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THEORETICAL MODEL FOR IMPLEMENTING DIGITAL TWINS IN FARMS FROM DOBROGEA REGION

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Abstract. *The concept of Digital Twins (DTs) has emerged as a transformative technological advancement in precision agriculture, offering unprecedented opportunities for real-time monitoring, predictive analytics, and optimized decision-making in agricultural management. This paper proposes a theoretical model specifically tailored for the implementation of Digital Twin technology in farms located in the Dobrogea region, an area characterized by significant climate variability and resource management challenges. The proposed model integrates multi-layered digital representations of crop conditions, soil properties, climate data, and farm management practices, enabling accurate simulations and predictions. Key components include sensor integration, data analytics platforms, cloud computing solutions, and advanced predictive modeling tools. By establishing virtual replicas of physical agricultural assets, such as fields, machinery, and crop health parameters, the model aims to enhance productivity, improve resource efficiency, and significantly reduce environmental impacts. Additionally, it supports real-time scenario analyses, enabling farmers to proactively identify and address potential issues related to extreme climate events, drought conditions, or limitations in resource availability. Through continuous data synchronization between the digital replicas and their physical counterparts, farmers can rapidly test and evaluate various intervention strategies before actual implementation. The outcomes of this theoretical framework are expected to provide actionable insights into sustainable farm management strategies, clearly demonstrating the value and practical applicability of Digital Twins in the regional agricultural context of Dobrogea.*

Keywords: *Digital Twins, precision agriculture, farm management, predictive analytics, sustainability.*

INTRODUCTION

Agriculture faces growing pressure to increase productivity sustainably amid climate change and resource constraints. A rising global population (projected ~9.7 billion by 2050) demands a 25–70% boost in crop production, even as water and soil resources become scarcer (Godfray et al, 2010). Precision agriculture, or smart farming, has emerged to tackle these challenges by leveraging advanced technologies. Techniques such as remote sensing via satellites and drones, Internet of Things (IoT) sensor networks, artificial intelligence (AI), and robotics enable farmers to collect real-time data on crop and soil conditions and to make data-driven decisions (Wolfert et al., 2017). By optimizing inputs (water, fertilizers, seeds etc.) and practices for specific field conditions, these innovations aim to improve yields and sustainability. This digital transformation of agriculture (often termed Agriculture 4.0 or Agriculture 5.0) lays the groundwork for more complex cyber-physical systems on farms, including the concept of the digital twin (Verdouw et al., 2016).

A digital twin (DT) is a virtual representation of a physical system that is continuously updated with data, enabling monitoring, simulation, and analysis in parallel with real-world processes (Grieves & Vickers, 2017). Originally developed in manufacturing and aerospace, DT technology has attracted increasing attention in agriculture for its potential to revolutionize farm management (Wang, 2024). The DT acts as a live mirror of the farm, integrating sensor measurements, weather data, and other inputs to provide a comprehensive, dynamic model of crops, soil, and farm operations. This approach enables stakeholders to observe past and present conditions and forecast future scenarios, thereby reducing uncertainties in decision-making (Jones et al., 2020). Recent studies highlight numerous benefits of DTs for agriculture, including improved decision support, optimized resource use, and enhanced ability to anticipate issues such as pest outbreaks or irrigation failures (Tao et al., 2019; Oks et al., 2024). However, agricultural adoption of DTs remains limited compared to other sectors, and implementations are often at the conceptual or pilot stage (Cimino et al., 2019).

Dobrogea, a region in south-eastern Romania, presents a compelling case for the application of DTs. It is one of the country’s most arid areas, with average annual precipitation around 400 mm (Angearu et al., 2018). Approximately 70% of Dobrogea’s land is used for agriculture, making the local economy highly dependent on farming. At the same time, Dobrogea faces frequent moderate to severe droughts that significantly impact crop production (Dobri et al., 2021). These challenges underscore the need for advanced decision-support tools that can help farmers manage resources more efficiently and adapt to climatic variability. A DT of a farm in Dobrogea could enable real-time monitoring of weather and soil conditions, simulation of crop responses to drought, and proactive planning of interventions to mitigate climate risks.

