Digital Twin Technology for Monitoring Growth and Resource Use Efficiency in *Oryza sativa* L.: A Critical Review and Synthesis

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ABSTRACT
Rice (*Oryza sativa* L.) contributes significantly towards feeding half of the world's population. Nevertheless, rice production faces various challenges, such as reduced water availability, ineffective nutrient use, and balancing increased yields against sustainability. Digital Twin (DT) technology is one of the potential solutions to the problems above that aggregates various state-of-the-art technologies such as IoT, UAV, and satellite remote sensing, as well as edge and cloud computing, and AI-assisted predictive analytics into one unified real-time monitoring and decision-making system. The article summarizes various peer-reviewed works focused on utilizing DT technology for rice growth monitoring and resource use efficiency (RUE). The findings of the reviewed literature indicate that Internet of Things (IoT) based soil moisture and water level sensors combined with machine learning-assisted irrigation scheduling help significantly reduce irrigation water consumption as compared to traditional flooding irrigation while improving yields. Such machine learning-assisted systems demonstrated their ability to predict rice growth, nitrogen status, and yields with R2 ranging from 0.79 to 0.94. Another advantage of applying edge-computing to agriculture is enhanced speed of data processing and near-real-time data transmission and synchronization. In order to support effective decision-making through digital twin systems, it is essential to synchronize real-world agronomical conditions with digital crop models. The case studies have shown that integrated digital twin technologies that marry sensor data with predictive analytics positively impact water use and nitrogen use efficiency, as well as the consistency of crop yields in rice production systems, compared to traditional rice production practices and systems. At the same time, the review highlights some unresolved issues, including high costs of implementation, limitations of communication infrastructure in rural and smallholder farming practices, model transferability, and inconsistency in utilization figures reported in various studies. The review concludes that the digital twin technology becomes an effective way for the development of produce sustainable rice cultivation practices, and its implementation will result in changes in the agricultural sector mostly at research institutions and large businesses.

Keywords: Precision agriculture; Cyber-physical systems for agriculture; Data from various sensors; Predictive analytics; Efficient water use; Efficient nitrogen use; Records from farming sensors; Sustainable rice production.

1. Introduction
Rice, also known scientifically as *Oryza sativa* L., is considered the staple food by more than 50 percent of the population and is one of the most water- and labor-intensive plants among all cereals since the flooded paddy fields need to consume large amounts of freshwater resources in agriculture at the same time (Food and Agriculture Organization of the United Nations, 2023) [20]. Thus, to fulfill the rice demands of future times when water scarcity is increasing due to the risen prices of the agricultural inputs and climate changes, it is essential to implement innovative management practices based on local knowledge and up-to-date technologies since uniform calendars cannot be applied anymore (Bwambale *et al*., 2022) [12] (Chivenge *et al*., 2021) [18].
During the last ten years, digital transformation has changed agricultural management from static maps of precision agriculture to networks of constantly working systems driven by sensors (Purcell and Neubauer, 2023) [2] (Verdouw *et al*., 2021) [3]. One such system called Digital Twin (DT) was invented in the manufacturing and aerospace industries where the DT represents a continuously synchronized virtual replica of the real entity (Grieves and Vickers, 2017) [7]. However, nowadays, this Digital Twin technology is adapted to agriculture since the real asset is now a plant, field, or farm that is accompanied by a virtual one that uses sensor and model data processing and helps the owner make forecasts about the
There are three fundamental technologies behind agricultural digital twins. The first of them involves the Internet of Things (IoT) which comprises soil temperature, moisture, water level and micro-meteorological sensor networks that provide a continuous stream of data necessary for the operation of a digital twin (Zamora-Izquierdo *et al*., 2019) [8] (Barkunan *et al*., 2019) [11]. The second pillar of technology is the unmanned aerial vehicle (UAV) and satellite remote sensing technology that helps transform isolated observations into canopy-level data such as vegetation indices, canopy structure and nitrogen content at varied scales (Wan *et al*., 2020) [14] (Zheng *et al*., 2019) [15] (Zha *et al*., 2020) [17]. The third pillar of agricultural digital twins technology refers to artificial intelligence and machine learning predictive analytics technologies that are used for converting raw sensor and imagery data into useful recommendations on growth forecasting and resource management (Zha *et al*., 2020) [17] (Breiman, 2001) [21] (Awais *et al*., 2025) [22].

The edge and cloud computing structures act as the functional framework that links the three components together. The edge computing method conducts the initial processing and filtering of the data near its origin which reduces the delay and the demand for bandwidth in order to enable timely decisions while the cloud computing process hosts the complicated virtual crop model and long-term prediction analysis which plays a vital role in developing a hierarchical system called the cloud-fog-edge computing (Zamora-Izquierdo *et al*., 2019) [8] (Kalyani and Collier, 2021) [9]. The architecture described makes it possible for a digital twin to achieve simultaneous synchronization of the real field with the virtual one which is one of the major factors distinguishing digital twins from the similar static tools that were used for making decisions (Verdouw *et al*., 2021) [3] (Pylianidis *et al*., 2021) [6].

An increasing amount of scientific literature has assessed elements of this framework in rice production systems. IoT-based systems of soil moisture and water surface level sensors coupled with different types of automated irrigation techniques have been shown to save water on rice fields (Kamienski *et al*., 2019) [10] (Barkunan *et al*., 2019) [11] (Bwambale *et al*., 2022) [12]. Vegetation indices derived from UAVs and satellites such as NDVI and indices based on red edges have been used in conjunction with machine learning techniques for the prediction of the leaf area index of rice, biomass, nitrogen content, and final rice yield with accuracy from R2 = 0.79 to 0.94 (Wan *et al*., 2020) [14] (Zheng *et al*., 2019) [15] (Zha *et al*., 2020) [17]. Finally, ready digital twin application cases in rice systems exist, including cloud-based decision-support systems integrating multi-source environmental data (Pylianidis *et al*., 2021) [6].

