrum, complex crop growth models [24,50], such as DSSAT [44], APSIM [43], or WOFOST [21], mathematically simulate crop development as a function of crop characteristics, weather, (nutrient) inputs, and soil conditions.

Accurate synchronization between a digital twin and its physical counterpart is essential, as it directly affects the quality and applicability of its outputs. Synchronization is typically achieved through a two-stage process, namely (1) initial model calibration and (2) continuous data assimilation throughout the growing season to update model states with real-world observations.

Model calibration involves tuning the parameters of the (agricultural) model using historical or experimental data, or values from the literature. In crop growth models, calibration usually focuses on parameters that influence key physiological processes, such as photosynthesis, biomass partitioning, and phenology (i.e. the timing of plant growth stages). Calibration of crop growth models is a well-researched area. While many protocols exist and several parameters have clear physiological interpretation, there is no single universally accepted best practice [96,82], and empirical parameter estimation remains common.

Continuous synchronization throughout the growing season is maintained through data assimilation techniques. Generally, three methods are employed to incorporate incoming field data into crop growth models: forcing, updating and recalibration [47]. In the forcing method, state variables in the crop model are replaced with observed data, which generally comes from remote sensing data or ground-based measurements, where the observed data is matched to the crop model's time step. Interpolation is used to fill the gap between the timing of observed data and the time steps of the crop model. The updating method utilizes observation data to update a state variable at a specific time step of the simulation. The new state variables are computed as a weighted combination between the simulated state variables and the observed state variables. In the recalibration method, model parameters or initial conditions are re-estimated. Key data assimilation anchor points typically include observations of Leaf Area Index, soil moisture, and vegetation indices [61,22].

2.2. Artificial intelligence

The integration of AI may further improve agricultural decision support within digital twins. While traditional digital twins often rely on predefined rules to guide management actions, AI introduces more adaptive and data-driven strategies. One particularly powerful AI technique, Reinforcement Learning (RL), has shown great promise in optimizing complex agricultural decisions [11,68,36]. The potential of RL in precision agriculture has been demonstrated across various (research) applications, including climate control in greenhouses [58], irrigation and fertilization scheduling [68,19,88,53], crop planning [90], and scheduling data collection [7].

RL is a machine learning paradigm where intelligent agents learn optimal policies through a process of trial and error [8]. Intelligent agents interact with an environment, exploring various strategies and learning from the rewards they receive for achieving desirable outcomes. In the context of agriculture, this environment is often a simulated agricultural model, such as a crop growth model. Examples of such simulation environments for crop management tasks include frameworks like CropGym [68,53], gym-DSSAT [35], CyclesGym [90], and FarmGym [63].

The learning behavior of RL agents can be shaped by defining and using different reward functions which focus on specific objectives, like maximizing yield, minimizing resource use, or enhancing environmental sustainability. Flexibility in designing rewards helps tailoring decision support systems for various agricultural needs. Once trained, RL agents can act on top of a digital twin, using its current state (e.g., crop health, weather conditions, soil moisture) to recommend an action (e.g., apply a specific amount of fertilizer), based on its learned policy [38].

2.3. Interoperability

Smart farming often integrates various systems from multiple vendors, which typically leads to significant interoperability challenges [94,84,77,3]. Interoperability encompasses syntactic (common data formats and protocols) and semantic (shared understanding of data meaning via ontologies) levels [92,34,83,81,80]. Semantic interoperability is crucial for enabling advanced decision-making, such as in smart spraying applications [77].

Achieving interoperability at scale requires the existence of comprehensive and widely used standards. Syntactic interoperability is handled with a family of TCP/IP standard protocols and higher-level standards based on them (e.g., MQTT, HTTP, JSON, XML). In the context of smart farming, ISO 11783 - ISOBUS is a standard for machinery and other field equipment, while the ISO 23247 series addresses digital twins [67]. Semantic interoperability requires common ontologies, which extend traditional definitions into computable knowledge representations [33,94]. Typical ontologies in agriculture include FAO's AGROVOC [2], Seamless [5], SAREF4Agri [72] and FoodOn [26], alongside best practice models from research projects such as DEMETER's Agriculture Information Model [69] and Ploutos' Common Semantic Model [16].

However, an ontology is only one part of the solution. The wider adoption of these standards and ontologies depends on the availability of a wider ecosystem of tools and validated methodologies that make the integration of the standards and ontologies cost effective. One such ecosystem is the FIWARE framework comprising smart data models, context brokers, and standard interface/model NGSI-LD. The latest initiative is to build agricultural data spaces [57] as collaborative environments for exchange of data and knowledge in a trusted and interoperable manner while maintaining data sovereignty.

3. System design

This paper presents a decision-support system that brings together digital twins, reinforcement learning, and interoperability frameworks. Fig. 1 shows the concept of the designed system and how each component is involved. The digital twins are based on agricultural models that are kept in sync with field conditions through data assimilation. AI agents, provide data-driven recommendations for pesticide and fertilizer application. The AI agents are trained using reinforcement learning within dedicated training environments that wrap around the agricultural models, preparing them for deployment in the farm. We use the FIWARE framework to support consistent and scalable data exchange between cloud and edge systems, relying on Smart Data Models and the NGSI-LD standard to ensure interoperability.

In the following sections, we detail the components of our system: the digital twins for crop monitoring, the RL-based AI agents for spraying recommendations, and the interoperability framework.

3.1. Digital twin catalog

3.1.1. Apple scab management model

The digital twin for apple scab management is based on the A-scab model, a well-established dynamic simulation model for predicting primary infections of *Venturia inaequalis* in apple orchards, originally developed by [76]. The A-scab model captures key stages of the disease cycle, including pseudothecia development, ascospore maturation, discharge, deposition, and infection risk assessment throughout the growing season. The model computes a risk score for each infection, and predicts the onset of symptoms.

We extended the original A-scab model by adding a module for pesticide application with contact fungicides. The module simulates the impact of fungicide treatments on the survival rate of released spores, taking into account the development stage of the spores. Furthermore, the module considers pesticide coverage dynamics, including wash-off due to rainfall, and the growth of new biomass. The model assimilates observational field data, including the biofix date—defined as either the first observed ascospore release or the date of bud break—as well as crop state indicators such as LAI. The model is driven by hourly weather data, which we derive from OpenMeteo [98].

3.1.2. Wheat fertilization management model

The digital twin for wheat is based on the World Food Studies (WOFOST) crop growth model [21]. WOFOST is a generic crop model that supports a wide range of crops. WOFOST simulates water-limited and nitrogen-limited crop growth, which allows simulations of outcomes of different fertilization actions [10]. The model is driven by weather data derived from OpenMeteo [98]. Soil conditions are calibrated by sourcing from SoilGrids [71], while crop parameters are selected from the WOFOST crop parameter database based on the specific variety grown [21]. In addition, any discrepancies regarding mirroring can be addressed through data assimilation [22,45]. Within the digital twin, we have adopted a variational approach in which crop model parameters are fully-automated recalibrated using an objective function that minimizes the differences between observed measurements and simulated outputs, with the recalibrated parameters constrained within physiologically plausible bounds to ensure realistic values. Specifically, the model integrates Leaf Area Index (LAI) and phenology observations to refine growth predictions dynamically. The following key crop model parameters are re-estimated: TSUM1 (temperature sum from emergence to anthesis), TSUM2 (temperature sum from anthesis to maturity), TDWI (initial total crop dry weight), and SPAN (life span of expanding leaves). These parameters were selected in accordance with [20], given their strong influence on phenological development and leaf growth. These processes, in turn, affect biomass and nutrient partitioning, photosynthesis, and ultimately yield formation. Given the non-differentiable nature of the crop model, we employ a derivative-free optimization strategy using the Subplex algorithm [78] from the NLOpt library [48].

Fig. 2 illustrates how the digital twin operates for the winter wheat use case. The system uses observed data to align the digital twin to the physical crop through calibration and provides simulations for crop development over the forecast period.

