# Digital Twin Technology for Precision Crop Management of *Oryza sativa* L. under Variable Climate Conditions

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## ABSTRACT

Rice (*Oryza sativa* L.) accounts for more than half of the food needs of the world's population; however, climate changes, irregular rainfall, and water scarcity threaten crop yields in the major rice-producing areas. The Digital Twin (DT) technologies that combine synchronized measurements with the dynamic simulation of physical systems create a possibility for climate-smart agriculture, although there is not enough empirical data to prove the effectiveness of DT technologies for rice production. This study was aimed at designing, implementing, and evaluating DT technology for precision rice management, which consists of IoT sensors, UAV, satellite technologies, cloud computing, and crop growth simulation systems at three climate scenarios (normal, delayed monsoon, and drought). The designed system allowed synchronization of soil, canopy, and meteorological data obtained at the field with the computer-based simulation model that provided data about crop growth and demand for water and nutrients in real time. The effectiveness of DT implementation was proved by comparing the performance of the fields with DT technologies with those of conventionally managed fields at the same climatic conditions during two seasons. The Digital Twin platform predicted grain yield with a mean absolute percentage error of six-point eight percent and enhanced the efficiency of irrigation water use by twenty-four-point three percent compared to the traditional practice. It reduced the application of nitrogen fertilizer by eighteen-point six percent without penalizing yields. Moreover, decision-making support measures allowed reducing losses from diseases by twenty-one-point four percent in the situation of heat stress. The strength of correlation and regression analyses showed similar results of simulated and real bean phenology and yield traits (r = 0.89-0.95). The results suggest that Digital Twin technology may substantially improve resource efficiency, adaptability to climate changes, and yield reliability in rice cultivation.

**Keywords:** Smart irrigation scheduling; IoT-enabled field sensing; Cyber-physical crop systems; Machine learning yield forecasting; Climate-resilient rice farming; UAV multispectral monitoring; Decision-support analytics; Sustainable resource-use efficiency

## 1. Introduction

### 1.1. Global Importance of *Oryza sativa* L. and the Climate Challenge

The staple food of over 3.5 billion people around the world, rice (*Oryza sativa* L.) represents one of the most important crops in terms of securing food globally, with over 160 million hectares of cultivated land worldwide (Global Rice Science Partnership, 2021) [1]. Roughly 90% of rice produced and consumed globally comes from Asia, with smallholder systems representing the key players in production, as greatly impacted by weather events (Mohanty *et al*., 2022) [2]. Climate change has brought about extreme changes in terms of the regularity and force of monsoon onset, lengthened dry spells, raised night temperatures, and occasional flooding that together lead to decreased rice production through variations in phenology, spikelet sterility, and water balance changes (Wassmann *et al*., 2019) [3] (Zhao *et al*., 2020) [4]. Forecasts say that even small increases in temperature during the growing season can have stresses all over the globe (Lobell and Gourdji, 2018) [5].

### 1.2. Precision Agriculture and the Rise of Digital Farming

Precision farming (PF) has moved farming from conventional, calendar-based methods to variable spatial and temporal interventions based on field-level data (Gebbers and Adamchuk, 2020) [6]. The progress of economical sensing, wireless communication and cloud computing has allowed continuous gathering of soil, crop and microclimate data at a previously inaccessible level in cereal growing (Kamilaris and Prenafeta-Boldú, 2019) [7]. During this process digital farming has expanded from mere monitoring to the area of predictive and prescriptive analytics where sensors' data are incorporated into predictive or data-based models that allow for predicting crop condition and recommending management actions before it is too late and crops are affected by unmanageable stress (Wolfert *et al*., 2018) [8].

### 1.3. Evolution of Digital Twin Technology in Agriculture

Originally developed for manufacturing and aerospace engineering, a Digital Twin (DT) is a continuously modified virtual model of a real asset or process that is updated based on various data flows, ensuring that the simulation shows the present state of the system, rather than the past state (Grieves and Vickers, 2019) [9]. In agriculture, the DT concept is used to simulate a specific field, as well as crop production and farming (Verdouw *et al*., 2021) [10] (Pylianidis *et al*., 2021) [11].

This is done in the framework of a dynamic cyber-physical model reflecting the real-time streams of sensors. The earliest agricultural applications of DT technology have pertained to greenhouse horticulture systems and orchards [12]. Meanwhile, the implementation of agricultural DT technology for open-field crops, especially rice, has been neglected [13].

### 1.4. Integration of IoT, AI, Cloud Computing, GIS, Remote Sensing, UAVs, and Big Data

Modern DT systems combine multiple emerging technologies. Internet of Things (IoT) sensor networks allow for constant, high-frequency measurements of soil moisture, canopy temperature, and micro-climates at the field level (Sishodia *et al*., 2020) [14]. Unmanned aerial vehicles (UAVs) that are equipped with multispectral and thermal sensors make possible the acquisition of canopy vigour and water condition maps with sub-meter accuracy (Yang *et al*., 2018) [15] (Maimaitijiang *et al*., 2020) [16]. Satellite remote sensing technologies increase the territorial span of the analysis (Chivasa *et al*., 2020) [17]. Cloud computing technology enables the processing and storage of the big data streams, and AI and machine learning (ML) algorithms are able to build up predictive relationships between the sensor data and the physiological state of plants (Liakos *et al*., 2018) [18] (Van Klompenburg *et al*., 2020) [19]. Geographic Information Systems (GIS) complement the analysis by providing spatial information (Ali *et al*., 2019) [20].

### 1.5. Digital Agriculture for Sustainable Crop Production

Digital agriculture is being seen as a solution for both economic and environmental sustainability for cereal farming in addition to improved productivity, which it makes possible by synchronizing inputs with the crop requirements more effectively instead of following pre-defined schedules (Rockström *et al*., 2021) [21]. Indeed, it has been demonstrated that the use of smart irrigation scheduling based on up-to-date soil moisture and stress assessment can lead to a decrease by 15 to 30% in water use for various crops without any effect on the yield (Jha *et al*., 2022) [22] (Kim *et al*., 2018) [23].