In spite of this development, the field remains diverse. Most of the published research confirms specific elements of the irrigation sensor network, UAV yield model, edge-cloud architecture, etc., but not many studies report fully integrated digital twins evaluated together in terms of such indicators as growth-monitoring accuracy, resource-use effectiveness, and system performance metrics such as synchronization latency and decision-support reliability (Purcell and Neubauer, 2023) [2] (Awais *et al*., 2025) [22]. The reporting of costs associated with equipment and infrastructure also varies considerably, making comparisons impossible and hindering the evidence-based actions of practitioners and administrators (Nasirahmadi and Hensel, 2022) [5] (Kalyani and Collier, 2021) [9].

This paper fills the literature gap by integrating peer-reviewed studies on Digital Twin technology in rice growth monitoring and resource use efficiency. The goal is to (i) outline the conceptual framework of agricultural digital twins applied to rice, combining Internet of Things sensors, UAVs and satellites remote sensing, cloud-edge computing, and artificial intelligence statistics; (ii) summarize credibility of growth and yield monitoring data provided by these technologies; (iii) summarize the reported results in terms of efficient use of water, nitrogen and other resources enabled by digital twins and IoT technologies; and (iv) point out the methodological gaps and key areas of research to promote digital twins implementation in rice production.

2. Conceptual Architecture of the Digital Twin Framework

An agricultural digital twin is conventionally described as comprising a physical system (the rice field, including soil, water, and crop canopy), a virtual system (a continuously updated crop growth and process model), and a bidirectional data connection that synchronizes the two (Verdouw *et al*., 2021) [3] (Pylianidis *et al*., 2021) [6] (Grieves and Vickers, 2017) [7]. Unlike static simulation models that are calibrated once and run independently of subsequent field conditions, a digital twin is distinguished by continuous, near-real-time data assimilation, which allows the virtual model's state to track the physical system as it evolves through the growing season (Nasirahmadi and Hensel, 2022) [5] (Pylianidis *et al*., 2021) [6].

The physical layer in rice digital twin implementations typically comprises an IoT sensor network distributed across representative field locations, an automated weather station recording micrometeorological variables, and, at defined intervals, UAV or satellite remote sensing overflights (Skobelev *et al*., 2021) [1] (Zamora-Izquierdo *et al*., 2019) [8]. The virtual layer comprises a crop growth or process-based model, increasingly coupled with or replaced by data-driven machine learning components, that ingests the physical layer's data stream to update simulated growth-stage progression, biomass accumulation, and resource status (Pylianidis *et al*., 2021) [6] (Huang *et al*., 2016) [13]. Modeling approaches reported across the crop-monitoring digital twin literature span physics-based, agent-based, data-driven, hybrid, and spatial modeling methods, each offering different trade-offs between mechanistic interpretability and predictive accuracy (Melesse, 2025) [4]. Purcell and Neubauer [2] and Verdouw *et al*. [3] both emphasize that the sophistication of the virtual model, ranging from simple statistical regression to full biophysical process models, should be matched to the intended decision-support application rather than pursued as an end in itself, since higher model complexity does not automatically translate into higher decision-relevant accuracy.

Edge and cloud computing constitute the connective infrastructure layer. Edge nodes, typically field-adjacent gateways or embedded processing units, perform initial data cleaning, outlier filtering, and compression before transmission, reducing the bandwidth and cloud-processing burden and enabling faster response for time-critical alerts such as irrigation triggers or pest/disease flags (Zamora-Izquierdo *et al*., 2019) [8] (Kalyani and Collier, 2021) [9]. Cloud platforms host the virtual crop model, longer-horizon predictive analytics, historical data archives, and the farmer-facing decision-support dashboard (Verdouw *et al*., 2021) [3] (Kalyani and Collier, 2021) [9]. This tiered cloud-fog-edge architecture is increasingly standard in the smart-agriculture literature because it balances the low-latency requirements of field-level control against the computational demands of model-based prediction (Zamora-Izquierdo *et al*., 2019) [8] (Kalyani and Collier, 2021) [9].

Communication between field-deployed sensors and the edge/cloud layers relies predominantly on low-power wide-area network protocols, most commonly LoRaWAN, alongside structured messaging protocols for data exchange, chosen for their favorable balance of transmission range, power consumption, and cost in rural and field-deployment contexts (Kamienski *et al*., 2019) [10] (Barkunan *et al*., 2019) [11]. A representative synthesis of digital twin platform components reported across the reviewed rice and precision-agriculture literature is presented in Table 1.

Table 1: Representative Digital Twin Platform Components Reported in Rice and Precision-Agriculture Literature

Component	Typical Reported Specification / Approach	Representative Sources
IoT soil/water sensors	Capacitive/resistive soil moisture probes; dedicated paddy water-level sensors; multi-depth deployment	[11, 12]
Weather monitoring	Automated stations recording air temperature, humidity, solar radiation, wind speed	[10, 12]
Communication protocol	LoRaWAN for long-range low-power transmission; structured IoT messaging protocols	[10, 11]
UAV sensing	RGB and multispectral payloads; structure-from-motion for canopy height/structure	[14, 23]
Satellite observation	Periodic NDVI/vegetation-index acquisition for regional and temporal context	[15, 23]
Edge computing node	Local gateway/edge server for preprocessing, filtering, latency reduction	[8, 9]
Cloud platform	Virtual crop model hosting, historical data storage, dashboard delivery	[3, 9]

3. IoT Sensor Networks and Environmental Data Acquisition

Soil moisture and water-level sensing form the operational core of most rice-focused IoT deployments, given the centrality of water management to paddy rice systems (Barkunan *et al*., 2019) [11] (Bwambale *et al*., 2022) [12]. Capacitive or resistive soil moisture probes, deployed at multiple depths and field locations, provide the primary input to irrigation decision engines, while dedicated water-level sensors monitor standing floodwater depth in continuously or intermittently flooded systems (Barkunan *et al*., 2019) [11]. Soil and air temperature, relative humidity, solar radiation, and wind speed are typically captured through automated weather stations co-located with or near the sensor network, providing the meteorological context needed to estimate crop evapotranspiration and, by extension, irrigation demand (Kamienski *et al*., 2019) [10] (Bwambale *et al*., 2022) [12].