3.2. Reinforcement learning

3.2.1. Pesticide recommendations with RL

The pesticide recommendation system is based on reinforcement learning, with the RL agent trained to prevent yield loss resulting from apple scab infections while minimizing pesticide usage. Training was conducted in *AscabGym* [51], which utilizes the A-scab model as described in section 3. The RL agent can apply pesticide daily, at one of six discrete levels: 0, 0.2, 0.4, 0.6, 0.8, and 1. These levels pertain to spraying volume. *In silico*, the trained RL agent exhibits precise spraying actions compared to a common weather forecast spraying heuristic, minimizing risk of apple scab infections while reducing use of pesticide.

3.2.2. Fertilizer recommendations with RL

The fertilizer recommendation system is based on reinforcement learning, with the RL agent trained to maximize nitrogen use efficiency (NUE). Here, we utilize the EUNEP framework [29], where NUE is defined as a ratio N_{output}/N_{input}. N_{output} refers to the amount of N in the yield of a crop, and N_{input} includes all N inputs, such as fertilizer, initial

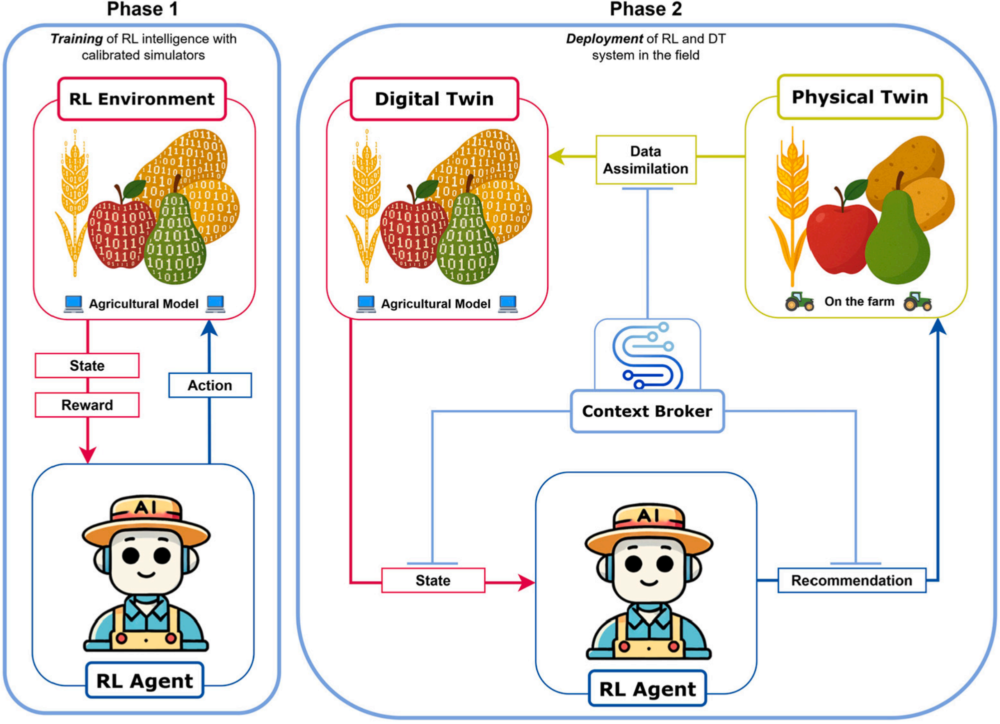

Fig. 1. A concept diagram depicting the main principle of our approach. In phase 1, the RL agent is trained *offline* with calibrated agricultural models. In phase 2, the digital twin is deployed. The digital twin provides current states to the RL agent, which then provides recommendations for the physical twin. The digital twin is kept in sync with its physical counterpart by means of data assimilation. Communication between each entity is provided by the context broker.

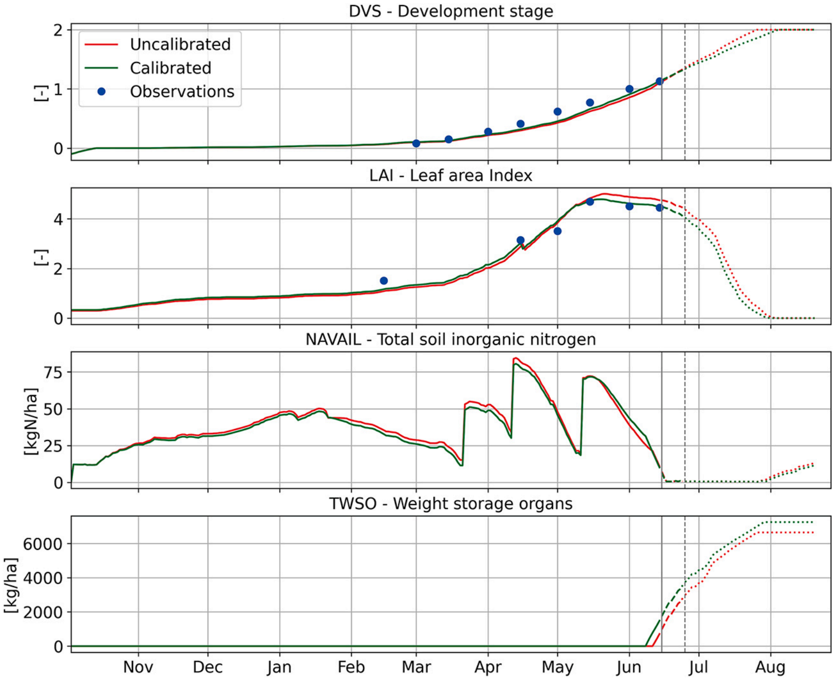

Fig. 2. Example output of the digital twin system for winter wheat, illustrating how the system integrates calibration, reinforcement learning (RL) decisions, and model simulations. The plot shows the evolution of key crop variables over time. Calibration is performed using a variational approach that updates crop model parameters by minimizing discrepancies between simulated outputs and observed values. Observations of Development Stage (DVS) and Leaf Area Index (LAI) are assimilated to refine crop model parameters related to phenology and leaf development. A simulation is triggered on 15 June, as denoted by the solid vertical line, using weather forecasts for the first 10 days, followed by historical weather averages. Three nitrogen fertilization applications were included, as recommended by the RL agent: 60 kg on 20 March, 80 kg on 10 April, and 60 kg on 10 May.

Table 1
Components and their descriptions.

Component	Description
Edge Field Systems	Components for retrofitted tractors, including vision systems for crop monitoring and smart sprayers for crop management.
Orion Context Broker	Main interoperability component, providing an NGSI-LD compliant API for basic CRUD operations on platform entities such as crops, fields, tractors, and measurements.
MongoDB	Entity context database for the Orion Context Broker. Storing the current state of platform entities.
QuantumLeap	REST middleware for storing and querying NGSI-LD spatial-temporal data, ensuring proper storage of digital twin outputs in CrateDB.
CrateDB	Database behind QuantumLeap used for storing time-series data.
Digital Twin Simulator	Cloud intelligence component capable of monitoring and simulating (future) crop states.
AI Recommender	RL-based AI agent deciding when to fertilize or spray with pesticides.
Dashboard	User interface for the platform, providing an overview of parcels, the ability to enter farm management data, trigger digital twin simulations, and view simulator outputs.

soil nitrogen, nitrogen in seeds, and atmospheric deposition. The training setup, including reward design and agent constraints, is described in [6]. Training was conducted in CropGym [68,53], which employs the WOFOST crop growth model to simulate crop growth under different fertilization regimes. The trained RL policy showed improved NUE, compared to standard practice. The RL agent can apply nitrogen fertilizer at one of nine discrete levels: 0, 10, 20, 30, 40, 50, 60, 70, 80 kg/ha per week. The reward function incentivizes maintaining NUE within an optimal range, avoiding both soil depletion and excessive nitrogen usages that can lead to leaching and pollution. Additionally, an action constrainer was implemented to limit the number of recommended fertilization events throughout the growing season.

