Review

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Posted Date: 5 February 2026

doi: 10.20944/preprints202602.0211.v1

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Advances in Emerging Digital Technologies for Sustainable Agriculture: Applications and Future Perspectives

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Abstract

Sustainable agriculture is under increasing pressure due to climate variability, resource scarcity, and the need to reduce environmental impacts without compromising productivity. This study aimed to systematically analyze recent advances in emerging digital technologies applied to sustainable agriculture. The PRISMA protocol was applied to Scopus and Web of Science, considering publications from 2020 to 2025, which were analyzed using RStudio 4.5.10 and VOSviewer 1.6.20, resulting in 101 relevant articles. The findings indicate that multisensor monitoring and precision agriculture enable high-resolution characterization of soil–crop variability, supporting site-specific irrigation, fertilization, and phytosanitary management. Likewise, machine learning-based predictive models improve decision-making by forecasting yield, water stress, nutrient deficiencies, and disease outbreaks. In addition, edge computing and autonomous systems enhance operational efficiency and reduce labor dependency. Blockchain strengthens transparency and sustainability certification through secure traceability, while digital twins optimize management strategies through prior simulation. Despite these advances, limitations remain, including platform fragmentation, limited interoperability, uneven adoption among smallholders, and challenges in model generalization across heterogeneous agroecosystems. Therefore, further progress toward integrated and interoperable digital ecosystems is recommended.

Keywords: precision agriculture; digital transformation; data mining; internet of things; technology 4.0

1. Introduction

Agriculture is facing a systemic crisis driven by the pressure to feed a population expected to exceed 9.7 billion by 2050, while the availability of additional arable land is projected to increase by only about 5% [1]. Moreover, it is estimated that 33% of the world's agricultural soils are moderately or severely degraded, and the sector accounts for approximately 70% of global freshwater withdrawals [2]. This scenario is further aggravated by climate variability, which causes annual agricultural losses exceeding USD 96 billion in developing countries [3]. In this context, it has become essential to transition from extensive production systems toward sustainable agriculture models capable of optimizing input use, reducing environmental impacts, and maintaining productivity under uncertain conditions. This technical transformation requires tools that integrate multidimensional data in real time to support efficient decision-making [4].

Emerging digital technologies provide big data-driven solutions, which have become a highly technical alternative to address the challenges currently faced by the agricultural sector. Therefore, predictive models based on machine learning algorithms, together with the use of remote sensing, have attracted increasing interest over the last decade, particularly among organizations and farmers [5]. Technological approaches such as deep neural networks, computer vision, expert systems, and blockchain integration enable the automation of tasks including disease detection, yield prediction, irrigation scheduling, and agri-food traceability [6,7]. Likewise, the deployment of the Internet of Things (IoT) in agriculture enables extensive connectivity across production systems, reaching more than 12 million active sensors in the field. This generates data streams that can be exploited by intelligent models, forming the core of so-called "smart agriculture" or Agriculture 4.0 [8].

Despite the rapid growth of these technologies in the agri-industrial sector, their implementation shows marked disparities across agricultural systems [9]. In regions such as Western Europe and East Asia, more than 45% of farms use some AI-based component, whereas in Latin America this figure barely exceeds 7% [10]. Gaps in digital infrastructure, rural connectivity, access to open data platforms, and technical training limit the adoption of these solutions in low-resource settings [11]. In addition, many technologies have been developed for non-tropical contexts or under industrial agriculture conditions; therefore, their direct transfer is often inefficient or unfeasible for small-scale farming systems [12]. In this scenario, technological sustainability involves not only technical feasibility, but also inclusion, adaptability, and data governance in rural territories, aiming to sustain agricultural productivity over time [13].

Digitalization in agriculture has made significant contributions to crop productivity and sustainability and has grown substantially in recent years. However, a large portion of the literature remains fragmented and focused on technologies applied in isolation [14]. In other words, there is still a lack of studies that comprehensively systematize the multiple applications of technology according to agro-environmental, economic, and social sustainability criteria, as well as identifying which crops or challenges have been most frequently addressed [15]. This limits the development of evidence-based public policies and hinders the prioritization of strategic research and innovation lines in agriculture [16]. Furthermore, there is a lack of analytical frameworks that simultaneously integrate both the technological and territorial perspectives [17]. Within this context, the following research question is posed: What are the main applications, limitations, and trends of artificial intelligence and emerging digital technologies in sustainable agriculture?