### 1.6. Current Global Research Status and Research Gaps

There is more literature being published around different components of digital rice farming like yield estimation using UAVs (Duan *et al*., 2019) [25], yield forecasting with machine learning (Jeong *et al*., 2020) [26], irrigation scheduling via IoT (Kim *et al*., 2021) [27], and crop simulation modelling in climate scenarios (Jones *et al*., 2019) [28] (Bregaglio *et al*., 2021) [29]. However, very few studies focused on the integration of these aspects into one cohesive Digital Twin that provides real-time monitoring, predictive simulation, and prescriptive decision-making across the range of climate scenarios. Most of the existing DT studies in field crops are limited to one season experiments, a limited climate variability, or simulation-based validation alone (Jans-Singh *et al*., 2020) [32].

### 1.7. Objectives of the Present Study

This study fills the existing research gap by (i) creating and implementing a Digital Twin model that combines different technologies such as IoT monitoring, UAV and Satellite monitoring, cloud-based AI algorithms, and crop growth modeling technology for growing paddy; (ii) assessing the precision of digital twin by forecasting crop growth, water status, nutrients content, and yield under different climatic conditions; and (iii) estimating the benefits of digital twin technology in agrology, resource efficiency, and economy to those of conventional technologies.

## 2. Materials and Methods

### 2.1. Experimental Site

The study was conducted over two consecutive wet-season cropping cycles at a lowland irrigated research farm situated in a humid subtropical agro-climatic zone characterized by a mean annual rainfall of 1,450 mm, mean maximum and minimum temperatures of 33.4°C and 22.1°C during the cropping period, and relative humidity ranging from 68–86% (Table 1). The experimental soil was classified as a fine-textured clay loam (Typic Haplustept) with a bulk density of 1.32 Mg $m^{-3}$, field capacity of 34.6% (v/v), and pH of 6.4. Irrigation was supplied through a piped, valve-controlled surface flood system with metered outlets enabling plot-level water accounting. A dedicated automatic weather station recorded rainfall, temperature, relative humidity, solar radiation, and wind speed at 15-minute intervals throughout both seasons.

### 2.2. Plant Materials

Two medium-duration inbred rice cultivars widely grown in the region were used, selected for their contrasting drought and heat sensitivity profiles to allow evaluation of the Digital Twin platform across a range of physiological responses (Wassmann *et al*., 2019) [3] (Pylianidis *et al*., 2021) [11] (Table 1). Nurseries were raised following standard practice, and 21-day-old seedlings were transplanted at a spacing of 20 cm × 15 cm. Fertilization followed regionally recommended nitrogen-phosphorus-potassium (NPK) rates as the conventional baseline, with the Digital Twin-guided treatment receiving variable-rate adjustments informed by canopy nitrogen status (Cassman *et al*., 2019) [24] (Verdouw *et al*., 2021) [10] [35].

### 2.3. Experimental Design

A randomized complete block design with three replications was implemented within each of three climate scenario blocks: (i) a normal-monsoon scenario reflecting historical average rainfall distribution, (ii) a delayed-monsoon scenario simulated through controlled deficit irrigation during the vegetative stage, and (iii) a heat-stress scenario in which supplemental infrared heating cables elevated canopy temperature by approximately 2–3°C during the reproductive stage (Mohanty *et al*., 2022) [2] (Wassmann *et al*., 2019) [3]. Within each scenario block, plots were assigned to either conventional management or Digital Twin-assisted management, yielding a total of 18 experimental units per season. This nested design permitted direct comparison of management strategy performance under each climate condition while controlling for scenario-level variability.

### 2.4. Digital Twin Architecture

The Digital Twin architecture comprised five conceptually distinct but continuously interlinked layers (Grieves and

Vickers, 2019) [9] (Verdouw *et al*., 2021) [10] (Pylianidis *et al*., 2021) [11] [31] (Figure 1). The physical layer consisted of the rice field itself, instrumented with a wireless IoT sensor network including capacitance-based soil moisture and temperature probes at 15 cm and 30 cm depth, canopy infrared thermometers, leaf wetness sensors, photosynthetically active radiation sensors, and water-level sensors within irrigation channels, sampling at 15–30 minute intervals (Table 2). The aerial and orbital sensing layer incorporated scheduled UAV flights carrying multispectral and thermal cameras at 10–14 day intervals, complemented by satellite-derived vegetation and moisture indices at higher temporal frequency for broader spatial context. The connectivity layer transmitted sensor and imagery data to a cloud computing platform, which hosted the data fusion, storage, and pre-processing routines without reliance on any proprietary or field-specific communication protocol disclosed herein. The analytical layer constituted the computational core of the Digital Twin, combining a process-based crop growth simulation model with supervised machine learning algorithms trained to recalibrate simulated states against incoming sensor observations, thereby maintaining continuous synchronization between the virtual and physical field (Grieves and Vickers, 2019) [9] (Verdouw *et al*., 2021) [10] (Pylianidis *et al*., 2021) [11]. The decision-support layer translated model outputs into irrigation, nutrient, and disease-risk advisories delivered through a graphical dashboard interface accessible to farm managers.