3.3. Smart data models

Our system integrates data from a variety of sources, including autonomous field systems, historical data on crops and fields, manual feedback from end users, and third-party data. These data sources form the upstream data pipelines, which feed into the digital twins and their connected reinforcement learning-based decision-making agents which operate in the cloud. Actionable decisions are then sent downstream to autonomous field systems at the edge.

Syntactic interoperability is supported through the Next Generation Service Interface - Linked Data (NGSI-LD) [28], which is developed and maintained by the FIWARE organization. NGSI-LD is based on JSON-LD [86] and serves as both a standardized data model and an API for exchanging and managing contextual data. It defines entities with explicit attributes and relationships. As such it ensures structured interoperability. Contexts in NGSI-LD specify an entity's domain, attributes, and relationships, enabling seamless data exchange between services. NGSI-LD also defines a common interface for handling contextual information on entities, supporting create, update, query, and delete operations, with built-in event subscriptions for real-time updates to dependent applications interested in the status of specific entities.

The Orion Context Broker, which is an open-source FIWARE component, serves as the core interoperability hub, linking all components of the system. The project manages agricultural entities such as crops, fields, fertilizers, and pests, along with interconnected components like autonomous tractors, vision systems, and farm operations. The definitions of entities are standardized using Smart Data Models [32].

Fig. 3 depicts the relationships between different Smart Data Model entities used. Contextual data on these entities is stored by the Orion Context Broker, and is used to build the digital twins of crops in order to simulate their development.

3.4. Components

The platform covers both edge and cloud components, as shown in Fig. 4 and Table 1. All components are deployed in the cloud as Kubernetes pods. Services are registered for the dashboard and pods which expose APIs for data querying, like the Orion Context Broker and QuantumLeap. During cluster startup, subscriptions are registered in the Orion Context Broker for the Digital Twin simulator and QuantumLeap, as these services need to be notified of new data on field operations, and simulation results from the Digital Twin simulator.

Data communication occurs in two main flows: one for data acquisition, and the other for communicating simulation results to the user and command messages to edge devices in the field. Data acquisition is mainly carried out at the edge by autonomous field systems. Along with this, 3rd party weather (forecast) data is collected. Lastly, farmers can manually enter data on field operations or enter legacy data for specific crops and fields. The upstream and downstream flows are visualized in Fig. 4. Following data acquisition, simulations are conducted automatically by the Digital Twin simulator on a daily basis, analyzing the state of crops and providing predictions and recommendations to optimize yield while minimizing pesticide and fertilizer use. Simulation runs can also be triggered manually by farmers through manual data entry.

Fig. 5 illustrates the sequence of interactions between the components of the platform, showing (i) a general case when a user wishes to check the predictions of the digital twin along with future management recommendations of the RL components for the whole growing season, (ii) a daily loop that advances a simulation step, and (iii) a case where the user has acquired measurements in the field, triggering an update of the digital twin. The daily cron job case entails automatic alignment of weather data and farming context (i.e., management actions that have been done in the parcel).

4. Deployment in pilot studies

The platform is deployed in two pilot sites for two different use cases: one on disease control in apple production, and one on nitrogen fertilization in winter wheat cultivation. With these pilot deployments, started in the 2025 growing season, we aim to evaluate the practical feasibility of our solution in real-world farming environments.

4.1. Disease control (apple, Spain)

Apple (Malus × domestica) is a key commercial fruit crop in temperate zones, where apple scab stands out as the most widespread fungal disease impacting production [17]. Failure to control this disease adequately can result in economic losses reaching as high as 70% of the production value [87]. Consequently, managing this disease represents a major annual expenditure for apple producers in most growing areas [9]. A critical aspect of successful control, particularly for later infections on leaves and fruit, is preventing the initial ascospore infections, which often demands multiple fungicide applications during the growing season.

The system is deployed in an apple orchard located in Girona, Spain (42.16°N, 3.09°E). The 130-hectare orchard is divided into multiple fields, each dedicated to a single apple variety. A digital twin is instanti-

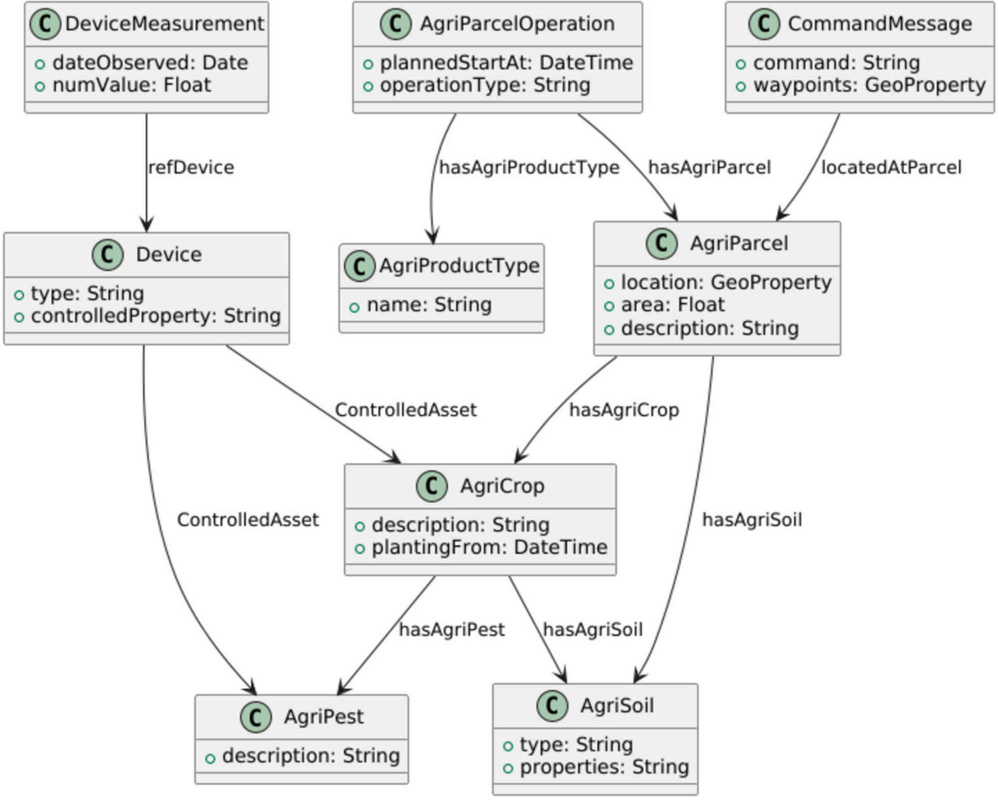

Fig. 3. Key entities and relationships modeled in the digital twin, using definitions from FIWARE Smart Data Models to enable semantic interoperability.