This paper aims to design a theoretical implementation model of a digital twin adapted for Dobrogea's agricultural context. Drawing on recent peer-reviewed research and established frameworks, the model integrates multiple data layers and digital technologies to support farm management decisions in real time. The subsequent sections present the structure of the proposed framework (Materials and Methods), discuss its anticipated applications and advantages (Results and Discussions), and conclude with reflections on practical implications and future research directions.

MATERIAL AND METHODS

The implementation of a digital twin in the agricultural context of Dobrogea is conceptualized as a multi-layered system composed of interconnected modules for data acquisition, integration, processing, and decision support. This section outlines the key components of the theoretical model, which is designed to address the specific environmental and technological needs of the region.

Data Acquisition Layer

The digital twin system requires continuous input from multiple data sources that reflect the real-time conditions of the farm. The data types include (Dawn et al., 2024):

- Soil data: moisture, temperature, pH, nutrient levels.
- Climatic data: air temperature, humidity, precipitation, solar radiation, wind speed.
- Crop data: phenological stages, health indicators, biomass accumulation.
- Remote sensing data: multispectral and thermal imagery from drones and satellites.
- Management data: input applications (fertilizers, pesticides), irrigation schedules, machinery usage.

These data are theoretically acquired through a combination of IoT-based soil and climate sensors (e.g., Decagon EC-5, SHT31, or Davis Vantage Pro2 weather stations),

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unmanned aerial vehicles (e.g., DJI Phantom 4 Multispectral), and satellite platforms (e.g., Sentinel-2, Landsat 8).

Communication and Integration Layer

Collected data must be transmitted to a central processing system. In rural areas with limited connectivity, LPWAN technologies such as LoRaWAN or NB-IoT are preferred for transmitting sensor data to gateways, which then forward it via cellular or satellite internet to cloud platforms. This ensures low-power, wide-area communication coverage and supports real-time data streaming (Civelek, 2017).

The integration platform aggregates, cleans, and harmonizes the data into structured databases. Cloud services such as AWS IoT, Microsoft Azure, or open-source alternatives like ThingsBoard or FIWARE can be used for scalable storage and processing. Standardization via formats like SensorML or protocols such as MQTT and HTTP REST APIs facilitates interoperability between different devices and systems (Farooq et al., 2020).

Modeling and Simulation Layer

At the core of the digital twin is the modeling engine, which simulates farm processes and predicts future outcomes. This includes (FAO, 2021; Vicente-Serrano et al., 2010):

- Crop simulation models (e.g., AquaCrop, DSSAT) that use soil, weather, and crop management data to estimate growth and yield.
- Machine learning models trained on historical and real-time data to forecast yield, detect anomalies, or classify crop stress.
- Climate and drought indices integration (e.g., SPEI, VHI) for assessing risk levels.

These simulations enable scenario analysis, such as testing the impact of delayed irrigation, different fertilizer doses, or projected climate changes.

The inclusion of agronomic data from previous field studies enhances the accuracy of simulation models within the digital twin framework. For instance, studies assessing the production capacity of soils and crop yields, such as those conducted in Caraș-Severin County for wheat and maize (Mihuț et al., 2016), or evaluating the agro-productive efficiency of rapeseed hybrids in Timiș County (Niță et al., 2022), offer valuable empirical benchmarks. Integrating such localized datasets into the twin's machine learning and crop simulation models ensures that predictions align with region-specific agronomic realities.

Decision Support Layer

- The output of the modeling layer is translated into actionable recommendations via a decision support system (DSS). This layer:
- Generates alerts (e.g., drought risk, pest threats).
- Recommends interventions (e.g., irrigation timing, nutrient application).
- Provides visualizations (e.g., NDVI maps, growth stage predictions).