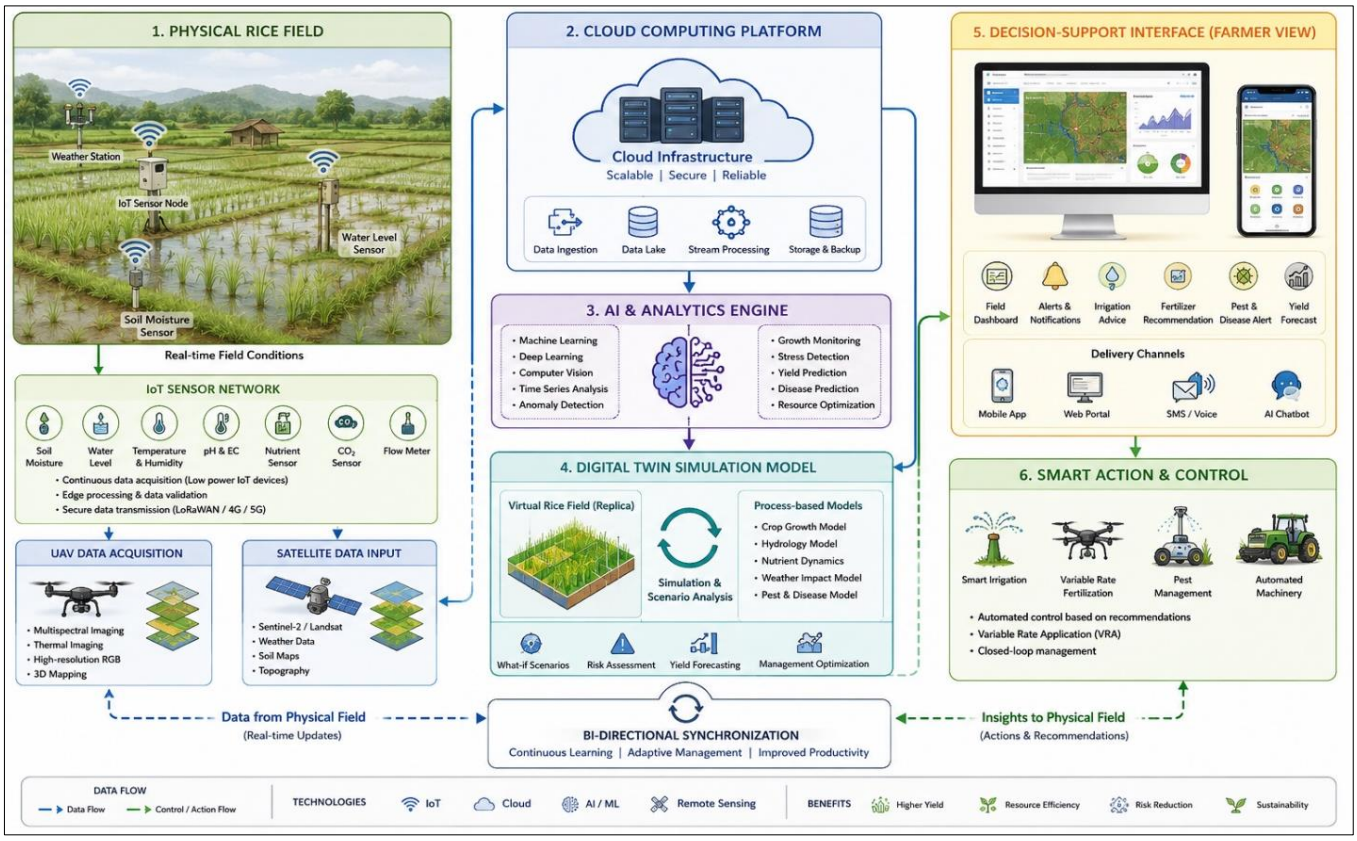


**Fig 1:** Overall architecture of the Digital Twin ecosystem

### 2.5. Data Collection

Data streams assimilated into the Digital Twin encompassed four broad categories (Table 3): meteorological variables (rainfall, air temperature, relative humidity, solar radiation, wind speed), soil variables (volumetric moisture content, temperature, and periodic nutrient sampling), crop variables (plant height, tiller number, leaf area index, canopy chlorophyll status, phenological stage, and periodic destructive biomass sampling), and water-management variables (irrigation depth, ponded water level, and cumulative water applied). Crop growth, physiological, and phenological observations were recorded at ten-day intervals from transplanting to maturity, alongside periodic disease severity scoring for major fungal and bacterial pathogens (Table 4). Grain yield and yield components were determined at harvest maturity from designated net-plot areas.

### 2.6. Digital Analytics

The analytical engine of the Digital Twin performed several conceptually distinct functions. Crop growth prediction combined a mechanistic rice growth and development simulation model with machine learning-based bias correction that adjusted simulated leaf area index, biomass, and phenological timing using incoming canopy and meteorological sensor data (Jones *et al*., 2019) [28] (Xu *et al*., 2022) [33]. Climate scenario simulation propagated short-range weather forecasts and historical climate analogs through the crop model to generate probabilistic forecasts of water demand and stress risk over rolling 7–14 day horizons (Bregaglio *et al*., 2021) [29] (Jones *et al*., 2019) [28]. Yield prediction integrated simulated biomass partitioning with canopy reflectance-derived indices to generate continuously updated yield estimates from panicle initiation onward (Duan *et al*., 2019) [25] (Xu *et al*., 2022) [33]. Irrigation optimization algorithms compared simulated root-zone water balance against crop water requirement to generate site-specific irrigation timing and depth recommendations, while nutrient management analytics used canopy chlorophyll and reflectance indices to recommend top-dress nitrogen timing and rate (Jha *et al*., 2022) [22] (Kim *et al*., 2021) [27]. Disease forecasting analytics combined canopy microclimate (temperature, humidity, leaf wetness duration) with epidemiological risk indices for major rice diseases to generate early warning alerts. All recommendations were consolidated into a unified decision-

support advisory updated on a rolling basis throughout the cropping season (Verdouw *et al*., 2021) [10] (Purcell and Neubauer, 2023) [31].