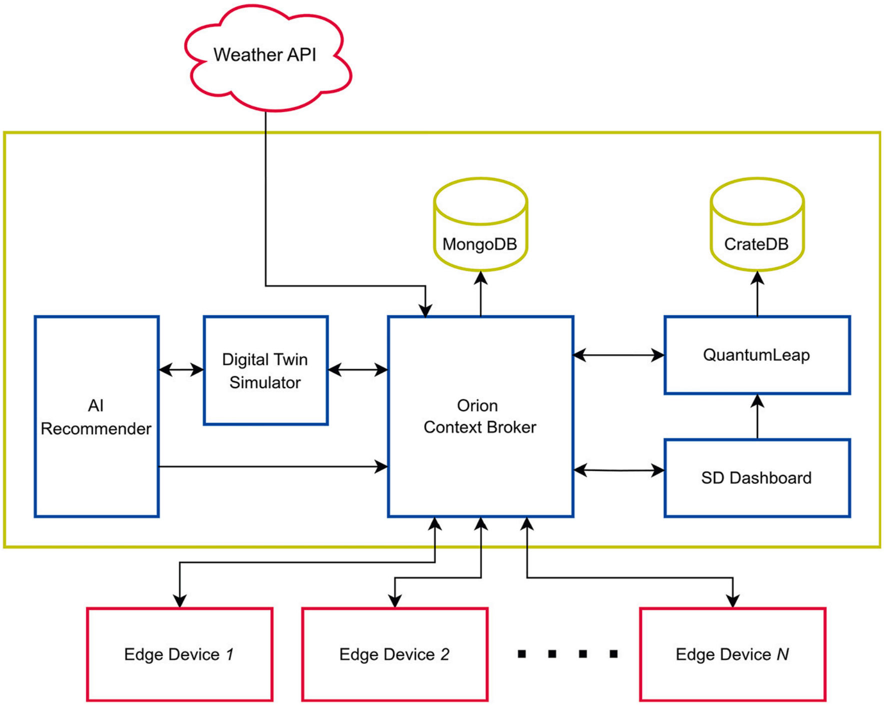

Fig. 4. The platform and communication between the various edge and cloud components. A brief description of each component is provided in Table 1.

ated for each field, providing field-level resolution of disease dynamics. To complement this, a fine-grained vision system, based on a tractor-mounted camera, captures images from the orchard to detect early symptoms of apple scab. Pesticide application decisions are informed by two components: a reinforcement learning agent operating on the digital twins, and the vision system identifying visible symptoms in the field. Spraying is triggered if either system indicates a need. The digital twin recommended seven sprays, matching the number applied under standard practice by the orchard manager. The timing of most applications was broadly consistent, with a marginally higher total dose and slightly lower estimated cumulative infection risk. Additional details are provided in our repository [46].

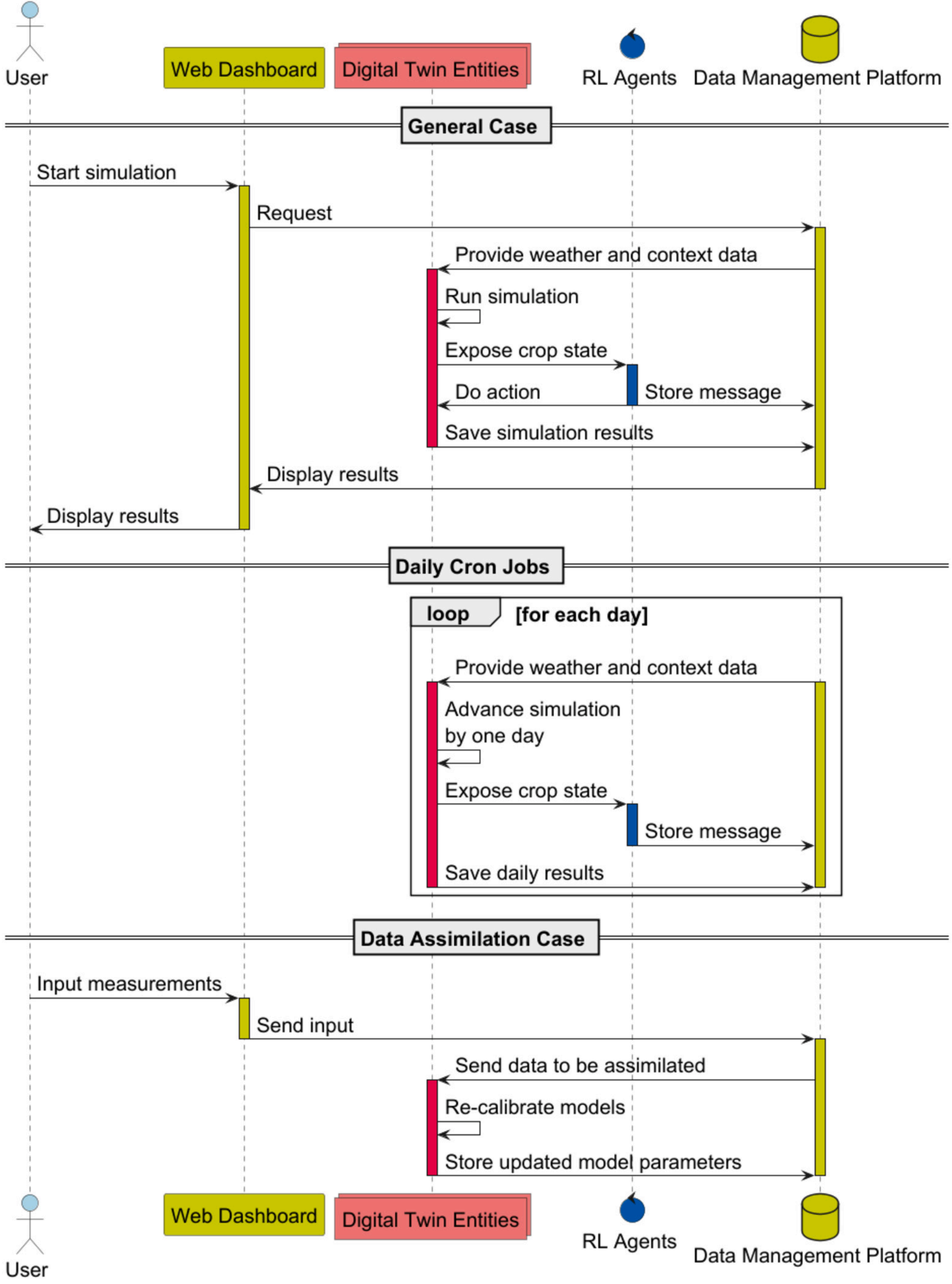

Fig. 5. Sequence diagram describing internal interactions between the system components for different use cases.

4.2. Nutrient management (winter wheat, Lithuania)

Wheat is the most widely cultivated crop globally [27]. In rainfed winter wheat systems, nitrogen is a key driver of yield. However, excessive nitrogen application can have harmful environmental consequences, such as the eutrophication of freshwater bodies and increased greenhouse gas emissions [97]. It is therefore crucial to effectively manage nitrogen application. Conventional farming strategies, which are often informed by experience or reactive observations, may struggle to capture the complex, and dynamic nature of daily field conditions [1,12].

The system is deployed across multiple plots of winter wheat, covering a total area of 90 hectares, in Radviliškio, Lithuania (55.75°N, 23.58°E) (see Fig. 6). This area is divided into 24 subfields based on soil parameter zonation established at the start of the season. A digital twin is created for each subfield. In-season synchronization between the digital twins and the physical crops is achieved through data assimilation, utilizing observations of Leaf Area Index and BBCH scale [64]. Reinforcement learning agents, operating on the digital twins, provide recommendations for nitrogen fertilization. The system is trained to restrict the number of applications to two per season, in line with standard farming practices. Recommendations are transmitted as command messages for approval by the farmer. In aggregation, the digital twin system recommended two side-dress fertilization events—40 kg N/ha in early March and 70 kg N/ha in early April—matching the number and total nitrogen advised by local agronomists (30 and 80 kg N/ha), though timing differed slightly. Estimated effects on crop development were similar. Additional details are provided in our repository [46].