The fragmentation of studies hinders the extraction of integrated conclusions that can guide public policies, technological investments, or sustainable innovation strategies. Furthermore, there is a marked asymmetry in the geographical and thematic distribution of research, with a predominance of highly technological contexts and little attention paid to rural regions. Therefore, a rigorous and cross-cutting systematization of the available scientific evidence is required to identify trends, gaps, challenges, and opportunities related to emerging technologies in agriculture. The objective of this study is to systematically review the applications of emerging digital technologies in sustainable agriculture, identifying technological trends, application domains, implementation gaps, and opportunities for improvement.

2. Materials and Methods

2.1. Methodological Design

This study was designed as a systematic review of the scientific literature aimed at providing a technical and strategic analysis of the applications of artificial intelligence and emerging digital technologies in sustainable agriculture. An exploratory–analytical approach with an applied orientation was adopted and structured according to the PRISMA 2020 guidelines (Preferred

 doi:10.20944/preprints202602.0211.v1

Reporting Items for Systematic Reviews and Meta-Analyses), which are widely recognized for supporting rigorous evidence synthesis. This approach was complemented with advanced bibliometric analysis, text mining, and computational visualization techniques to identify technological patterns, thematic gaps, and relevant interdisciplinary relationships within the field of study [18]. The entire methodological process was documented and implemented in the RStudio statistical environment, ensuring traceability and reproducibility of the procedures and results obtained.