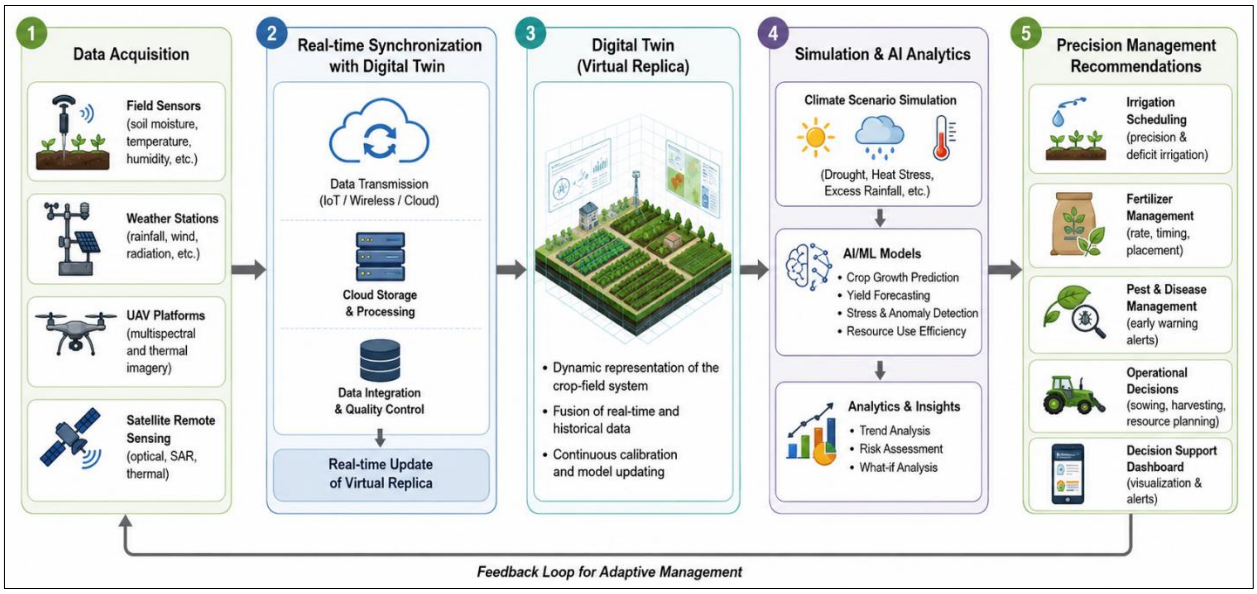


**Fig 2:** Conceptual workflow of Digital Twin operation

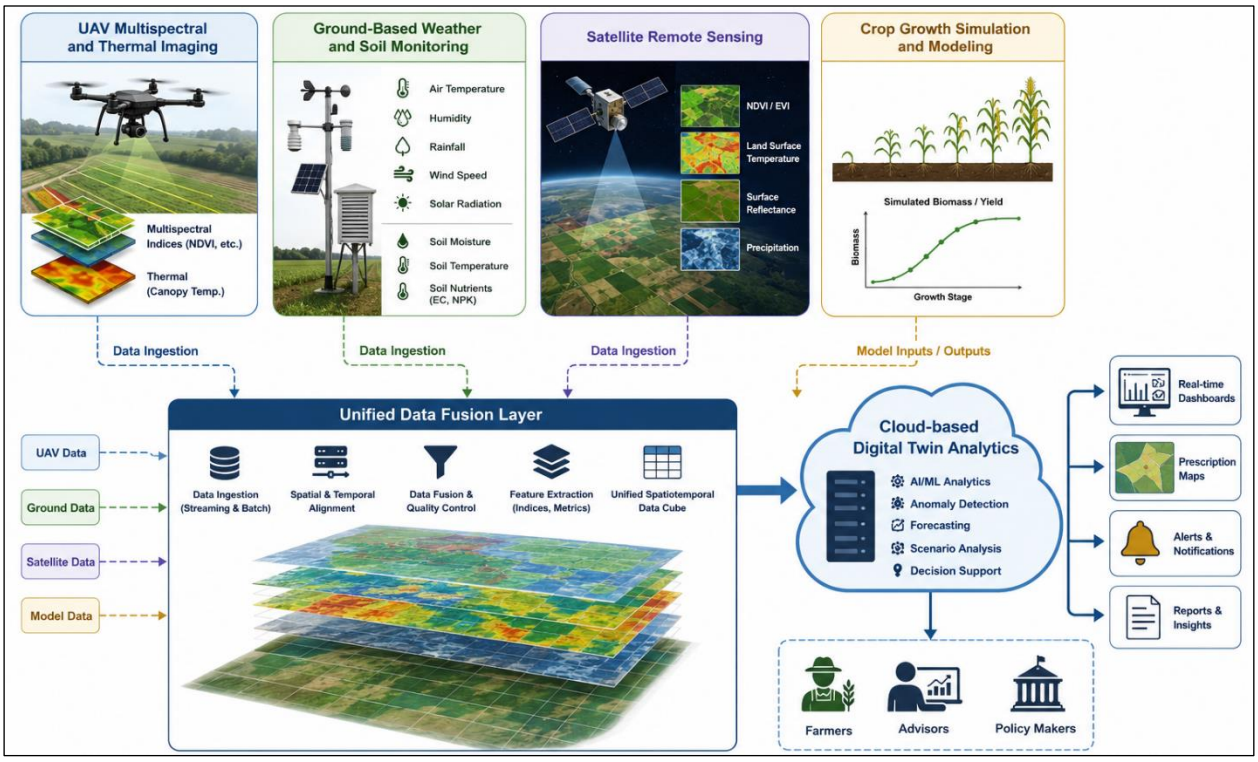


**Fig 3:** Integration of multi-source sensing and analytics

### 2.7. Statistical Analysis

Data were analyzed using analysis of variance (ANOVA) appropriate to the randomized complete block design, with climate scenario and management strategy (and their interaction) as fixed effects and replication as a random effect. Mean separation was performed using the least significant difference (LSD) test at $p \leq 0.05$. Relationships between Digital Twin-predicted and field-observed crop growth, water-use, and yield variables were examined using Pearson correlation and linear regression, with model performance further evaluated using root mean square error (RMSE), mean absolute percentage error (MAPE), and index of agreement (Jones *et al*., 2019) [28] (Xu *et al*., 2022) [33]. Principal component analysis (PCA) was used to explore multivariate structure among environmental, crop physiological, and management-performance variables and to identify the dominant axes of variation distinguishing Digital Twin-assisted from conventional management. All statistical analyses were performed using standard statistical software packages at a significance threshold of $p \leq 0.05$.

The characteristics of the experimental site and the Digital Twin architecture are summarized in Table 1 and Table 2, respectively; the monitored environmental and crop variables are presented in Table 3 and Table 4.