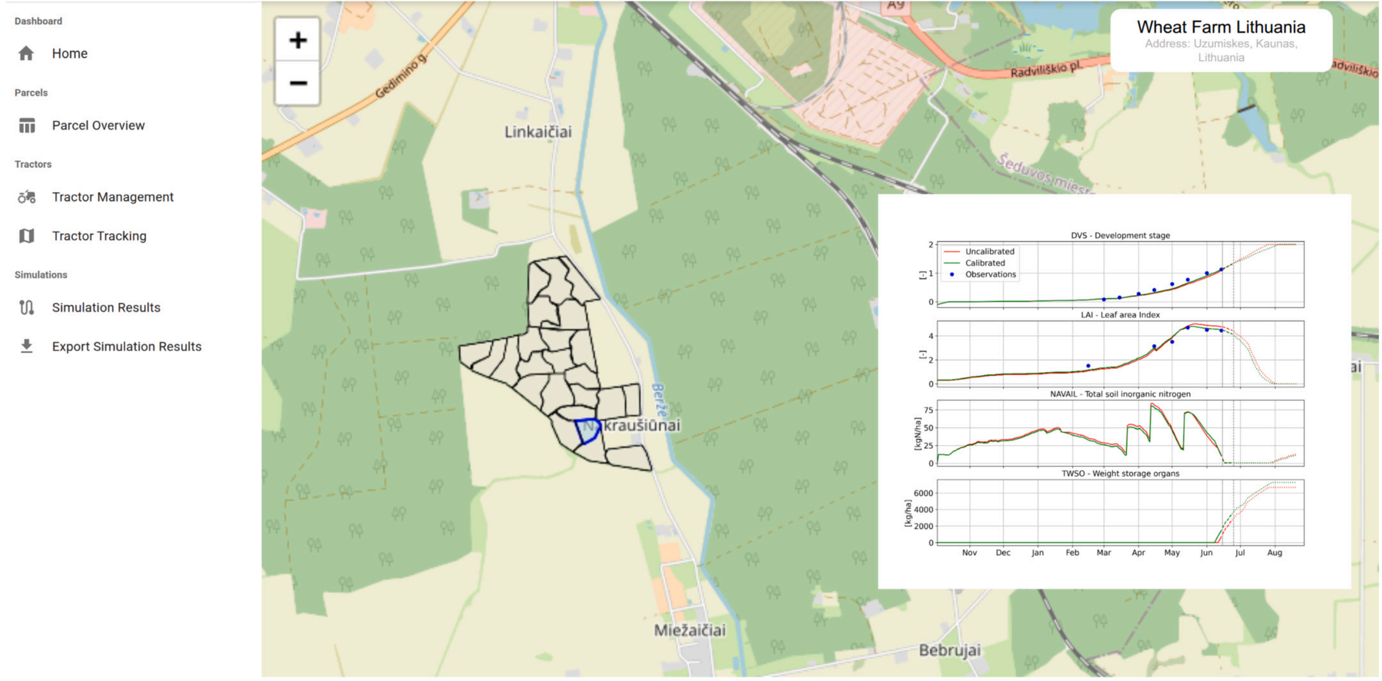

Fig. 6. Screenshot of the dashboard showing an overview of the winter wheat pilot area. For a selected subfield, the dashboard displays a visualization of crop growth over time.

5. Discussion

This study demonstrates a modular and interoperable system architecture that combines digital twins with reinforcement learning to support agricultural decision-making. The use of FIWARE and Smart Data Models facilitates cross-domain adaptation. By implementing digital twins for both apple scab control and nitrogen fertilization, we show that the system can accommodate distinct use cases, illustrating its flexibility and potential for generalization. The system is currently being piloted at two farm sites, each addressing a different use case, to explore its practical relevance and feasibility in real-world agricultural settings.

5.1. Lessons learned

A significant strength of our approach is its model-agnostic architecture. While our pilot studies focused on specific digital twin implementations for apple scab and winter wheat, the underlying framework is inherently flexible. Even within the concrete implementations used in these pilots, extending the system to other crops is well supported, as the WOFOST model can simulate a wide range of crops. Similarly, the RL agent can be adapted to new crops by retraining in e.g., the CropGym environment [53,68]. This flexibility also extends to additional farm management tasks, such as irrigation or the allocation of fertilization budgets across different parcels.

A key limitation is that the accuracy of any digital twin depends on both the underlying model and the rigor of its calibration. Calibration of digital twins particularly benefits from local historical data, ideally with sufficient variation in farm management practices and weather conditions [73]. However, such data is not always available. To minimize potential inaccuracies, in this work we incorporate data assimilation techniques.

Another practical limitation observed during our ongoing pilot studies is the cost associated with data collection. While we currently collect data regularly using a camera system mounted on a tractor, this approach may be too expensive for broader adoption. To reduce costs we can incorporate freely available remote sensing data [39,41], or utilizing a recommendation engine that identifies opportune moments for data measurements, as in Baja et al. [7], optimizing the efficiency of data collection efforts.

5.2. Outlook

Broader adoption depends on multiple factors, including agronomic effectiveness as well as socio-economic considerations such as cost-benefit trade-offs and user trust [25]. In particular, the opaque nature of reinforcement learning–based recommendations may pose challenges for acceptance. To address this, the system includes simulation-based visualizations aimed at increasing transparency and supporting informed decision-making.

Looking ahead, the digital twins that currently constitute the digital twin catalog (i.e., the A-scab model and the WOFOST crop model) are mechanistic, process-based models. Notwithstanding, we recognize the potential of data-driven and hybrid modeling approaches. Data-driven models can effectively capture complex relationships from large datasets, without restrictive assumptions, potentially improving predictive accuracy. We anticipate that future (agricultural) digital twins may incorporate hybrid models, which combine the scientific rigor of process-based models with the data-driven flexibility of machine learning [15,40,52,60,62]. More broadly, the core principles underpinning our approach—digital twins and RL-based control—are applicable across a variety of domains beyond smart farming. Adapting the system to new domains involves integrating a suitable process-based or data-driven model of the system dynamics, alongside retraining the RL agent within that environment.

6. Conclusion

This work introduced an interoperable architecture employed in smart farming, that combines digital twins, reinforcement learning agents, and (semantic) interoperability. Digital twins are implemented as process-based models of crop growth and disease risk, where data assimilation is used to sync with current field conditions. AI agents, which are trained through reinforcement learning, provide recommendations for pesticide and fertilizer application. Various components included in this system communicate through an interoperability layer built on the FIWARE framework, allowing them to work together effectively.

The architecture was demonstrated through two pilot studies: one focused on disease control in apple orchards in Spain, and the other on nitrogen fertilization in winter wheat fields in Lithuania. The pilots showcased the system's potential for real-world application. Although our initial focus was on spraying operations, the framework's modular design and interoperability make it adaptable to other areas of (precision) agriculture and other domains.

Future work includes scaling up the pilot studies to broader field conditions and farm types, and performing a more detailed evaluation of agronomic efficiency and cost-effectiveness. Scientific extensions involve expanding the digital twin catalog to cover additional crops and management tasks, such as irrigation, weeding and resource allocation, further enhancing the system's versatility and impact.

CRediT authorship contribution statement

Michiel Kallenberg: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Hilmy Baja:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Mihailo Ilić:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Aleksandar Tomčić:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Milenko Tošić:** Writing – review & editing, Software, Resources, Funding acquisition, Conceptualization. **Ioannis Athanasiadis:** Writing – review & editing, Visualization, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Software and data availability

The complete codebase is publicly available via GitHub at https://github.com/Smart-Droplets-Project. The repository was created and is maintained by the authors, with development initiated in 2023. The core components are written in Python, with the dashboard built using Next.js. Example data are included in the repository for demonstration purposes. The software is designed to be deployed in a Kubernetes environment. Contact: michiel.kallenberg@wur.nl.

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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Data availability

The codebase is available at https://github.com/Smart-Droplets-Project. Example data are included for demonstration purposes. The software is designed to be deployed in a Kubernetes environment.

References

[1] S. Abbas, M.T. Javed, Q. Ali, M. Azeem, S. Ali, et al., Nutrient deficiency stress and relation with plant growth and development, in: Engineering Tolerance in Crop Plants Against Abiotic Stress, CRC Press, 2021, pp. 239–262.

[2] AGROVOC, The AGROVOC multilingual dictionary of the United Nations food and agriculture organization, Available online, www.fao.org/agrovoc/, 2006.

[3] N. Ahmed, N. Shakoor, Advancing agriculture through iot, big data, and ai: a review of smart technologies enabling sustainability, Smart Agric. Technol. 100848 (2025).