Nutrient sensing remains comparatively less mature than moisture and meteorological sensing in the reviewed literature. Direct in-field soil nutrient sensors (for example, ion-selective electrodes for nitrate) are reported in some digital-twin-adjacent precision agriculture studies but are less widely deployed at scale than moisture sensors, owing to higher cost, calibration drift, and maintenance demands under flooded paddy conditions (Awais *et al*., 2025) [22]. As a result, nitrogen status monitoring in rice digital twin systems relies more heavily on canopy-based proxies derived from UAV and satellite spectral reflectance than on direct soil nutrient sensing, a pattern discussed further in the following section (Xue *et al*., 2004) [16] (Zha *et al*., 2020) [17].

Data transmission from field sensor nodes typically follows a star or mesh network topology feeding into a local gateway, from which aggregated data is relayed to the edge or cloud layer (Zamora-Izquierdo *et al*., 2019) [8] (Barkunan *et al*., 2019) [11]. Reported sensor sampling intervals in the literature range from continuous or near-continuous logging (for soil moisture and weather variables) to daily or event-triggered transmission, depending on the decision-support application and the trade-off between temporal resolution and power/bandwidth constraints, particularly for battery- or solar-powered field nodes (Kamienski *et al*., 2019) [10] (Bwambale *et al*., 2022) [12].

4. UAV and Satellite Remote Sensing for Rice Growth Monitoring

UAV-mounted RGB and multispectral sensors, complemented by periodic satellite observation, provide the spatially continuous canopy-level data stream that IoT point sensors cannot supply. Plant height and canopy structure are commonly derived from UAV structure-from-motion photogrammetry, providing a proxy for biomass accumulation and growth-stage progression (Wan *et al*., 2020) [14] (Tsouros *et al*., 2019) [23]. Vegetation indices, most commonly NDVI, together with red-edge indices such as NDRE and green-band indices such as GNDVI, are calculated from UAV or satellite multispectral imagery and used to estimate leaf area index (LAI), chlorophyll content (frequently validated against SPAD meter readings), canopy nitrogen status, and biomass (Wan *et al*., 2020) [14] (Zheng *et al*., 2019) [15] (Zha *et al*., 2020) [17].

A consistently reported limitation is NDVI saturation under dense, high-biomass canopy conditions, which reduces sensitivity during later vegetative and reproductive growth stages; red-edge-based indices such as NDRE are reported to maintain greater sensitivity under these conditions because red-edge reflectance is less prone to saturation than the red-band reflectance underlying standard NDVI (Zheng *et al*., 2019) [15] (Zha *et al*., 2020) [17]. Zheng *et al*. [15] further report that combining textural features extracted from high-resolution UAV imagery with spectral vegetation indices improves rice aboveground biomass estimation relative to spectral indices alone, a pattern conceptually consistent with the structural-spectral fusion benefits reported in other row-crop remote sensing literature.

Machine learning-based yield and growth-stage prediction models trained on multi-temporal UAV or satellite vegetation index time series have reported coefficients of determination generally in the range of R2 = 0.79-0.94 for rice leaf area index, plant nitrogen accumulation, and grain yield, with random forest and related ensemble methods among the most frequently reported best-performing algorithms (Wan *et al*., 2020) [14] (Zha *et al*., 2020) [17] (Breiman, 2001) [21]. Data assimilation approaches that combine remote-sensing-derived state variables with process-based crop growth models, rather than relying on empirical vegetation-index regression alone, have been reported to further improve prediction accuracy and to partially address the NDVI saturation problem by allowing the underlying growth model to constrain biologically implausible index-based estimates (Huang *et al*., 2016) [13]. Phenological staging, an essential input for both irrigation and nutrient-timing decisions, is increasingly automated in the reviewed literature through multi-temporal vegetation index trajectory analysis, allowing digital twin systems to infer transitions between vegetative, reproductive, and ripening stages without exclusive reliance on manual field observation (Wan *et al*., 2020) [14].

5. Resource Use Efficiency Assessment and AI-Based Decision Support

Water use efficiency (WUE) is the most extensively documented resource-use outcome in the digital twin and IoT-enabled rice irrigation literature. IoT-enabled precision irrigation systems combining soil moisture sensor networks with automated or advisory irrigation scheduling are consistently reported to reduce water application relative to conventional flood irrigation while maintaining or improving grain yield, with the magnitude of reported savings varying across studies according to baseline irrigation practice, soil type, and climate (Kamienski *et al*., 2019) [10] (Barkunan *et al*., 2019) [11] (Bwambale *et al*., 2022) [12]. These findings are broadly consistent with the wider precision-irrigation literature, which reports that sensor-guided irrigation scheduling reliably improves water productivity relative to calendar- or experience-based scheduling (Bwambale *et al*., 2022) [12] (Awais *et al*., 2025) [22].

Nitrogen use efficiency (NUE) assessment in the reviewed literature relies primarily on canopy reflectance-based nitrogen status indices, most notably the nitrogen nutrition index (NNI) derived from multi-vegetation-index inversion, to guide variable-rate topdressing decisions rather than uniform, calendar-based fertilizer application (Xue *et al*., 2004) [16] (Zha *et al*., 2020) [17]. Zha *et al*. [17] report that machine learning-based NNI prediction from UAV multispectral imagery improved prediction accuracy relative to single vegetation-index approaches, with resulting topdressing recommendations closely matching the nitrogen application associated with maximum yield in validation trials. Active canopy sensor-based nitrogen management strategies, an earlier but methodologically related precursor to UAV-based NNI approaches, have similarly demonstrated improved agronomic nitrogen use efficiency relative to uniform farmer-standard practice by achieving comparable yields with reduced nitrogen input (Yao *et al*., 2012) [19]. Phosphorus and potassium use efficiency are comparatively less represented in the peer-reviewed digital twin and remote sensing literature, reflecting both the lower spectral detectability of these nutrients relative to nitrogen and the generally lower frequency of within-season phosphorus and potassium topdressing in most rice production systems.