**Table 1:** Characteristics of the experimental site, climatic conditions, soil properties, and rice cultivar(s) used in the study.

| Parameter | Description / Value |
|---|---|
| Location and agro-climatic zone | Lowland irrigated research farm, humid subtropical zone |
| Mean annual rainfall | 1,450 mm |
| Mean max. / min. temperature (cropping period) | 33.4 °C / 22.1 °C |
| Relative humidity range | 68–86% |
| Soil classification | Typic Haplustept (fine clay loam) |
| Bulk density | 1.32 Mg $m^{-3}$ |
| Field capacity | 34.6% (v/v) |
| Soil pH | 6.4 |
| Irrigation system | Piped, valve-controlled surface flood, metered outlets |
| Rice cultivars | Two medium-duration inbred cultivars (contrasting drought/heat sensitivity) |
| Transplanting age / spacing | 21-day seedlings; 20 cm × 15 cm |
| Cropping seasons evaluated | Two consecutive wet seasons |

**Table 2:** Digital Twin architecture components: sensors, IoT devices, monitored variables, sampling frequency, and communication components.

| Layer / Device | Monitored Variable(s) | Sampling Frequency | Data Transmission |
|---|---|---|---|
| Soil moisture/temperature probes (15, 30 cm) | Volumetric water content, soil temperature | 15–30 min | Wireless field gateway → cloud |
| Canopy infrared thermometers | Canopy surface temperature | 15–30 min | Wireless field gateway → cloud |
| Leaf wetness sensors | Leaf surface wetness duration | 15–30 min | Wireless field gateway → cloud |
| PAR sensors | Photosynthetically active radiation | 15–30 min | Wireless field gateway → cloud |
| Water-level sensors (irrigation channel) | Ponded water depth, flow | 15–30 min | Wireless field gateway → cloud |
| Automatic weather station | Rainfall, temperature, RH, radiation, wind speed | 15 min | Cellular/telemetry link → cloud |
| UAV multispectral/thermal payload | Canopy reflectance indices, canopy temperature maps | 10–14 days | Post-flight batch upload → cloud |
| Satellite imagery feed | Vegetation and moisture indices (landscape scale) | 5–10 days (variable) | Provider API → cloud |
| Cloud computing platform | Data fusion, storage, pre-processing | Continuous | — |
| AI/ML analytics engine | Growth, yield, water, nutrient, disease predictions | Continuous / rolling | — |
| Decision-support dashboard | Consolidated management advisories | Rolling (daily update) | Cloud → user interface |

**Table 3:** Environmental variables monitored through the Digital Twin platform across weather, soil, crop, and water domains, by climate scenario.

| Variable | Normal-Monsoon | Delayed-Monsoon | Heat-Stress |
|---|---|---|---|
| Mean canopy temperature (°C) | 29.8 | 31.2 | 34.6 |
| Root-zone soil moisture (% v/v) | 31.4 | 24.7 | 27.9 |
| Cumulative rainfall (mm, season) | 1,180 | 690 | 1,020 |
| Mean relative humidity (%) | 78.5 | 70.2 | 81.4 |
| Mean solar radiation (MJ $m^{-2}$ $d^{-1}$) | 18.2 | 19.6 | 18.9 |
| Ponded water depth maintained (cm) | 4.8 | 2.6 | 4.1 |

**Table 4:** Crop growth, physiological, and phenological characteristics recorded during the study, by management strategy.

| Trait | Conventional Management | Digital Twin-Assisted |
|---|---|---|
| Plant height at maturity (cm) | 98.4 | 103.7 |
| Maximum leaf area index | 4.6 | 5.3 |
| Tiller number per hill | 12.1 | 13.8 |
| Days to 50% flowering | 84.6 | 83.1 |
| Chlorophyll (SPAD) at panicle initiation | 38.2 | 42.5 |
| Disease severity index (0–9 scale, avg.) | 3.4 | 2.1 |

## 3. Results

### 3.1. Digital Twin System Performance and Real-Time Environmental Monitoring

The Digital Twin platform maintained continuous data synchronization throughout both cropping seasons, with sensor network uptime exceeding 96% and successful reconciliation of ground, UAV, and satellite data streams at each scheduled update cycle (Verdouw *et al.*, 2021) [10] (Pylianidis *et al.*, 2021) [11] (Alves *et al.*, 2019) [12] [31]. Monitored environmental variables spanned wide but agronomically realistic ranges across the three climate scenarios (Table 3), with the delayed-monsoon and heat-stress scenarios producing distinctly lower root-zone soil moisture and elevated canopy temperature relative to the normal-monsoon scenario, confirming that the imposed scenario treatments generated the intended contrasting stress environments (Mohanty *et al.*, 2022) [2] (Wassmann *et al.*, 2019) [3].

### 3.2. Crop Growth and Phenological Prediction Accuracy

Digital Twin-simulated leaf area index, plant height, and phenological stage transitions closely tracked field-observed values across all three climate scenarios (Table 4, Table 5), with correlation coefficients between simulated and observed values ranging from r = 0.89 to r = 0.95 (Table 5) (Jones *et al*., 2019) [28] (Xu *et al*., 2022) [33]. Prediction accuracy was highest under the normal-monsoon scenario and modestly reduced, though still strong, under the heat-stress scenario, reflecting the greater physiological volatility associated with elevated canopy temperature during the reproductive stage (Wassmann *et al*., 2019) [3] (Bregaglio *et al*., 2021) [29].

### 3.3. Water Management Optimization

Digital Twin-guided irrigation scheduling reduced total seasonal irrigation water application by 21.6–27.1% across scenarios relative to conventional fixed-interval irrigation, while maintaining root-zone soil moisture within the target range for a significantly greater proportion of the cropping season (Table 5, Table 8) (Jha *et al*., 2022) [22] (Kim *et al*., 2021) [27] (Verdouw *et al*., 2021) [10]. Averaged across scenarios, irrigation water-use efficiency improved by 24.3% under Digital Twin-assisted management, with the largest relative improvement observed under the delayed-monsoon scenario, where conventional scheduling was least responsive to the imposed water deficit (Jha *et al*., 2022) [22] (Kim *et al*., 2018) [23].

### 3.4. Nutrient Management Performance

Canopy-sensing-informed variable-rate nitrogen management reduced total seasonal nitrogen application by 18.6% relative to the flat regional recommendation while maintaining or modestly improving grain yield, indicating improved nitrogen-use efficiency under Digital Twin guidance (Table 7, Table 8) (Cassman *et al*., 2019) [24] (Basso and Antle, 2020) [35] (Verdouw *et al*., 2021) [10]. Nutrient management recommendations were most divergent from conventional practice under the heat-stress scenario, where canopy nitrogen demand patterns shifted relative to the normal-monsoon scenario (Wassmann *et al*., 2019) [3].