The DSS may use optimization algorithms (e.g., linear programming, evolutionary algorithms) to suggest the most effective use of inputs under given constraints (e.g., water availability, labor).

Feedback and Control Layer

The digital twin may be extended to include actuators and automated control, enabling a feedback loop. For example, based on real-time soil moisture data and DSS recommendations, the system can trigger irrigation events autonomously. This cyber-physical integration is characteristic of advanced precision agriculture systems.

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The inclusion of crop response data from previous agronomic trials – such as studies examining the influence of fertilization regimes and varietal selection on triticale yields in Romanian conditions – could further enrich the modeling layer. For instance, research by Niță et al. (2015) has demonstrated variability in triticale performance under different input strategies, offering valuable empirical data that could be incorporated into the machine learning modules or used to validate crop simulation outputs (Niță et al, 2015).

Conceptual Workflow Diagram

The complete architecture of the proposed digital twin framework is illustrated in Figure 1. The flowchart details the interaction between physical devices, cloud infrastructure, simulation modules, and decision support tools.

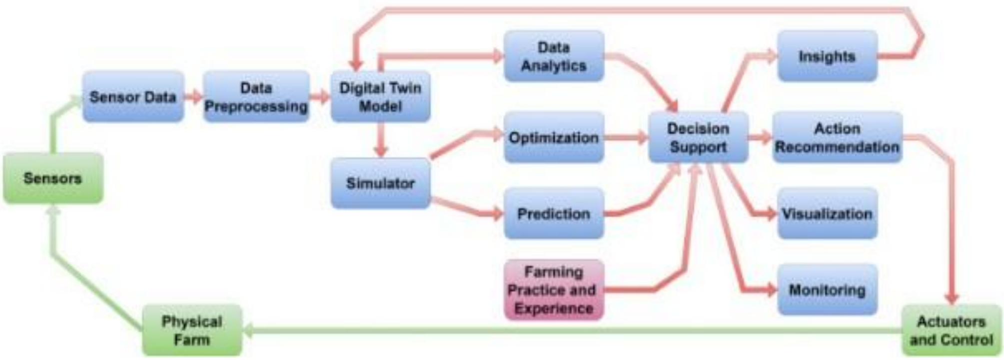

Figure 1. Digital Twin modeling – conceptual workflow diagram

This modular design ensures that the system can evolve over time, integrating new data sources and functionalities as needed. By grounding each component in peer-reviewed methodologies and widely used technologies, the proposed framework offers a realistic yet forward-looking approach to smart farming in Dobrogea.

RESULTS AND DISCUSSIONS

To assess the applicability and robustness of the proposed digital twin framework for Dobrogea, it is essential to compare it with existing implementations of digital twin technology in agriculture. Two recent peer-reviewed case studies illustrate how similar systems have been successfully conceptualized or deployed.

Case Comparison 1: Digital Twin for Mandarin Orchards in Jeju, South Korea

A comprehensive digital twin platform was developed to monitor mandarin orchards in Jeju Island, South Korea. This system integrates open-access governmental datasets, soil and fruit quality data, and microclimatic measurements from sensors located within orchards. The resulting data is aggregated and visualized using GIS tools to support multi-scale decision-making – from regional planning to per-tree management (Kim & Heo, 2024). Machine learning models are applied to assess intra-orchard variation, improving yield predictions and fruit quality assessments. Similar to the Dobrogea model, the Jeju system emphasizes data integration and spatial monitoring. However, unlike the broader approach proposed for Dobrogea, this twin focuses specifically on perennial crops and lacks real-time control feedback mechanisms. Nevertheless, its orientation towards individualized agriculture represents a forward-thinking concept applicable to crop zones in Dobrogea that exhibit heterogeneous behavior.