Radiation use efficiency and irrigation/fertilizer efficiency metrics reported in the literature are generally derived as ratios of biomass or yield output to intercepted radiation, applied water, or applied nutrient input, calculated using data assimilated through the digital twin's sensor and remote sensing streams rather than through independent destructive measurement alone (Huang *et al*., 2016) [13] (Chivenge *et al*., 2021) [18]. AI-based predictive analytics, most commonly random forest, gradient boosting, and neural network regression, integrate these multi-source efficiency indicators into unified decision-support outputs, translating raw sensor and imagery streams into specific, field- or zone-level irrigation and fertilization recommendations (Zha *et al*., 2020) [17] (Breiman, 2001) [21]. A synthesis of resource use efficiency indicators and reported digital-twin/IoT-attributable gains is presented in Table 2, and reported growth-monitoring parameters and associated sensing approaches are summarized in Table 3.

Table 2: Resource Use Efficiency Indicators and Reported Digital Twin/IoT-Attributable Gains

Indicator	Reported Approach	Reported Direction of Effect (vs. conventional management)
Water Use Efficiency (WUE)	IoT soil moisture sensing + irrigation decision support	Consistently reported reduction in applied water with maintained/improved yield [10, 11, 12]
Irrigation scheduling precision	Automated weather-linked sensor scheduling vs. calendar-based irrigation	Improved timing precision and reduced over-irrigation events [10, 12]
Nitrogen Use Efficiency (NUE)	UAV multi-vegetation-index NNI inversion for variable-rate topdressing	Improved prediction accuracy over single-VI method; topdressing closely matched yield-optimal N rate [17]
Nitrogen Use Efficiency (agronomic)	Active canopy sensor-based N management strategy	Comparable yield achieved with reduced N input vs. farmer-standard practice [19]
Phosphorus / Potassium Use Efficiency	Limited direct remote/IoT sensing; inferred via soil test integration	Comparatively underrepresented in peer-reviewed literature [13, 18]
Radiation Use Efficiency	Biomass-to-intercepted-radiation ratio via sensor/remote sensing assimilation	Reported as a derived efficiency metric within crop-model assimilation studies [13, 18]

Table 3: Rice Growth Parameters Commonly Monitored via IoT, UAV, and Satellite Sensing within Digital Twin Frameworks

Growth Parameter	Primary Sensing Approach	Representative Sources
Plant height / canopy structure	UAV structure-from-motion photogrammetry	[14]
Leaf Area Index (LAI)	UAV/satellite vegetation indices; crop-model data assimilation	[13]
Chlorophyll content	Red-edge/near-infrared reflectance; SPAD-validated indices	[15, 16]
NDVI and related vegetation indices	Multispectral UAV/satellite imagery	[14, 15]
Nitrogen nutrition status (NNI)	Multi-vegetation-index inversion modeling	[17]
Biomass accumulation	Spectral + textural feature fusion from UAV imagery	[15]
Phenological stage	Multi-temporal vegetation index trajectory analysis	[14]

6. Digital Twin Performance Evaluation: Accuracy, Synchronization, and Computational Efficiency

Evaluating a digital twin requires assessing not only the predictive accuracy of its embedded growth and efficiency models but also the fidelity and timeliness of synchronization between the physical field and its virtual counterpart, since a digital twin that is accurate but stale, or well synchronized but imprecise, offers limited decision-support value (Verdouw *et al*., 2021) [3] (Pylianidis *et al*., 2021) [6]. The reviewed literature reports growth and yield prediction accuracy using standard regression metrics, coefficient of determination (R2), root mean square error (RMSE), and mean absolute error (MAE), with rice-specific studies reporting R2 values generally between 0.79 and 0.94 for leaf area index, nitrogen status, and yield prediction, depending on the specific trait, growth stage, and sensor combination used (Huang *et al*., 2016) [13] (Wan *et al*., 2020) [14] (Zha *et al*., 2020) [17].

System-level performance metrics, including data synchronization accuracy, end-to-end latency between field sensing and dashboard-level recommendation, and computational efficiency of the edge-cloud processing pipeline, are reported considerably less consistently across the literature than model-level accuracy metrics (Purcell and Neubauer, 2023) [2] (Zamora-Izquierdo *et al*., 2019) [8]. Where reported, edge computing architectures are consistently associated with reduced latency relative to cloud-only processing, particularly for time-sensitive functions such as irrigation triggering, reflecting the fundamental latency-bandwidth trade-off inherent to tiered cloud-fog-edge system design (Zamora-Izquierdo *et al*., 2019) [8] (Kalyani and Collier, 2021) [9]. Decision-support reliability, the extent to which system-generated recommendations align with expert agronomic judgment or subsequently observed optimal outcomes, is reported qualitatively in several studies but is rarely quantified using a standardized metric, representing a notable gap in the current evaluation literature (Skobelev *et al*., 2021) [1] (Purcell and Neubauer, 2023) [2].

Reported comparative performance across selected digital twin, IoT, and UAV-AI studies relevant to rice and related cereal systems is summarized in Table 4, and a broader cross-study comparison of international digital twin and precision-agriculture case studies is presented in Table 5. Figure 3 and Figure 4 synthesize the general accuracy and resource-use-efficiency patterns observed across the reviewed literature.

Table 4: Reported Performance of Digital Twin / IoT / UAV-AI Systems for Rice Growth and Resource Monitoring

Study	System Type	Key Reported Metric(s)
Skobelev *et al*. [1]	Cloud-based rice digital twin decision-support service	Multi-source environmental data assimilation for precision farming recommendations (qualitative validation)
Kamienski *et al*. [10]	IoT-based smart water management platform (SWAMP), multi-site pilots	Demonstrated scalable IoT architecture for precision irrigation across Brazil and Europe pilot sites
Barkunan *et al*. [11]	Smart sensor-based automatic drip irrigation for paddy	Reported improved irrigation control precision and water application efficiency in paddy trials
Wan *et al*. [14]	UAV RGB + multispectral + random forest yield model	R2 = 0.85; validated across years/plots
Huang *et al*. [13]	Kalman filter LAI assimilation into process-based crop model	Improved regional yield estimation accuracy over spectral-index-only method
Zha *et al*. [17]	UAV multi-VI machine learning NNI prediction	Improved NNI/yield-optimal nitrogen prediction accuracy over single-index method