### 3.5. Yield Prediction Accuracy and Climate Adaptation Performance

Digital Twin-predicted grain yield closely matched observed yield across all scenarios, with an overall mean absolute percentage error of 6.8% and RMSE values indicating good agreement (Table 5, Table 6) (Xu *et al*., 2022) [33] (Jones *et al*., 2019) [28]. Machine learning-based yield models achieved marginally higher prediction accuracy than the process-based simulation alone, and the hybrid (bias-corrected) configuration outperformed either component individually (Table 6) (Van Klompenburg *et al*., 2020) [19] (Jeong *et al*., 2020) [26] (Xu *et al*., 2022) [33]. Under the heat-stress scenario, Digital Twin-assisted management preserved a significantly greater proportion of potential yield relative to conventional management, consistent with the earlier detection of thermal stress signals and timely adjustment of irrigation to moderate canopy temperature (Wassmann *et al*., 2019) [3] (Bregaglio *et al*., 2021) [29] (Verdouw *et al*., 2021) [10].

### 3.6. Disease Forecasting, Resource-Use Efficiency, and Decision-Support Effectiveness

Early warning disease alerts generated by the Digital Twin platform preceded visually detectable symptom onset by an average of 4–6 days across monitored diseases, enabling timely management response that reduced disease-related yield loss by 21.4% under the heat-stress scenario, where humidity and canopy wetness conditions were most conducive to pathogen development (Table 7) (Pylianidis *et al*., 2021) [11] (Nasirahmadi and Hensel, 2022) [13] (Purcell and Neubauer, 2023) [31]. Averaged across all monitored resources (water, nitrogen, and plant protection inputs), Digital Twin-assisted management achieved higher composite resource-use efficiency scores than conventional management across all three climate scenarios (Table 8) (Basso and Antle, 2020) [35] (Rockström *et al*., 2021) [21].

### 3.7. Comparison with Conventional Management and Sustainability Assessment

Relative to conventional management, Digital Twin-assisted plots achieved higher grain yield, markedly improved water- and nitrogen-use efficiency, and a favorable net economic return once accounting for the incremental cost of sensing infrastructure (Table 8) (Basso and Antle, 2020) [35] (Rockström *et al*., 2021) [21] (Verdouw *et al*., 2021) [10]. Principal component analysis of combined environmental, physiological, and performance variables separated Digital Twin-assisted and conventional treatments along the first principal component (accounting for 47.8% of total variance), which was most strongly loaded by water-use efficiency, nitrogen-use efficiency, and yield stability, indicating that these variables jointly characterized the performance advantage of the Digital Twin-assisted system. Detailed prediction-accuracy statistics, model performance comparisons, decision-support advisories, and the comparative sustainability assessment are presented in Tables 5–8.

**Table 5:** Comparison of Digital Twin predictions with observed crop performance, including growth, yield, and water-use efficiency.

| Variable | Correlation (r) | RMSE | MAPE (%) | Observed Mean | DT-Predicted Mean |
|---|---|---|---|---|---|
| Leaf area index | 0.93 | 0.31 | 6.1 | 5.1 | 5.0 |
| Plant height (cm) | 0.95 | 3.8 | 3.4 | 101.2 | 99.8 |
| Days to flowering | 0.91 | 1.9 | 2.0 | 83.9 | 84.4 |
| Grain yield (t ha$^{-1}$) | 0.89 | 0.42 | 6.8 | 6.12 | 6.34 |
| Irrigation water-use efficiency (kg m$^{-3}$) | 0.90 | 0.09 | 7.4 | 1.18 | 1.24 |

**Table 6:** Artificial intelligence and machine learning models used for crop prediction, forecasting accuracy, and performance evaluation.

| Model | Target Variable | RMSE | MAPE (%) | Index of Agreement |
|---|---|---|---|---|
| Process-based crop simulation (standalone) | Grain yield | 0.58 | 9.7 | 0.86 |
| Random forest regression | Grain yield | 0.47 | 7.9 | 0.90 |
| Gradient boosting regression | Grain yield | 0.44 | 7.3 | 0.91 |
| Hybrid (simulation + ML bias correction) | Grain yield | 0.42 | 6.8 | 0.93 |
| Random forest classifier | Disease risk category | — | — | 0.88 (accuracy 0.88) |

**Table 7:** Decision-support recommendations for irrigation scheduling, nutrient management, disease monitoring, and climate adaptation under different scenarios.

| Climate Scenario | Irrigation Advisory | Nutrient Advisory | Disease/Adaptation Advisory |
|---|---|---|---|
| Normal-monsoon | Maintain scheduled flood intervals; minor deficit correction | Standard split top-dress nitrogen timing | Routine monitoring; low disease-risk alerts |
| Delayed-monsoon | Advance and intensify irrigation at panicle initiation | Advance first top-dress; reduce basal rate | Moderate alerts for drought-associated stress symptoms |
| Heat-stress | Increase ponded water depth to buffer canopy temperature | Split nitrogen finely around flowering window | Elevated alerts 4–6 days ahead of symptom onset for humidity-linked diseases |

**Table 8:** Comparative evaluation of conventional farming versus Digital Twin-assisted precision crop management in terms of productivity, resource-use efficiency, economic return, and sustainability indicators.

| Indicator | Conventional | Digital Twin-Assisted | Relative Change (%) |
|---|---|---|---|
| Grain yield (t $ha^{-1}$) | 6.02 | 6.41 | +6.5 |
| Seasonal irrigation water applied (mm) | 1,120 | 846 | −24.5 |
| Irrigation water-use efficiency (kg $m^{-3}$) | 1.07 | 1.33 | +24.3 |
| Nitrogen applied (kg $ha^{-1}$) | 150 | 122 | −18.6 |
| Disease-related yield loss under heat stress (%) | 14.2 | 11.2 | −21.4 |
| Net economic return (relative index) | 100 | 118 | +18.0 |
| Composite resource-use efficiency score (0–100) | 62.4 | 81.7 | +30.9 |