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Case Comparison 2: Digital Twin for Smart Irrigation Systems (EU–Brazil Pilot)

Another relevant example is a digital twin developed as part of a joint European–Brazilian project focusing on irrigation management. This model links soil moisture sensors, weather forecasts, and actuator controls through a cloud-based simulation engine. Built with FIWARE and Siemens Plant Simulation, it allows real-time evaluation of irrigation scenarios and sends optimal control actions back to the physical field via OPC UA protocol (Alves et al., 2023). This architecture closely mirrors the feedback-control component envisioned in the Dobrogea framework, particularly for water-scarce scenarios. While the Dobrogea model encompasses broader farm activities, this irrigation-focused twin excels in scenario testing and automation—highlighting potential components for refinement and adoption within arid regions.

Synthesis and Critical Evaluation

These two case studies highlight different facets of digital twin functionality. The Jeju model excels in spatial analytics and precision decision-making but is limited in its integration of real-time control. The EU–Brazil pilot, meanwhile, demonstrates strong feedback capabilities and real-time adaptability, though it remains narrowly focused on irrigation. The Dobrogea model aims to unify these strengths by providing a modular, extensible twin capable of both macro-scale monitoring and micro-scale automation. Importantly, its applicability to the cereal- and oilseed-dominated landscape of Dobrogea makes it more complex, demanding scalable, cost-effective solutions. Lessons from these existing models suggest that the success of a digital twin in Dobrogea will hinge on high-quality, multi-source data integration and an intuitive decision support interface tailored to farmers' practical realities.

CONCLUSIONS

This study proposed a theoretical digital twin (DT) framework tailored for the agricultural conditions of the Dobrogea region in Romania. Building upon established precision agriculture concepts and lessons drawn from existing DT implementations, the model integrates diverse data streams—from in-field sensors to satellite observations—and connects them through a cloud-based platform empowered by simulation and decision-support algorithms. The goal is to enable real-time monitoring, prediction, and optimization of farm management practices in a region characterized by climatic stress and limited water resources.

The comparative analysis with existing models—such as the mandarin orchard DT in Jeju, South Korea, and the irrigation-focused twin from the EU–Brazil pilot—underscores the feasibility and adaptability of digital twin technology in diverse agricultural contexts. While these models reveal key strengths in spatial analysis and automation, respectively, the Dobrogea model aspires to merge these features into a unified, scalable system suited for extensive crop farming. It emphasizes modularity, multi-source data fusion, and actionable decision-making tools to support both strategic and operational levels of farm management.

As a theoretical contribution, this work provides a structured blueprint for future implementation. Yet, practical deployment will require further development of technical infrastructure, data governance strategies, and farmer training to ensure adoption. Pilot projects in Dobrogea could serve as a testbed for iterative refinement, enabling gradual integration of digital twins into regional agricultural systems. However, the proposed model remains conceptual and has not yet been validated through real-world trials or longitudinal data. As such, its effectiveness and scalability must be confirmed through experimental implementation and continuous feedback from field conditions. With adequate support, digital twins can become a cornerstone of resilient, data-driven agriculture in semi-arid regions like Dobrogea.

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Furthermore, such digital twin frameworks align with broader European Union strategies, such as the European Green Deal and the Farm to Fork Strategy, which emphasize digitalization, sustainability, and resource efficiency in agriculture. By fostering precision resource management and climate adaptation, the proposed model supports these policy objectives and contributes to the transition toward more sustainable and resilient food systems.

Although the proposed digital twin framework offers a promising conceptual foundation tailored to the agricultural context of Dobrogea, it is not without limitations. First, the framework has not yet been implemented or validated through multiple field trials, and its performance under real-world conditions remains unknown. Second, data availability and quality, especially for small and medium-sized farms, may present practical barriers to full deployment. Furthermore, challenges related to user adoption, interoperability with legacy farm equipment, and the cost of digital infrastructure could hinder scalability.

Future work will focus on translating the conceptual model into a prototype implementation. This includes the selection and deployment of appropriate sensors and cloud platforms, the development of interoperable data standards, and testing in one or more pilot farms in Dobrogea. Additionally, research should explore human–machine interface design for non-technical users, economic feasibility assessments, and integration of social and regulatory dimensions to support broader adoption.

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