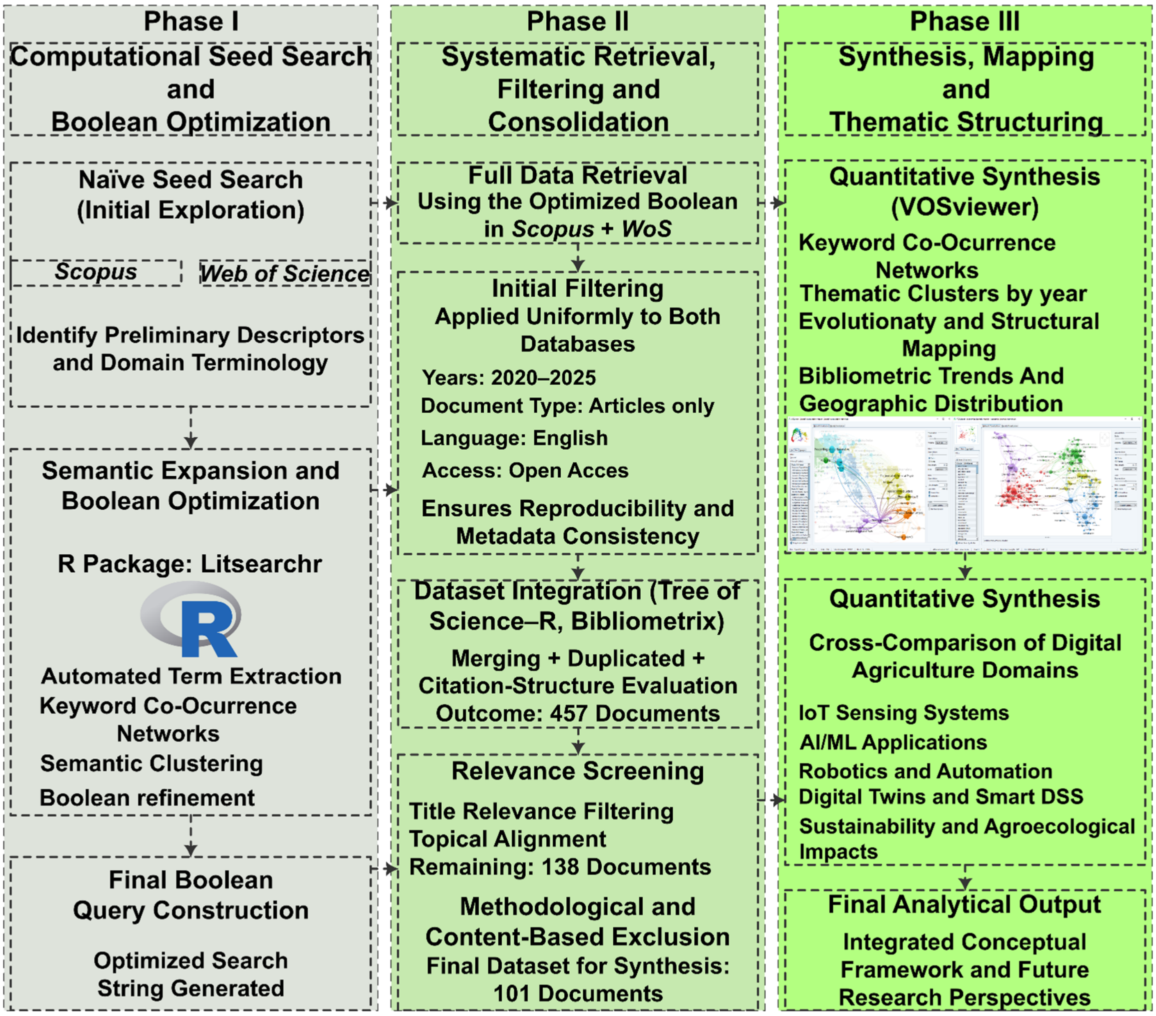

Figure 1. Integrated Methodological Flowchart. Computational Semantic Search (Litsearchr) Combined with PRISMA Systematic Selection.

The methodological procedure was structured into three specific phases to conduct the systematic review of the included studies. In Phase I (computational search and identification), the scientific literature retrieval strategy was defined using high-impact databases such as Scopus and Web of Science, generating an initial set of records. To optimize the query process, the litsearchr package in R was used, which improves semantic searching, refines keywords, and strengthens the consistency of the bibliometric dataset. In Phase II (screening and PRISMA-based selection), duplicates were removed using a reference manager, and records were subsequently filtered by title and abstract according to the inclusion/exclusion criteria. Then, during the eligibility stage, full texts were assessed and non-relevant studies were excluded until the final set of included articles was obtained. In Phase III, both quantitative synthesis (bibliometric mapping, trends, and geographical distribution) and qualitative synthesis (thematic coding) were performed, resulting in an integrated framework and future perspectives.

2.2. Inclusion and Exclusion Criteria

The articles were selected based on their thematic coherence, technological-empirical application, and methodological validity (Table 1); highlighting original articles that had a completed final state.

Table 1. General search strategy and identification filters.

Category	Strategy	Decision
Thematic domain.	Applications of emerging digital technologies (EDTs) in the agricultural context.	Inclusion
	Studies that do not address TDE with specific agricultural application.	Exclusion
Document type, year and access.	Original peer-reviewed scientific articles, from 2020-2025 and open access.	Inclusion
Methodological design.	Experimental studies of predictive or computational modeling.	Inclusion
	Narrative reviews, documents without methodological validation or without implementation of technologies	Exclusion
Technological relevance.	Studies with technical evidence of TDE application (machine learning, IoT, sensors, blockchain, etc.).	Inclusion

2.3. Document Search Strategy

The document search strategy was designed by formulating a search string based on key terms and their technical synonyms, connected through Boolean operators (AND, OR) and applied to the title, abstract, and keyword fields (TITLE-ABS-KEY). The initial search, considered as a seed or "naïve" query, combined terms related to emerging digital technologies ("emerging digital technologies") AND ("sustainable agriculture"). This strategy was preliminarily tested in the Scopus database, yielding a total of four documents.

2.4. Semantic Search and Term Analysis with Litsearchr

As a methodological complement and in order to strengthen the semantic coherence of the search strategy, the litsearchr package in RStudio was used, enabling automated term expansion and the analysis of textual co-occurrence networks. The articles retrieved from the seed search were exported in .bib format and imported into the R environment using the import_results() function. During the analysis, 52 records were identified as lacking keywords; therefore, semantic extraction from titles and abstracts was prioritized. Using the tagged method, 168 terms were extracted from keywords, whereas fakerake was applied to identify relevant multi-word expressions with a minimum frequency of three occurrences. This information was used to build a term–document matrix through the create_dfm() function and subsequently generate a semantic co-occurrence network using create_network(), where each node represented a term and the links reflected their strength of association.

To reduce dimensionality and refine the network, two cut-off methods were applied: the cumulative threshold (80%) and the changepoint method, identifying nodes with the highest relational strength. This process enabled the removal of generic terms such as "article", "development", "soil", or "internet", while retaining a robust set of 53 representative terms. The selected terms were thematically grouped into two categories: emerging digital technologies (EDTs) and sustainable agriculture (SA). This categorization supported the construction of a multi-class search string, which was automatically exported using the write_search() function in .txt format, without applying stemming and preserving exact phrase structures. The refined query was then used for new systematic searches in Scopus, maximizing coverage and reducing the loss of relevant literature.