[4] R.G. Alves, R.F. Maia, F. Lima, Development of a digital twin for smart farming: irrigation management system for water saving, J. Clean. Prod. 388 (2023) 135920.

[5] I.N. Athanasiadis, A.E. Rizzoli, S. Janssen, E. Andersen, F. Villa, Ontology for seamless integration of agricultural data and models, in: Metadata and Semantic Research, in: Communications in Computer and Information Science, Springer Berlin Heidelberg, Berlin, Heidelberg, 2009, pp. 282–293.

[6] H. Baja, M. Kallenberg, I.N. Athanasiadis, Adaptive fertilizer management for optimizing nitrogen use efficiency with constrained reinforcement learning, Comput. Electron. Agric. 237 (2025) 110554, https://doi.org/10.1016/j.compag.2025.110554.

[7] H. Baja, M. Kallenberg, I.N. Athanasiadis, To measure or not: a cost-sensitive, selective measuring environment for agricultural management decisions with reinforcement learning, Proc. AAAI Conf. Artif. Intell. 39 (2025) 27831–27840, https://doi.org/10.1609/aaai.v39i27.34999.

[8] A.G. Barto, Reinforcement learning: an introduction. By Richard's Sutton, SIAM Rev. 6 (2021) 423.

[9] T. Belete, N. Boyraz, Critical review on apple scab (venturia inaequalis) biology, epidemiology, economic importance, management and defense mechanisms to the causal agent, J. Plant Physiol. Pathol. 5 (2017) 2.

[10] H.N. Berghuijs, J.V. Silva, P. Reidsma, A.J. de Wit, Expanding the wofost crop model to explore options for sustainable nitrogen management: a study for winter wheat in the Netherlands, Eur. J. Agron. 154 (2024) 127099, https://doi.org/10.1016/j.eja.2024.127099.

[11] J. Binas, L. Luginbuehl, Y. Bengio, Reinforcement learning for sustainable agriculture, in: ICML 2019 Workshop Climate Change: How Can AI Help, 2019.

[12] R.E. Blackshaw, L.J. Molnar, H.H. Janzen, Nitrogen fertilizer timing and application method affect weed growth and competition with spring wheat, Weed Sci. 52 (2004) 614–622, https://doi.org/10.1614/WS-03-104R.

[13] G.S. Blair, Digital twins of the natural environment, Patterns 2 (2021).

[14] G.S. Blair, P.A. Henrys, The role of data science in environmental digital twins: in praise of the arrows, Environmetrics 34 (2023) e2789.

[15] R. van Bree, D. Marcos, I.N. Athanasiadis, Hybrid phenology modeling for predicting temperature effects on tree dormancy, in: Proceedings of the AAAI Conference on Artificial Intelligence, 2025, pp. 28458–28466.

[16] C. Brewster, N. Kalatzis, B. Nouwt, H. Kruiger, J. Verhoosel, Data sharing in agricultural supply chains: using semantics to enable sustainable food systems, Semant. Web 15 (2024) 1207–1237.

[17] O. Carisse, J. Bernier, Effect of environmental factors on growth, pycnidial production and spore germination of microsphaeropsis isolates with biocontrol potential against apple scab, Mycol. Res. 106 (2002) 1455–1462.

[18] S. Cesco, P. Sambo, M. Borin, B. Basso, G. Orzes, F. Mazzetto, Smart agriculture and digital twins: applications and challenges in a vision of sustainability, Eur. J. Agron. 146 (2023) 126809, https://doi.org/10.1016/j.eja.2023.126809.

[19] M. Chen, Y. Cui, X. Wang, H. Xie, F. Liu, T. Luo, S. Zheng, Y. Luo, A reinforcement learning approach to irrigation decision-making for rice using weather forecasts, Agric. Water Manag. 250 (2021) 106838, https://doi.org/10.1016/j.agwat.2021.106838.

[20] A. De Wit, H. Boogaard, A gentle introduction to wofost, https://www.wur.nl/en/show/a-gentle-introduction-to-wofost.htm, 2024. (Accessed 1 September 2025).

[21] A. De Wit, H. Boogaard, D. Fumagalli, S. Janssen, R. Knapen, D. van Kraalingen, I. Supit, R. van der Wijngaart, K. van Diepen, 25 years of the wofost cropping systems model, Agric. Syst. 168 (2019) 154–167.

[22] A.d. De Wit, C. Van Diepen, Crop model data assimilation with the ensemble Kalman filter for improving regional crop yield forecasts, Agric. For. Meteorol. 146 (2007) 38–56.

[23] M. Dhanaraju, P. Chenniappan, K. Ramalingam, S. Pazhanivelan, R. Kaliaperumal, Smart farming: Internet of things (iot)-based sustainable agriculture, Agriculture 12 (2022) 1745.

[24] A. Di Paola, R. Valentini, M. Santini, An overview of available crop growth and yield models for studies and assessments in agriculture, J. Sci. Food Agric. 96 (2016) 709–714, https://doi.org/10.1002/jsfa.7359.

[25] T. Dibbern, L.A.S. Romani, S.M.F.S. Massruhá, Main drivers and barriers to the adoption of digital agriculture technologies, Smart Agric. Technol. 8 (2024) 100459.

[26] D.M. Dooley, E.J. Griffiths, G.S. Gosal, P.L. Buttigieg, R. Hoehndorf, M.C. Lange, L.M. Schriml, F.S. Brinkman, W.W. Hsiao, Foodon: a harmonized food ontology to increase global food traceability, quality control and data integration, NPJ Sci. Food 2 (2018) 23.

[27] O. Erenstein, M. Jaleta, K.A. Mottaleb, K. Sonder, J. Donovan, H.J. Braun, Global trends in wheat production, consumption and trade, in: Wheat Improvement: Food Security in a Changing Climate, Springer International Publishing, Cham, 2022, pp. 47–66.

[28] ETSI, ISGCIM, Etsi gs cim 009 context information management (cim); ngsi-ld api, https://www.etsi.org/deliver/etsi_gs/CIM/001_099/009/01.09.01_60/gs_CIM009v010901p.pdf, 2025. (Accessed 1 September 2025).

[29] E.U. Nitrogen, Expert Panel, Nitrogen Use Efficiency (Nue) an Indicator for the Utilization of Nitrogen in Food Systems, Wageningen University, Alterra, Wageningen, Netherlands, 2015.