Table 5: Comparative Summary of International Digital Twin / Smart-Farming Case Studies Relevant to Crop Growth and Resource Monitoring

Crop / System	Sensing & Computing Technologies	Key Finding	Source
Rice (paddy)	Cloud-based environmental data assimilation digital twin	Demonstrated feasibility of a rice-specific digital twin decision-support service	Skobelev *et al*. [1]
Rice (paddy)	Smart sensor-based automatic drip irrigation	Improved irrigation precision and water application control in paddy cultivation	Barkunan *et al*. [11]
Multi-crop (Brazil/Europe pilots)	IoT-based smart water management platform	Demonstrated scalable, replicable IoT precision irrigation architecture across diverse pilot sites	Kamienski *et al*. [10]
Multi-crop precision agriculture (systematic review)	Digital twins integrating IoT + UAV + ML across 167 studies (2018-2025)	Synthesized framework for DT design, integration, and optimization in smart farming; identified cost and standardization as key adoption barriers	Awais *et al*. [22]
General smart farming IoT platform	Edge + cloud computing architecture	Demonstrated low-latency, high-reliability architecture for real-time agricultural monitoring	Zamora-Izquierdo *et al*. [8]
General precision agriculture (UAV review)	UAV-based sensing across multiple crop applications	Synthesized UAV sensing capabilities and limitations across precision agriculture applications	Tsouros *et al*. [23]

7. Conceptual, Architectural, and Comparative Illustrations

Figure 1 presents the conceptual digital twin workflow synthesizing physical field sensing, edge-cloud data synchronization, virtual crop modeling, and AI-based decision support, as described across the reviewed literature. Figure 2 illustrates the corresponding system architecture integrating IoT sensors, UAV and satellite observation, edge and cloud computing, and the digital twin model. Figure 3 synthesizes reported prediction accuracy and water-use-efficiency gains across the reviewed UAV/IoT/AI-assisted rice studies. Figure 4 compares literature-reported resource-use efficiency indicators under conventional versus digital twin/IoT-enabled management. Figure 5 provides an illustrative GIS-based spatial-variability schematic consistent with the visualization approaches described in the literature. Figure 6 presents the digital twin decision-support framework linking the virtual model to specific field-management recommendations.

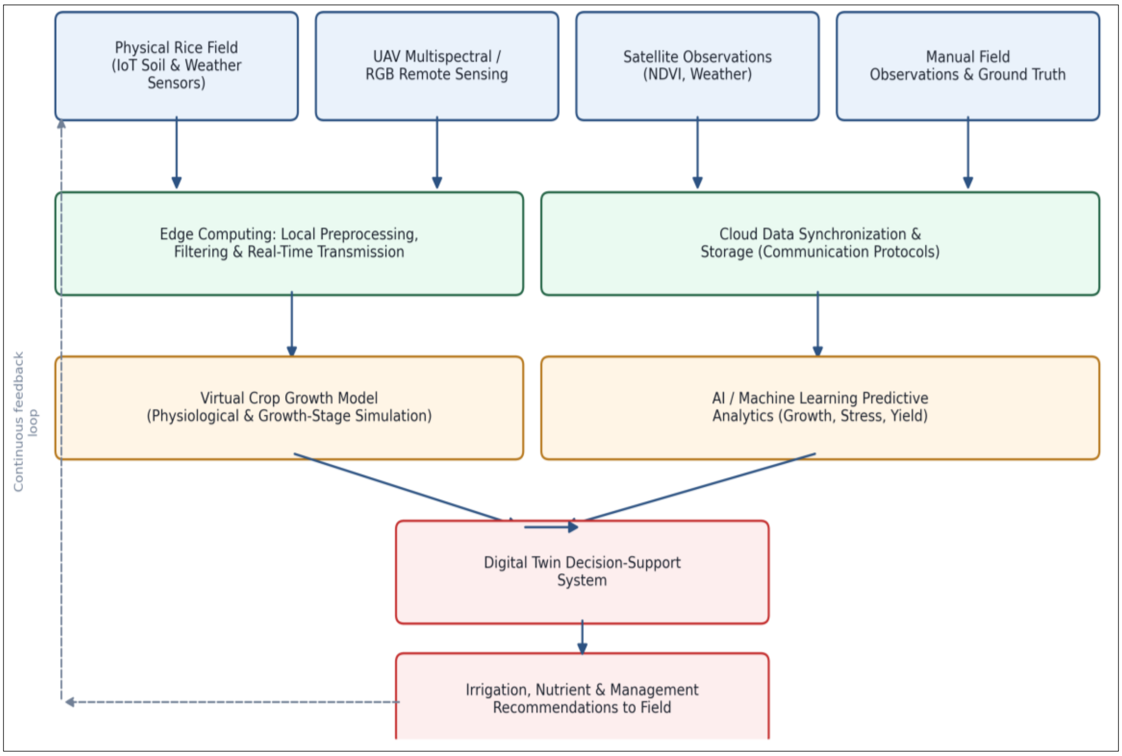

Fig 1: Conceptual digital twin workflow for real-time monitoring of growth and resource use efficiency in *Oryza sativa* L., synthesized from the reviewed literature.