The Boolean search code obtained was: (“emerging digital technologies” OR “digital technologies” OR “smart farming” OR “precision agriculture” OR “agriculture 4.0” OR “agtech” OR “digital innovation”) AND (“sustainable agriculture” OR “climate-smart agriculture” OR “eco-friendly agriculture”), yielding a total of 1825 articles in the Scopus database and 724 documents in Web of Science.

2.5. PRISMA Protocol Procedure

The methodological strategy rigorously followed the four phases defined by the PRISMA protocol: identification, screening, eligibility, and inclusion. The four-level PRISMA procedure began with the optimized Boolean code provided by the LitSearchr systematization, which yielded a total of 2549 articles. These were then selected according to the corresponding filters and specific inclusion and exclusion criteria.

In the identification phase, a systematic search strategy was structured in Scopus and Web of Science, databases selected for their editorial control, bibliometric traceability, and broad thematic coverage. Scopus initially identified 1825 records, 1684 of which corresponded to the period 2020–2025. After applying successive filters for document type (article), final publication status, source type (journal), language (English and Spanish), and open access, a refined set of 383 articles was obtained. Additionally, Web of Science retrieved 724 documents, reduced to 506 after the time filter, and subsequently to 348 articles after applying criteria for language, document type, and open access.

During the screening phase, a rigorous process of data cleaning and preliminary selection of the identified records was conducted. First, the results from both databases were merged into a single repository and duplicates were removed using semantic algorithms implemented in the R environment, which enabled the detection of partial matches and metadata variations. In total, 274 duplicate documents were identified, resulting in 457 remaining articles. Subsequently, a critical review of titles and abstracts was performed to assess thematic relevance and the presence of verifiable empirical outcomes. Priority was given to studies focused on smart agriculture, digital monitoring systems, advanced sensors, and Internet of Things applications in production contexts. As a result, 319 records that did not meet the predefined criteria were excluded, ensuring conceptual and methodological consistency of the preselected dataset, with 138 articles remaining.

The eligibility phase consisted of an exhaustive assessment of the full texts of the studies previously selected during screening. A detailed analysis was conducted to verify the alignment between research objectives, methodological design, and the reported results. In addition, the clarity of the descriptions regarding sensor systems, digital architectures, data acquisition protocols, and analytical approaches was examined. Documents presenting incomplete information, purely conceptual approaches, or weak links to practical applications in smart agriculture were excluded, resulting in the removal of an additional 37 articles.

The inclusion phase resulted in a final set of 101 articles, which provide relevant, up-to-date, and methodologically robust empirical evidence on the use of digital technologies, smart sensors, and the Internet of Things applied to agricultural systems. This body of documents enabled a comparative and synthetic analysis of trends, technological approaches, and experimental outcomes reported across different production contexts. The entire methodological workflow, from identification to final inclusion, was transparently documented in a reproducible manner through the PRISMA flow diagram presented in Figure 2, which quantitatively summarizes exclusions and justifies each decision made during the systematic selection process.