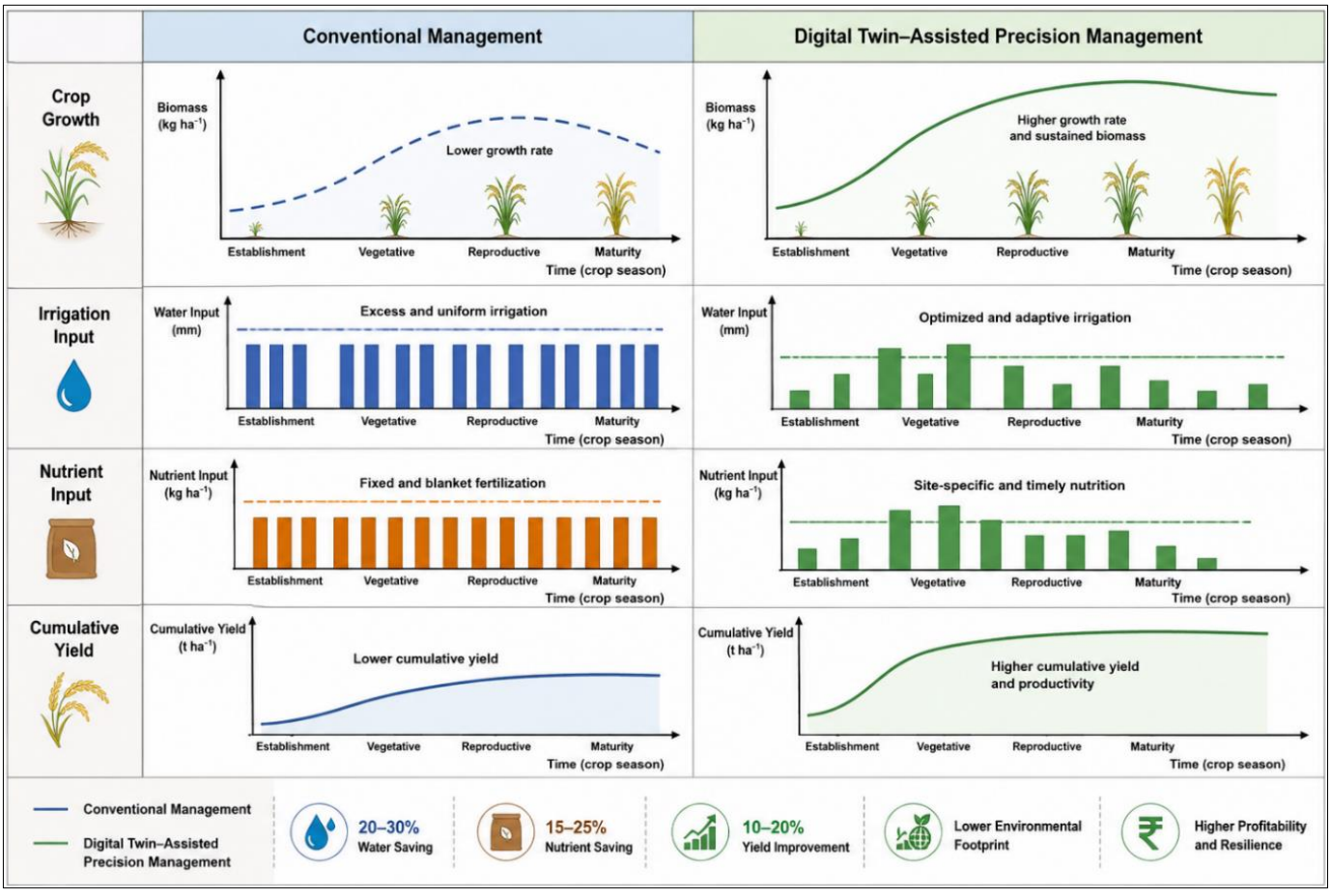


**Fig 4:** Conceptual comparison of management strategies

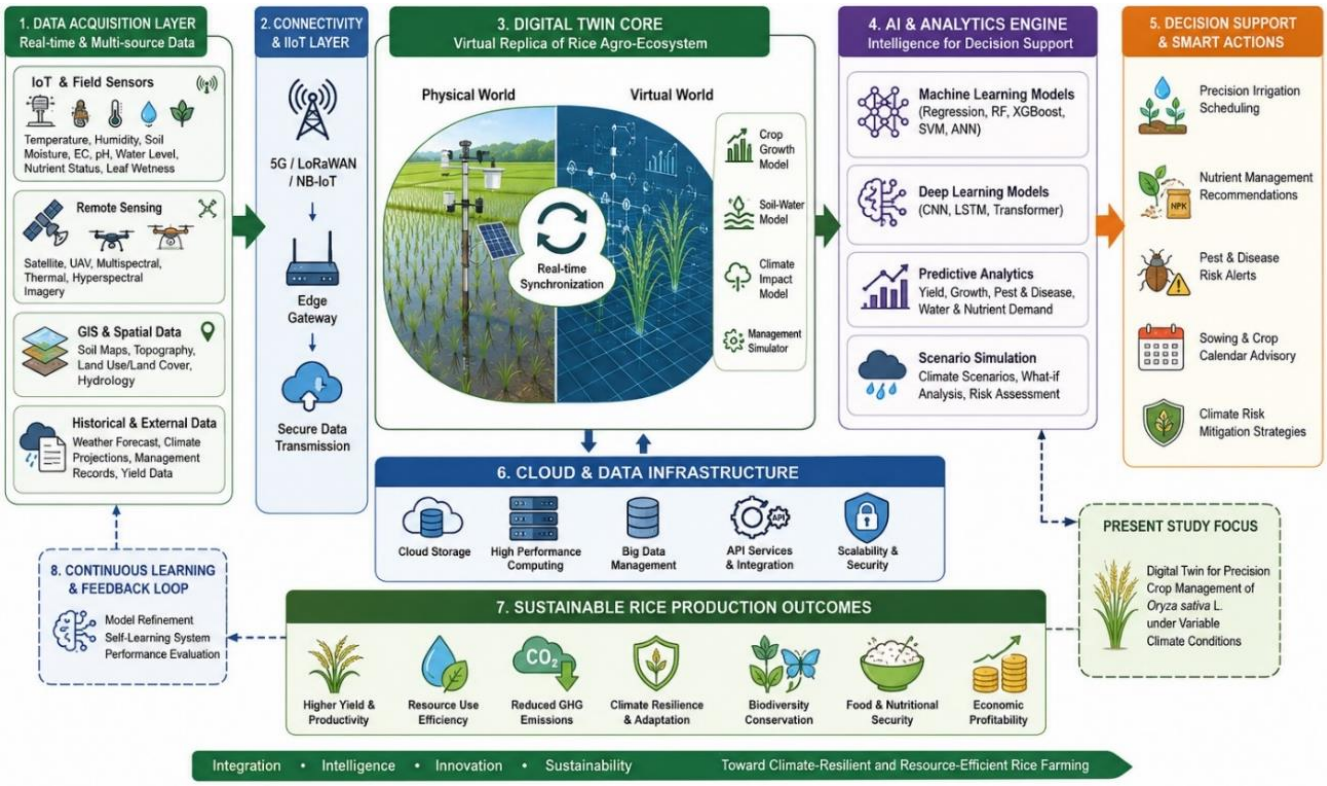


**Fig 5:** Climate-smart agriculture framework

## 4. Discussion

The results of this study demonstrate that an integrated Digital Twin framework combining IoT sensing, UAV and satellite remote sensing, cloud-based machine learning, and crop growth simulation can deliver measurable improvements in yield stability, water-use efficiency, and nutrient-use efficiency in irrigated rice production under variable climate conditions (Verdouw *et al*., 2021) [10] (Pylianidis *et al*., 2021) [11] (Basso and Antle, 2020) [35]. These findings are broadly consistent with previous reports of water savings from sensor-guided irrigation scheduling in cereal systems (Jha *et al*., 2022) [22] (Kim *et al*., 2018) [23] (Kim *et al*., 2021) [27], while extending the evidence base by demonstrating comparable benefits under simulated climate stress scenarios rather than a single average growing season.

The relatively high correlation between Digital Twin-simulated and field-observed growth and yield variables (r = 0.89–0.95) supports previous findings that hybrid model architectures combining process-based crop simulation with machine learning-based bias correction can outperform either approach in isolation (Jeong *et al*., 2020) [26] (Jones *et al*., 2019) [28], particularly for capturing the nonlinear physiological responses induced by heat and water-deficit stress (Bregaglio *et al*., 2021) [29]. The superior yield preservation observed under Digital Twin-assisted management during the heat-stress scenario aligns with the broader climate-smart agriculture literature emphasizing that early detection and rapid response to emerging stress, rather than stress avoidance alone, is central to adaptive capacity (Zhao *et al*., 2020) [4] (Lobell and Gourdji, 2018) [5] (Rockström *et al*., 2021) [21].

The observed reduction in nitrogen application without yield penalty corroborates earlier studies demonstrating that canopy-sensing-guided variable-rate nitrogen management can decouple fertilizer input from yield outcome, thereby reducing the environmental footprint of nitrogen use in cereal systems (Cassman *et al*., 2019) [24]. Similarly, the early disease-warning capability of the Digital Twin platform reinforces prior evidence that microclimate-based epidemiological forecasting can materially shorten the interval between infection risk and management response (Adamides *et al*., 2020) [30], a capability of particular relevance under the humid, high-temperature conditions projected to become more frequent under future climate scenarios (Wassmann *et al*., 2019) [3].