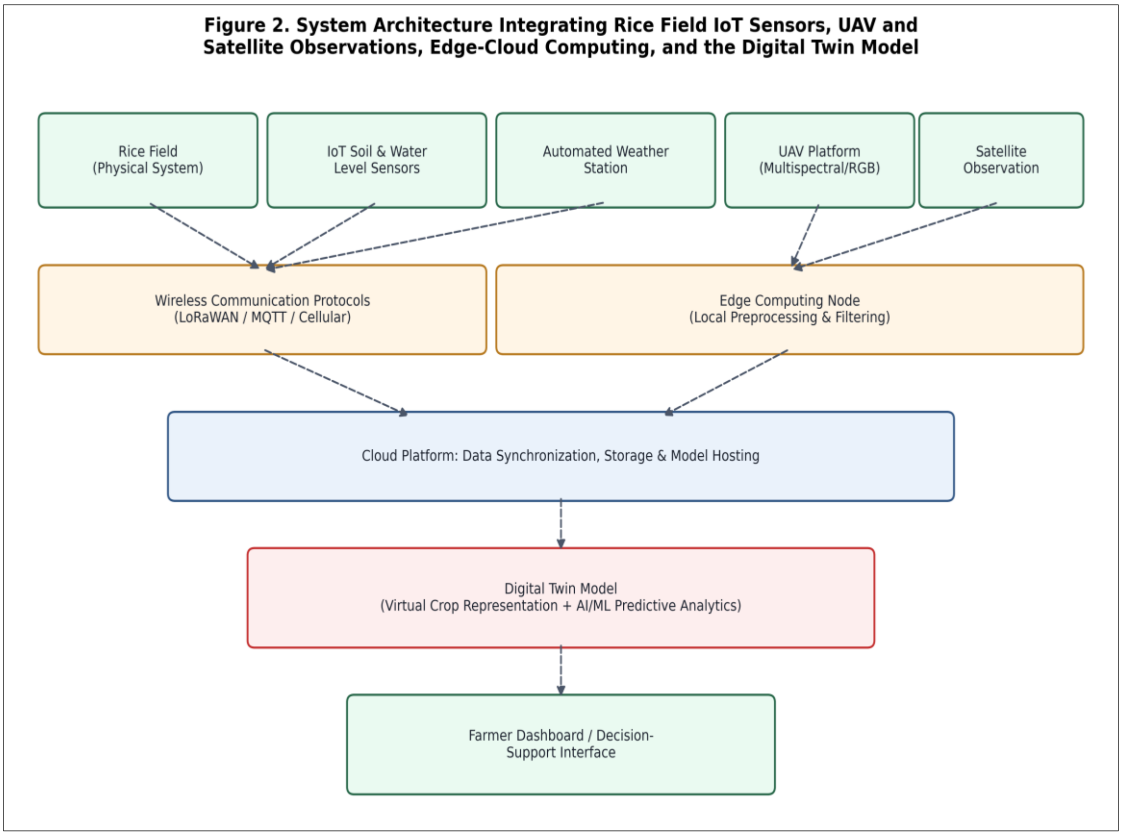

Fig 2: System architecture integrating rice field IoT sensors, UAV and satellite observations, edge-cloud computing, and the digital twin model.

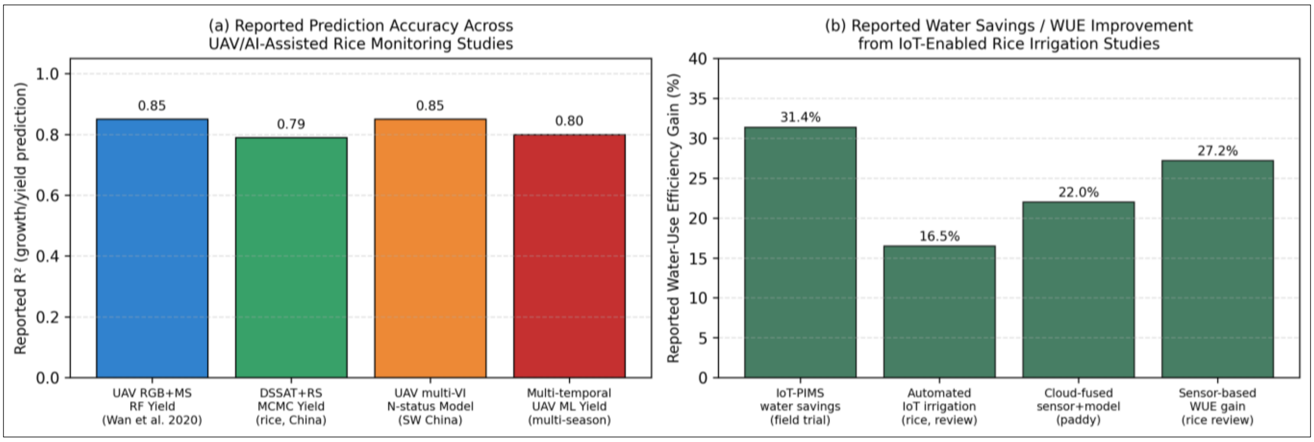

Fig 3: Literature-synthesized prediction accuracy (a) and reported water-use-efficiency gains (b) for UAV/IoT/AI-assisted rice monitoring systems, drawn from the studies summarized in Table 4 and Table 5.