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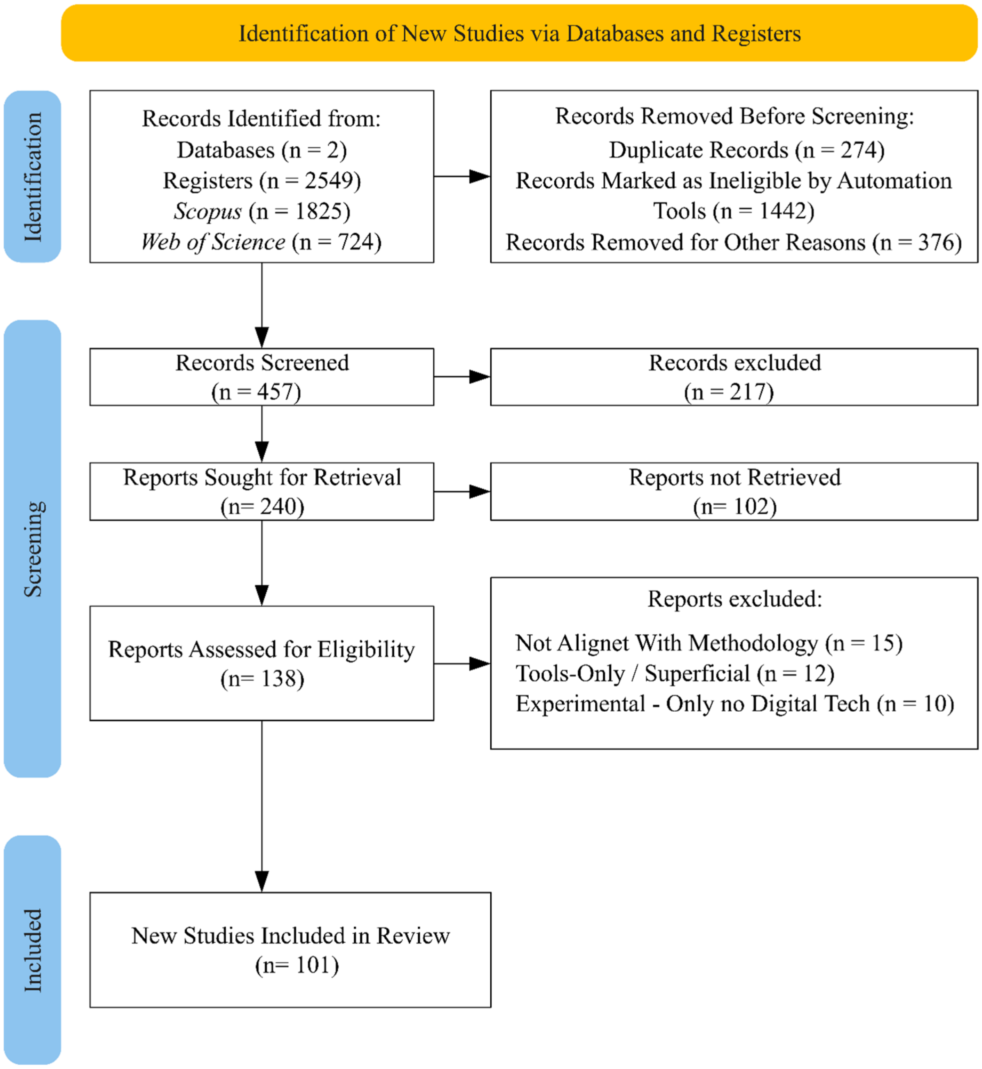

Figure 2. Four-level PRISMA protocol for document selection.

2.6. Quality Assessment of the Included Studies

To ensure the robustness and methodological consistency of the analyzed corpus, a structured quality assessment was conducted for the 101 included studies. This assessment considered five main criteria: (i) clarity of the research objectives and questions, (ii) internal validity of the experimental design or computational model, (iii) methodological replicability, (iv) consistency between results and conclusions, and (v) innovative contribution to the field. Only studies meeting at least four out of the five established criteria were retained for the final analysis. This stage enabled the exclusion of investigations with significant methodological bias, inconclusive results, or a lack of technical justification. The assessment matrix was applied by the same reviewers involved in the initial screening and jointly discussed in cases where inconsistencies were identified.

2.7. Data Extraction, Coding, and Analysis

Data extraction, coding, and analysis were performed using a structured matrix developed in RStudio and principal component analysis. The matrix recorded variables such as author, year of publication, country of institutional affiliation, type of applied technology (machine learning, neural networks, remote sensing, blockchain, etc.), type of agricultural system or crop addressed, reported sustainability indicators, and main findings. This matrix, treated as a *data.frame*, was analyzed using the R packages *tm, stringr, tidytext, dplyr*, and *ggplot2*. In addition, bibliometric metrics were applied, including Lotka's and Bradford's laws, term-frequency analysis, and thematic co-occurrence analysis.

Authorship relationships, the temporal evolution of technologies, and dominant geographical nodes were visualized using *igraph*, *ggraph*, and bibliometrix.

2.7. Assessment of Reporting Bias and the Certainty of the Evidence

The structured risk-of-bias assessment was examined through cross-validation of the stated objectives, measured variables, and reported evaluation criteria of each study, identifying potential selective outcome reporting and incomplete disclosure of experimental results. In addition, the availability of supporting materials (datasets, sensor calibration procedures, acquisition protocols, and code, when provided) was verified to detect discrepancies between methodological claims and the available evidence. Certainty was assessed by considering: (i) methodological robustness (experimental design, controlled conditions, replication), (ii) measurement reliability (sensor accuracy, uncertainty reporting, validation methods), (iii) consistency of effects across heterogeneous agricultural scenarios, (iv) directness with respect to IoT-based smart agriculture outcomes, and (v) the risk of residual bias.