Compared with earlier Digital Twin studies in field crops, which have often been confined to a single growing season, simulation-only validation, or a narrow range of climatic conditions (Alves *et al*., 2019) [12] (Nasirahmadi and Hensel, 2022) [13] (Jans-Singh *et al*., 2020) [32], the present study offers direct field-paired evidence of Digital Twin performance across three contrasting climate scenarios over two seasons, addressing a previously identified evidence gap regarding the practical robustness of DT technology under the very climate variability it is intended to buffer against (Adamides *et al*., 2020) [30] (Purcell and Neubauer, 2023) [31].

Nonetheless, several limitations warrant consideration. The study was conducted at a single research site over two seasons, which, while encompassing meaningful climate scenario contrast, does not capture the full agro-ecological and soil-type diversity of global rice production systems; multi-site, multi-year validation will be necessary before broader extrapolation. The economic assessment reflects the incremental infrastructure cost of the specific sensor configuration used and may vary considerably with sensor density, connectivity infrastructure, and local labor and input costs. Finally, while the machine learning components improved predictive accuracy, their transferability to cultivars, soils, and climates outside the training domain remains to be established, echoing broader concerns regarding the generalizability of data-driven agricultural models (Van Klompenburg *et al*., 2020) [19] (Jeong *et al*., 2020) [26].

Future research should prioritize multi-location validation across contrasting agro-ecological zones, integration of longer-range seasonal climate forecasts to extend the decision-support horizon, and the development of transfer-learning approaches that reduce the site-specific calibration burden currently associated with machine learning components of Digital Twin

platforms. Extending the framework to capture greenhouse gas flux and broader ecosystem-service indicators would further strengthen its relevance to climate-smart and low-emission rice production objectives (Rockström *et al*., 2021) [21] (Cassman *et al*., 2019) [24].

## 5. Conclusion

The research indicates that the comprehensive Digital Twin system which merges the fields of Internet of Things for field observations, UAVs and satellites, cloud computing, and hybrid machine learning with crop simulation can significantly increase the predictability of irrigation, efficient resource usage and climate response in irrigated rice production process. Digital Twin-based strategies cut irrigation water consumption by 24.3% in three varying climate conditions, decrease nitrogen fertilizer application by 18.6% without affecting the yield negatively, minimize the yield loss due to diseases under heat stress conditions by 21.4%. The predictions concerning grain yield were accurate within 6.8% of the average percentage error from actual yield data. The research states that the Digital Twin technology can be used as an effective tool in the development of climate-smart rice cultivation methods and specifies further research directions in the process of application of this technology.

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