[30] F.K. van Evert, T. Bresilla, A. Nieuwenhuizen, B. Veldhuisen, J. Hemming, G. Avgoustakis, S. Fountas, M. Koutsiaras, N. Mylonas, S. Baron, et al., Implementing a Digital Twin for Flexible Operation of Agricultural Robotics, Burleigh Dodds Science Publishing, 2024.
[31] C. Fetting, The European green deal, ESDN Report, December 2, 2020.
[32] FIWARE Foundation, Smart data models, https://smartdatamodels.org/. (Accessed 1 September 2025).
[33] L. Floridi, The Blackwell Guide to the Philosophy of Computing and Information, John Wiley & Sons, 2008.
[34] M. Ganzha, M. Paprzycki, W. Pawłowski, P. Szmeja, K. Wasielewska, Semantic interoperability in the Internet of things: an overview from the inter-iot perspective, J. Netw. Comput. Appl. 81 (2017) 111–124.
[35] R. Gautron, E.J.P. Gonzalez, P. Preux, J. Bigot, O.A. Maillard, D. Emukpere, gym-DSSAT: a crop model turned into a Reinforcement Learning environment, Ph.D. thesis, Inria Lille, 2022.
[36] R. Gautron, O.A. Maillard, P. Preux, M. Corbeels, R. Sabbadin, Reinforcement learning for crop management support: review, prospects and challenges, Comput. Electron. Agric. 200 (2022) 107182, https://doi.org/10.1016/j.compag.2022.107182.
[37] M. Ghaith, A. Yosri, W. El-Dakhakhni, Digital twin: a city-scale flood imitation framework, in: Canadian Society of Civil Engineering Annual Conference, Springer, 2021, pp. 577–588.
[38] G. Goldenits, K. Mallinger, S. Raubitzek, T. Neubauer, Current applications and potential future directions of reinforcement learning-based digital twins in agriculture, Smart Agric. Technol. (2024) 100512, https://doi.org/10.1016/j.atech.2024.100512.
[39] M. Guerif, C. Duke, Adjustment procedures of a crop model to the site specific characteristics of soil and crop using remote sensing data assimilation, Agric. Ecosyst. Environ. 81 (2000) 57–69.
[40] J. Han, L. Shi, Q. Yang, J. Yu, I.N. Athanasiadis, Knowledge-guided machine learning with multivariate sparse data for crop growth modelling, Field Crops Res. 328 (2025) 109912, https://doi.org/10.1016/j.fcr.2025.109912, https://www.sciencedirect.com/science/article/pii/S0378429025001777.
[41] A. Hartikainen, J. Backman, M. Pastell, Farmingpy: python package for developing digital twins and precision farming data processing, agriRxiv (2025) 20250099800.
[42] J. Hoffmann, P. Bauer, I. Sandu, N. Wedi, T. Geenen, D. Thiemert, Destination earth–a digital twin in support of climate services, 30, Climate Services (2023) 100394, https://doi.org/10.1016/j.cliser.2023.100394.
[43] D.P. Holzworth, N.I. Huth, P.G. deVoil, E.J. Zurcher, N.I. Herrmann, G. McLean, K. Chenu, E.J. van Oosterom, V. Snow, C. Murphy, A.D. Moore, H. Brown, J.P. Whish, S. Verrall, J. Fainges, L.W. Bell, A.S. Peake, P.L. Poulton, Z. Hochman, P.J. Thorburn, D.S. Gaydon, N.P. Dalgliesh, D. Rodriguez, H. Cox, S. Chapman, A. Doherty, E. Teixeira, J. Sharp, R. Cichota, I. Vogeler, F.Y. Li, E. Wang, G.L. Hammer, M.J. Robertson, J.P. Dimes, A.M. Whitbread, J. Hunt, H. van Rees, T. McClelland, P.S. Carberry, J.N. Hargreaves, N. MacLeod, C. McDonald, J. Harsdorf, S. Wedgwood, B.A. Keating, Apsim – evolution towards a new generation of agricultural systems simulation, Environ. Model. Softw. 62 (2014) 327–350, https://doi.org/10.1016/j.envsoft.2014.07.009.
[44] G. Hoogenboom, C.H. Porter, K.J. Boote, V. Shelia, P.W. Wilkens, U. Singh, J.W. White, S. Asseng, J.I. Lizaso, L.P. Moreno, et al., The dssat crop modeling ecosystem, in: Advances in Crop Modelling for a Sustainable Agriculture, Burleigh Dodds Science Publishing, 2019, pp. 173–216.
[45] J. Huang, L. Tian, S. Liang, H. Ma, I. Becker-Reshef, Y. Huang, W. Su, X. Zhang, D. Zhu, W. Wu, Improving winter wheat yield estimation by assimilation of the leaf area index from landsat tm and modis data into the wofost model, Agric. For. Meteorol. 204 (2015) 106–121.
[46] M. Ilić, M. Tošić, M. Kallenberg, H. Baja, I.N. Athanasiadis, GitHub repository smart droplets, https://github.com/Smart-Droplets-Project, 2025. (Accessed 1 September 2025).
[47] X. Jin, L. Kumar, Z. Li, H. Feng, X. Xu, G. Yang, J. Wang, A review of data assimilation of remote sensing and crop models, Eur. J. Agron. 92 (2018) 141–152.
[48] S.G. Johnson, J. Schueller, Nlopt: Nonlinear Optimization Library, Astrophysics Source Code Library, 2021, ascl–2111.
[49] D.B. Johnston, K.G. Pembleton, N.I. Huth, R.C. Deo, Comparison of machine learning methods emulating process driven crop models, Environ. Model. Softw. 162 (2023) 105634.
[50] J.W. Jones, J.M. Antle, B. Basso, K.J. Boote, R.T. Conant, I. Foster, H.C.J. Godfray, M. Herrero, R.E. Howitt, S. Janssen, B.A. Keating, R. Munoz-Carpena, C.H. Porter, C. Rosenzweig, T.R. Wheeler, Brief history of agricultural systems modeling, Agric. Syst. 155 (2017) 240–254, https://doi.org/10.1016/j.agsy.2016.05.014.
[51] M. Kallenberg, H. Baja, I.N. Athanasiadis, GitHub repository A-scab gym, https://github.com/WUR-AI/A-scab, 2025. (Accessed 1 September 2025).
[52] M.G. Kallenberg, B. Maestrini, R. van Bree, P. Ravensbergen, C. Pylianidis, F. van Evert, I.N. Athanasiadis, Integrating processed-based models and machine learning for crop yield prediction, arXiv preprint, arXiv:2307.13466, 2023.
[53] M.G. Kallenberg, H. Overweg, R. van Bree, I.N. Athanasiadis, Nitrogen management with reinforcement learning and crop growth models, Environ. Data Sci. 2 (2023) e34.
[54] E. Karunathilake, A.T. Le, S. Heo, Y.S. Chung, S. Mansoor, The path to smart farming: innovations and opportunities in precision agriculture, Agriculture 13 (2023) 1593.
[55] R. Klar, N. Arvidsson, V. Angelakis, Digital twins' maturity: the need for interoperability, IEEE Syst. J. 18 (2023) 713–724.
[56] K. de Koning, J. Broekhuijsen, I. Kühn, O. Ovaskainen, F. Taubert, D. Endresen, D. Schigel, V. Grimm, Digital twins: dynamic model-data fusion for ecology, Trends Ecol. Evol. 38 (2023) 916–926.
[57] K. Kosior, Towards a common agricultural data space in the European Union: a sustainable development perspective, Wieś Rol. 191 (2021) 65–89.
[58] B. van Laatum, E.J. van Henten, S. Boersma, Greenlight-gym: a reinforcement learning benchmark environment for greenhouse crop production control, arXiv:2410.05336, 2024.
[59] X. Li, M. Feng, Y. Ran, Y. Su, F. Liu, C. Huang, H. Shen, Q. Xiao, J. Su, S. Yuan, et al., Big data in Earth system science and progress towards a digital twin, Nat. Rev., Earth Environ. 4 (2023) 319–332.
[60] L. Liu, S. Xu, J. Tang, K. Guan, T.J. Griffis, M.D. Erickson, A.L. Frie, X. Jia, T. Kim, L.T. Miller, et al., Kgml-ag: a modeling framework of knowledge-guided machine learning to simulate agroecosystems: a case study of estimating n 2 o emission using data from mesocosm experiments, Geosci. Model Dev. 15 (2022) 2839–2858.
[61] L. Luo, S. Sun, J. Xue, Z. Gao, J. Zhao, Y. Yin, F. Gao, X. Luan, Crop yield estimation based on assimilation of crop models and remote sensing data: a systematic evaluation, Agric. Syst. 210 (2023) 103711, https://doi.org/10.1016/j.agsy.2023.103711.
[62] B. Maestrini, G. Mimić, P.A. van Oort, K. Jindo, S. Brdar, I.N. Athanasiadis, F.K. van Evert, Mixing process-based and data-driven approaches in yield prediction, Eur. J. Agron. 139 (2022) 126569.
[63] O.A. Maillard, T. Mathieu, D. Basu, Farm-gym: a modular reinforcement learning platform for stochastic agronomic games, in: AIAFS 2023-Artificial Intelligence for Agriculture and Food Systems, 2023.
[64] U. Meier, et al., Growth Stages of Mono- and Dicotyledonous Plants = Entwicklungsstadien Mono-und Dikotyler Pflanzen = Estadios de las Plantas Mono-Y Dicotiledóneas = Stades Phénologiques des Mono-et Dicotylédones Cultivées, Blackwell, Berlin, 1997 [etc.].
[65] A. Nasirahmadi, O. Hensel, Toward the next generation of digitalization in agriculture based on digital twin paradigm, Sensors 22 (2022) 498.
[66] S. Nativi, P. Mazzetti, M. Craglia, Digital ecosystems for developing digital twins of the Earth: the destination Earth case, Remote Sens. 13 (2021) 2119.
[67] I. Onaji, D. Tiwari, P. Soulatiantork, B. Song, A. Tiwari, Digital twin in manufacturing: conceptual framework and case studies, Int. J. Comput. Integr. Manuf. 35 (2022) 831–858.
[68] H. Overweg, H.N. Berghuijs, I.N. Athanasiadis, Cropgym: a reinforcement learning environment for crop management, in: ICLR Workshop Modeling Oceans and Climate Change, 2021.
[69] R. Palma, I. Roussaki, T. Döhmen, R. Atkinson, S. Brahma, C. Lange, G. Routis, M. Plociennik, S. Mueller, Agricultural information model, in: Information and Communication Technologies for Agriculture—Theme III: Decision, Springer, 2022, pp. 3–36.
[70] F. Pires, P. Leitão, A.P. Moreira, B. Ahmad, Reinforcement learning based trustworthy recommendation model for digital twin-driven decision-support in manufacturing systems, Comput. Ind. 148 (2023) 103884.
[71] L. Poggio, L.M. De Sousa, N.H. Batjes, G.B. Heuvelink, B. Kempen, E. Ribeiro, D. Rossiter, Soilgrids 2.0: producing soil information for the globe with quantified spatial uncertainty, Soil 7 (2021) 217–240.
[72] M. Poveda-Villalon, R. Garcia-Castro, L. Daniele, M. de Roode, SAREF4AGRI: an extension of SAREF for the agriculture and food domain, https://saref.etsi.org/saref4agri/, 2019.
[73] C. Pylianidis, M.G. Kallenberg, I.N. Athanasiadis, Domain adaptation with transfer learning for pasture digital twins, Environ. Data Sci. 3 (2024) e8.
[74] C. Pylianidis, S. Osinga, I.N. Athanasiadis, Introducing digital twins to agriculture, Comput. Electron. Agric. 184 (2021) 105942.
[75] C. Pylianidis, V. Snow, H. Overweg, S. Osinga, J. Kean, I.N. Athanasiadis, Simulation-assisted machine learning for operational digital twins, Environ. Model. Softw. 148 (2022) 105274, https://doi.org/10.1016/j.envsoft.2021.105274.
[76] V. Rossi, S. Giosue, R. Bugiani, A-scab (apple-scab), a simulation model for estimating risk of venturia inaequalis primary infections, EPPO Bull. 37 (2007) 300–308.
[77] I. Roussaki, K. Doolin, A. Skarmeta, G. Routis, J.A. Lopez-Morales, E. Claffey, M. Mora, J.A. Martinez, Building an interoperable space for smart agriculture, Digit. Commun. Netw. 9 (2023) 183–193, https://doi.org/10.1016/j.dcan.2022.02.004.
[78] T. Rowan, Functional Stability Analysis of Numerical Algorithms, Ph.D. Thesis, Department of Computer Sciences, University of Texas at Austin, 1990.
[79] V. Saiz-Rubio, F. Rovira-Más, From smart farming towards agriculture 5.0: a review on crop data management, Agronomy 10 (2020), https://doi.org/10.3390/agronomy10020207.
[80] A. Samourkasidis, I.N. Athanasiadis, A semantic approach for timeseries data fusion, Comput. Electron. Agric. 169 (2020) 105171, https://doi.org/10.1016/j.compag.2019.105171.
[81] A. Samourkasidis, E. Papoutsoglou, I.N. Athanasiadis, A template framework for environmental timeseries data acquisition, Environ. Model. Softw. 117 (2019) 237–249, https://doi.org/10.1016/j.envsoft.2018.10.009.
[82] S.J. Seidel, T. Palosuo, P. Thorburn, D. Wallach, Towards improved calibration of crop models–where are we now and where should we go?, Eur. J. Agron. 94 (2018) 25–35.
[83] N. Shadbolt, T. Berners-Lee, W. Hall, The semantic web revisited, IEEE Intell. Syst. 21 (2006) 96–101.