3. Emerging Digital Technologies in Agriculture

Emerging digital technologies are transforming agriculture through intelligent analysis and decision-support systems (Figure 3) based on high-resolution data. Recent studies show that artificial intelligence models applied to water management achieve accuracies close to 80%, indicating a solid capability to support agronomic decision-making, although with error margins associated with temperature and moisture variations that influence evapotranspiration and soil status [7]. In parallel, advances in computer vision have strengthened phytosanitary monitoring and weed control through hybrid CNN–Transformer architectures, such as SWFormer, which integrate local and global dependencies to improve crop segmentation. This approach has achieved mAP values above 76% and accuracies exceeding 83% on agricultural datasets, outperforming conventional models [10].

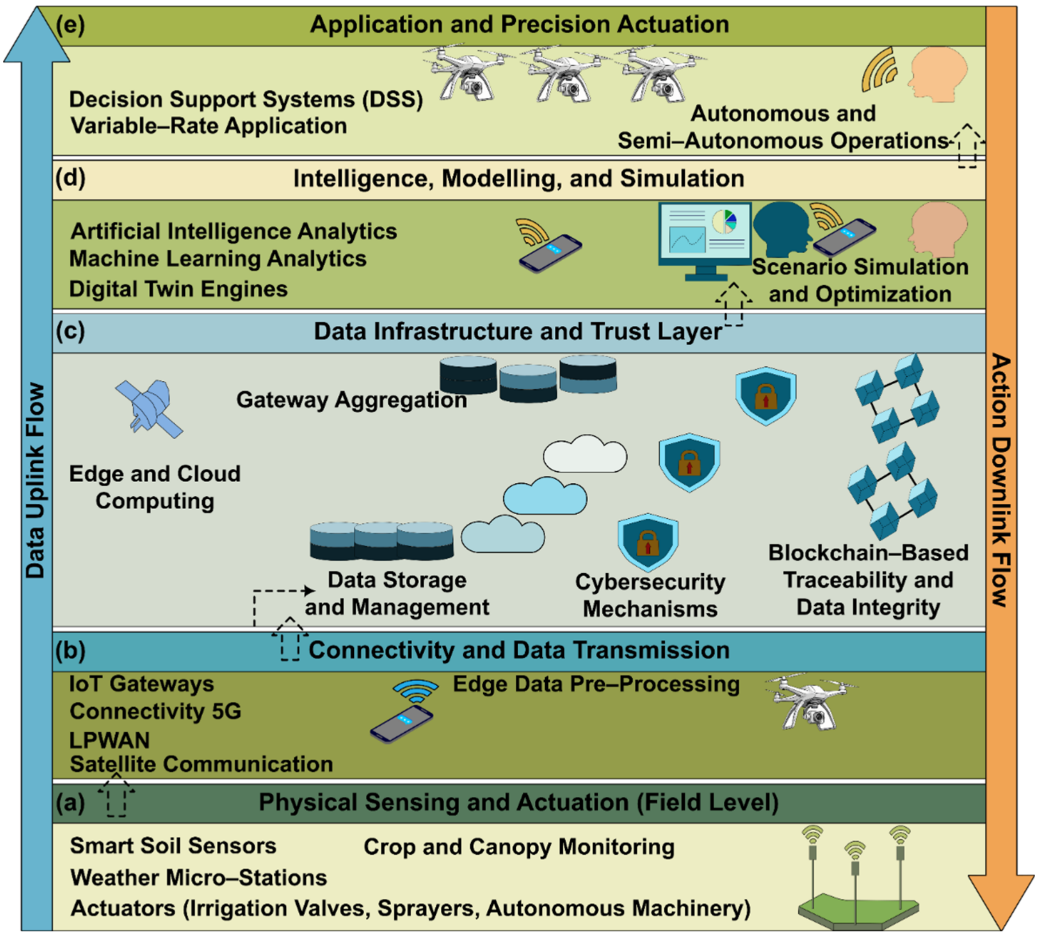

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Figure 3. Hierarchical architecture of the digital agriculture ecosystem, illustrating the bidirectional data and control flow. The system is organized into four interoperable layers: (1) Perception Layer: Real-time data acquisition via heterogeneous IoT sensors (soil moisture, NPK levels) and aerial remote sensing (UAVs) to capture phenotypic and environmental variability. (2) Connectivity Layer: Data transmission using low-power wide-area networks (LoRaWAN) for field sensors and high-throughput 5G protocols for video/image data, ensuring low latency. (3) Data Management & Trust Layer: Hybrid cloud/edge storage architecture. Blockchain protocols are implemented here to ensure data immutability and traceability across the supply chain. (4) Intelligence & Application Layer: Utilization of Machine Learning algorithms (e.g., Random Forest, CNNs) for predictive analytics. This layer generates actionable insights (e.g., irrigation scheduling) that are sent back to the physical layer as control commands (feedback loop).