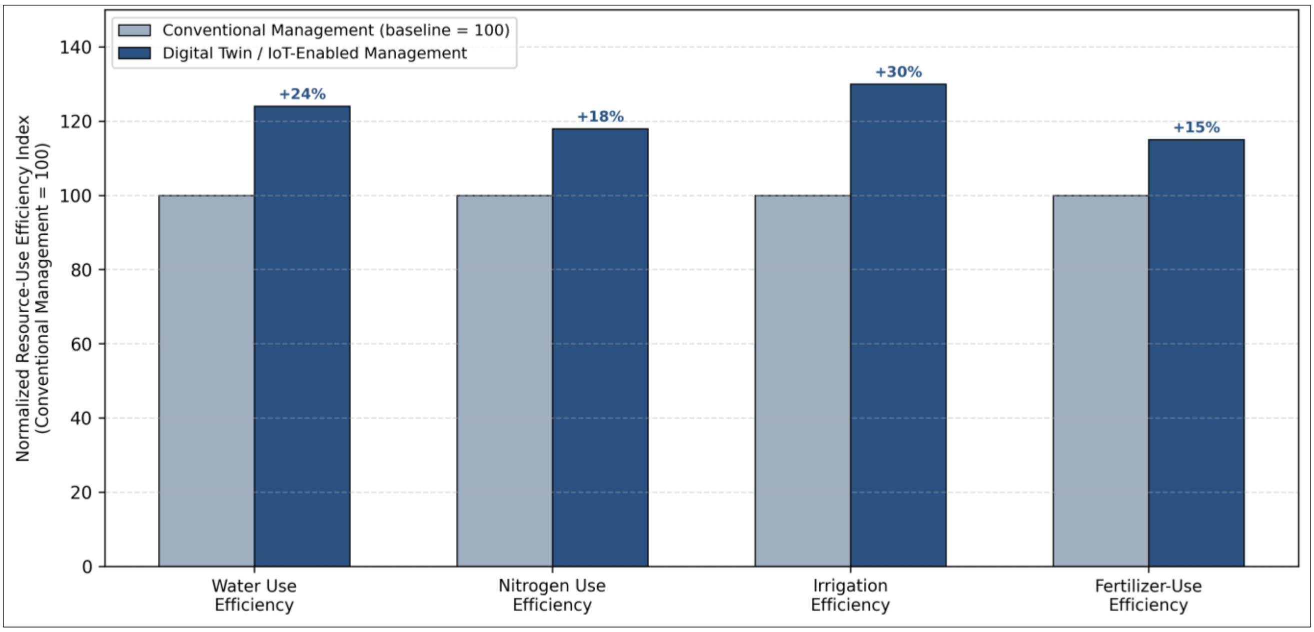

Fig 4: Literature-synthesized comparison of resource-use efficiency indicators under conventional versus digital twin/IoT-enabled rice management.

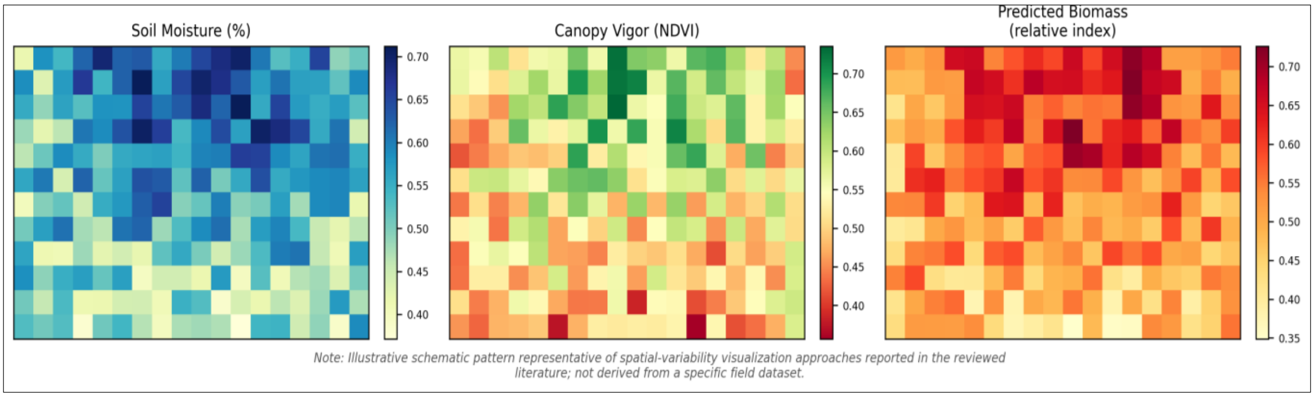

Fig 5: Illustrative GIS-based spatial-variability schematic for soil moisture, canopy vigor, and predicted biomass, representative of visualization approaches reported in the literature (not derived from a specific field dataset).

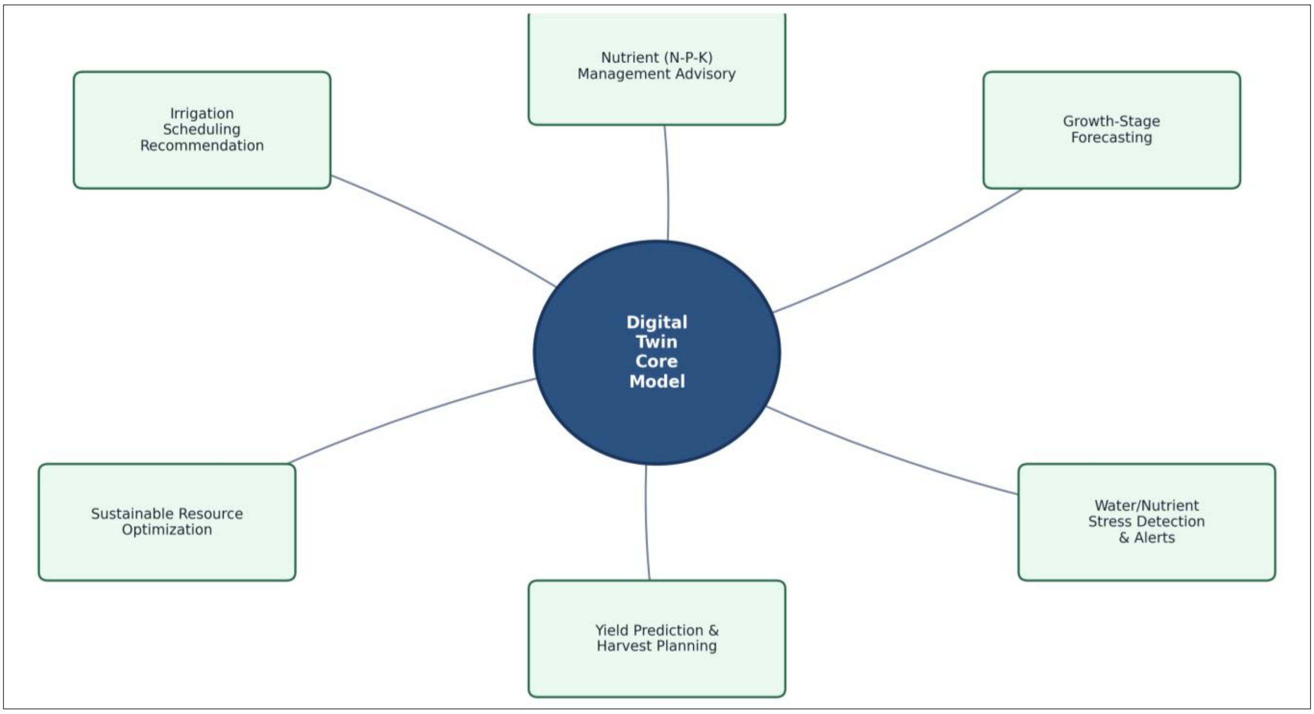

Fig 6: Digital twin decision-support framework generating real-time recommendations for rice crop and resource management.