[84] V. Sharma, A.K. Tripathi, H. Mittal, Technological revolutions in smart farming: current trends, challenges & future directions, Comput. Electron. Agric. 201 (2022) 107217.

[85] J. Skákala, K. Awty-Carroll, P.P. Menon, K. Wang, G. Lessin, Future digital twins: emulating a highly complex marine biogeochemical model with machine learning to predict hypoxia, Front. Mar. Sci. 10 (2023) 1058837.

[86] M. Sporny, D. Longley, G. Kellogg, M. Lanthaler, N. Lindström, 2014, Json-ld 1.0. W3C recommendation 16, 41.

[87] T.B. Sutton, H.S. Aldwinckle, A.M. Agnello, J.F. Walgenbach, Compendium of Apple and Pear Diseases and Pests, American Phytopathological Society, St. Paul, MN, 2014.

[88] R. Tao, P. Zhao, J. Wu, N.F. Martin, M.T. Harrison, C. Ferreira, Z. Kalantari, N. Hovakimyan, Optimizing crop management with reinforcement learning and imitation learning, arXiv preprint, arXiv:2209.09991, 2022.

[89] A. Trantas, R. Plug, P. Pileggi, E. Lazovik, Digital twin challenges in biodiversity modelling, Ecol. Inform. 78 (2023) 102357, https://doi.org/10.1016/j.ecoinf.2023.102357, https://www.sciencedirect.com/science/article/pii/S1574954123003862.

[90] M. Turchetta, L. Corinzia, S. Sussex, A. Burton, J. Herrera, I. Athanasiadis, J.M. Buhmann, A. Krause, Learning long-term crop management strategies with cyclesgym, Adv. Neural Inf. Process. Syst. 35 (2022) 11396–11409.

[91] A. Tzachor, O. Hendel, C.E. Richards, Digital twins: a stepping stone to achieve ocean sustainability? npj Ocean Sustain. 2 (2023) 16.

[92] K.H. Veltman, Syntactic and semantic interoperability: new approaches to knowledge and the semantic web, New Rev. Inf. Netw. 7 (2001) 159–183.

[93] C. Verdouw, B. Tekinerdogan, A. Beulens, S. Wolfert, Digital twins in smart farming, Agric. Syst. 189 (2021) 103046.

[94] F. Villa, I.N. Athanasiadis, A.E. Rizzoli, Modelling with knowledge: a review of emerging semantic approaches to environmental modelling, Environ. Model. Softw. 24 (2009) 577–587, https://doi.org/10.1016/j.envsoft.2008.09.009.

[95] P. Voosen, Europe builds 'digital twin'of earth to hone climate forecasts, Science 370 (2020) 6512, https://doi.org/10.1126/science.370.6512.16.

[96] D. Wallach, T. Palosuo, P. Thorburn, Z. Hochman, E. Gourdain, F. Andrianasolo, S. Asseng, B. Basso, S. Buis, N. Crout, et al., The chaos in calibrating crop models: lessons learned from a multi-model calibration exercise, Environ. Model. Softw. 145 (2021) 105206.

[97] X. Zhang, E.A. Davidson, D.L. Mauzerall, T.D. Searchinger, P. Dumas, Y. Shen, Managing nitrogen for sustainable development, Nature 528 (2015) 51–59.

[98] P. Zippenfenig, Open-meteo.com weather api, https://open-meteo.com/, 2023, https://doi.org/10.5281/zenodo.7970649.