In this regard, the convergence of IoT, remote sensing, and geographic information systems (GIS) consolidates precision agriculture approaches oriented toward production resilience. Multitemporal satellite image analysis using cloud-based platforms and machine learning algorithms has demonstrated high reliability for characterizing territorial and agricultural dynamics, achieving accuracies above 90% and kappa coefficients close to 0.9 in LULC classifications, supporting its use for sustainable land-use planning and management [5]. Complementarily, the use of advanced object-detection models based on YOLOv8, trained on large agricultural image datasets and data augmentation techniques such as mosaic, improves the automated identification of relevant field elements, strengthening monitoring and near real-time decision-making. These digital tools reinforce a smart agricultural ecosystem aligned with Industry 4.0 principles [11].

3.1. Internet of Things (IoT) and Smart Sensors

Within this framework, the integration of soil sensors with advanced data analysis models significantly enhances agronomic diagnosis and management. Intelligent disease detection systems, based on sensor-acquired data processed through deep learning, have demonstrated outstanding performance, achieving accuracies close to 98%, sensitivities above 94%, and F1-scores greater than 95%, evidencing their reliability for timely phytosanitary monitoring [13]. Additionally, the combined use of field sensors, official meteorological data, and virtual sensors based on machine learning enables hourly evapotranspiration estimation and automated irrigation with high efficiency. In horticultural crops, these approaches have optimized the balance between plant growth and water conservation, reaching consumptions close to 9 L per plant while increasing water productivity under irrigation schemes adjusted to crop evapotranspiration (ET) [17,19].

Sensor networks applied to sustainable agriculture represent an integrated system capable of continuously collecting, transmitting, and processing information across large production areas. By connecting sensors for soil moisture, temperature, nutrients, or pests, a constant data stream is generated to accurately characterize agroecosystem dynamics and detect spatial and temporal variability. This approach is enhanced by IoT technologies, such as passive battery-free UHF RFID sensors, which can measure volumetric soil moisture (VWC) with high accuracy and stability under real field conditions ($r = 0.9823$; $R^2 = 0.9648$; RMSE = 1.39; MAE = 1.21), operating between 4–33 °C and 45–80% RH without energy consumption [20]. Furthermore, UAV–WSN integration expands spatial coverage and monitoring reliability, optimizing data flow through temporal reduction methods such as SAX, which reduced relevant points from 502 to 98 (−80.5%) and data volume from 2,008 kB to approximately 400 B without losing significant patterns [21].

Continuous monitoring of these networks also plays a crucial role in agricultural prediction, as real-time data can be integrated with analytical algorithms and machine learning models to interpret historical patterns and current conditions. In this approach, sensor-based and modular IoT frameworks, supported by cloud computing, enable not only continuous acquisition of variables such as temperature, relative humidity, soil moisture, and CO_2, but also real-time automatic control, optimizing water and energy efficiency in protected systems such as greenhouses, while improving operational performance and reducing infrastructure costs [22]. Complementarily, the use of

 doi:10.20944/preprints202602.0211.v1

chemical macronutrient sensors enhances predictive capacity by providing direct information on crop nutritional status. For instance, low-cost colorimetric systems (M-CSS) quantified N-NO_3, P-PO_4, and K using smartphones, achieving $R^2 \geq 0.996$, high repeatability, and recoveries between 80–115%, meeting the standards of the Association of Official Analytical Chemists [23].

3.2. Artificial Intelligence and Machine Learning

The integration of artificial intelligence (AI) and machine learning in sustainable agriculture has enabled the development of predictive models capable of anticipating crop behavior under different environmental scenarios, based on the analysis of large volumes of data generated by IoT sensors and climate information systems. In particular, intelligent automation in greenhouses using hybrid IoT–AI approaches has demonstrated measurable operational impacts, achieving a 30% reduction in water consumption, a 15% increase in energy efficiency, and a 12% improvement in yield prediction through LSTM models, thereby enhancing sustainability and reducing manual intervention in climate variable management [24]. Similarly, smart irrigation systems based on machine learning and soil moisture sensors increase the accuracy of agronomic decision-making. For instance, the IoTML-SIS model achieved an accuracy of 0.938, outperforming algorithms such as KNN, SVM, logistic regression, MLP, and ELM, demonstrating higher reliability for optimizing irrigation scheduling and water savings [25].