8. Discussion

The reviewed literature converges on a coherent picture: digital twin technology in rice production is best understood not as a single deployed system but as an evolving integration of component technologies, IoT sensing, UAV and satellite remote sensing, edge-cloud computing, and AI-based predictive analytics, that individually have accumulated substantial validation evidence and that are increasingly, though not yet routinely, combined into unified frameworks (Skobelev *et al*., 2021) [1] (Purcell and Neubauer, 2023) [2] (Verdouw *et al*., 2021) [3] (Awais *et al*., 2025) [22]. Component-level evidence is strong: IoT-enabled precision irrigation reliably improves water use efficiency (Kamienski *et al*., 2019) [10] (Barkunan *et al*., 2019) [11] (Bwambale *et al*., 2022) [12], UAV/satellite-AI systems achieve credible accuracy for growth and yield prediction (Wan *et al*., 2020) [14] (Zha *et al*., 2020) [17], and edge-cloud architectures measurably reduce latency relevant to time-sensitive decisions (Zamora-Izquierdo *et al*., 2019) [8] (Kalyani and Collier, 2021) [9]. Evidence for fully integrated, digital-twin-labeled systems evaluated as complete pipelines, from field sensing through virtual model synchronization to decision-support output, remains comparatively sparse, and is concentrated in a smaller number of dedicated implementations such as the cloud-based rice decision-support service described by Skobelev *et al*. [1].

This pattern is broadly consistent with the wider agricultural digital twin literature, which similarly notes that digital twin technology in agriculture is at an earlier stage of practical maturity than in manufacturing or aerospace engineering, where the concept originated (Purcell and Neubauer, 2023) [2] (Nasirahmadi and Hensel, 2022) [5] (Grieves and Vickers, 2017) [7]. Reasons cited across the literature include the greater biological complexity and environmental variability of living crop systems relative to engineered mechanical systems, the comparatively higher cost and lower standardization of agricultural IoT infrastructure, and the absence of widely agreed interoperability standards for agricultural data exchange between sensor vendors, UAV service providers, and cloud platforms (Purcell and Neubauer, 2023) [2] (Verdouw *et al*., 2021) [3] (Kalyani and Collier, 2021) [9].

Several practical implementation challenges emerge consistently. First, communication infrastructure, particularly reliable, affordable connectivity for LoRaWAN gateways or cellular data transmission, remains a genuine constraint in many rice-growing regions, especially smallholder-dominated systems in South and Southeast Asia where a large share of global rice production originates (Zamora-Izquierdo *et al*., 2019) [8] (Barkunan *et al*., 2019) [11]. Second, cross-season and cross-cultivar model transferability is incompletely resolved: growth and yield prediction models trained in one environment or on one cultivar set do not automatically generalize with equivalent accuracy to different agro-climatic zones or cultivars, a limitation also documented in the broader UAV-AI crop monitoring literature (Zha *et al*., 2020) [17] (Tsouros *et al*., 2019) [23]. Third, reporting of computational cost, system latency, and total implementation cost remains inconsistent across studies, which constrains the ability of prospective adopters, whether individual farmers, cooperatives, or public irrigation-scheme managers, to conduct reliable cost-benefit analysis prior to investment (Purcell and Neubauer, 2023) [2] (Awais *et al*., 2025) [22].

Comparison with international case studies (Table 5) suggests that digital twin and related sensor-AI fusion approaches are not unique to rice; comparable architectures and accuracy gains have been reported for greenhouse and orchard systems, indicating that the underlying architectural principles, tiered edge-cloud computing, multi-source sensor fusion, and AI-based predictive analytics, generalize reasonably well across cropping systems even though specific sensor configurations and decision-support outputs must be tailored to each crop's physiology and management calendar (Pylianidis *et al*., 2021) [6] (Awais *et al*., 2025) [22].

Future research priorities identified through this synthesis include: standardized, multi-site field validation of fully integrated digital twin pipelines rather than isolated components; consistent reporting of synchronization latency, computational efficiency, and total implementation cost alongside predictive accuracy; deeper investigation of cross-season and cross-cultivar model transferability; and continued development of low-cost, low-power sensor and communication technologies suited to smallholder rice production contexts, where the potential resource-efficiency gains from digital twin adoption may be proportionally largest but where current cost and infrastructure barriers remain most acute.

9. Conclusion

This review brings together peer-reviewed literature on Digital Twin technology for monitoring crop and resource efficiency in rice (*Oryza sativa* L.). According to the literature, individual components of the technology, such as IoT-enabled soil moisture and water level monitoring, UAV and satellite-based crop monitoring, edge-cloud computing technology and AI-based predictive analytics, prove to be effective and validated through numerous applications: reduction of irrigation water uses while maintaining or even increasing yield, very high accuracy of predictions of growth/yield (R2=0.79-0.94). Fully integrated systems of digital twins that rely on the use of abovementioned elements are not very common in peer-reviewed literature, but there are a few examples of actual implementation of this technology that indicate that technology starts to transition from validation of components to integrated deployment.

The pressing tasks for the researchers consist of standardizing the multi-site validation of the complete digital twin pipeline as well as ensuring that the system performance metrics reporting, schedule latency, and computational performance, is done more transparently, along with the commonly used assessment metrics. Farmers and crop managers, especially the ones dealing with big commercial rice production systems or public irrigation plants have, because of the evidence presented in the current study, achieved a high level of confidence in the resource-use efficiency of IoT- and remote-sensing-supported management, but costs and infrastructures at the moment are making the adoption feasible in well-off industrial sectors compared to smallholder sectors. Policymakers and agricultural extension services should work on investing into rural internet infrastructure, services platform for shared sensors and drones as well as interoperability standards in order to lower the barrier to adopting digital twin technology for the rice production sectors where the majority of global rice production takes place.

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