Similarly, machine learning systems enable the anticipation of water stress, pest outbreaks, and nutrient imbalances before they become visually apparent in crops by integrating multi-source signals from sensors and historical records (Table 2). The hybrid HCS–DBN framework (deep belief networks with hybrid optimization) achieved 96.8% accuracy in detecting nutrient deficiencies, increased predictive capacity by 12%, and reduced computational overhead by 15% under various soil conditions, demonstrating its usefulness for estimating moisture and nutrient levels with lower error [26]. Likewise, computer vision models based on YOLOv8 enhance early detection of diseases and foliar anomalies in the field. While YOLOv8 small achieved higher accuracy, its inference speed was slower, whereas YOLOv8 nano showed minimal performance reduction (−1% in mAP50:95 and −0.4% in mAP50) but high efficiency, making it suitable for mobile monitoring applications. These predictive approaches facilitate early interventions—including precision irrigation, biological control, and site-specific fertilization—reducing losses, optimizing inputs, and increasing agroecosystem resilience [17].

Table 2. Development, design, architecture and validation of digital technologies.

Main digital technology	Architecture / Technological approach	Key technical contribution	Ref.
Battery-free RFID IoT sensor for floor use	Passive UHF RFID, embedded sensors	Continuous soil moisture measurement, zero energy consumption, and signal stability under field conditions were achieved, where the passive UHF RFID sensor estimated VWC with r = 0.9823, R^2 = 0.9648, RMSE = 1.39, and MAE = 1.21. It operated between 4–33 °C and 45–80% RH, demonstrating multi-soil stability without external power.	[20]
Digital twin for soil moisture	Digital twin, physical simulation, ML	Moisture estimation error, model–field correlation, and computational efficiency of the digital twin, where random forest achieved average accuracies of 96.0% in real data and 94.9% in digital twins, with variability ≤4.7%	[27]

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		between textures, surpassing ANN (−7.6%) and SVM (−3.2%) in predictive stability.	
Intelligent greenhouse automation	IoT + hybrid machine learning	The IoT–AI system with ML reduced water consumption by 30%, increased energy efficiency by 15%, and improved yield prediction by 12% using LSTM, optimizing resources, agricultural sustainability, controlled climate variables, system efficiency, and reducing manual intervention.	[24]
Sensor–ML analysis of moisture and nutrients	Deep belief networks, hybrid optimization	The HCS–DBN hybrid framework achieved 96.8% accuracy in detecting nutritional deficiencies, improved prediction by 12%, and reduced computational overhead by 15% under multiple soil conditions, achieving accuracy in predicting moisture, nutrients, and reducing estimation error.	[26]
Knowledge-assisted detection of agricultural objects	Deep learning with semantic rules	Accuracy, recall, and robustness of the model under variable conditions, where the KGDL-AOD model achieved mAP = 0.85, IoU = 0.82, and F1 = 0.80, outperforming reference models such as R-CNN, YOLO, and ECTB, with improvements of 6%, 2%, and 1%, respectively, in robust detection of agricultural objects.	[28]
Supply chain monitoring with blockchain	Multiblockchain, digital traceability	The SPOP algorithm reduces consensus rounds to one effective stage, maintains 51% fault tolerance, and improves multi-chain scalability compared to PBFT/RPCA (2/3, double round), optimizing distributed agricultural governance, data integrity, validation time, and transaction transparency.	[29]
Intelligent robotic spraying system	Computer vision, autonomous robotics	The system achieved spatial accuracy <0.4 mm, 73.3% of impacts within ±1σ, average consumption 61–63 W, and optimal operation at 0.2 MPa, enabling energy-efficient precision spraying, achieving spraying accuracy, drift reduction, and application efficiency.	[30]
UAV–WSN system for agricultural monitoring	UAVs, wireless sensor networks	The SAX method reduced 502 to 98 relevant points (−80.5%), decreasing the data volume from 2,008 kB to ~400 B, maintaining significant temporal patterns in distributed environmental monitoring, achieving spatial coverage, communication latency, and data reliability.	[21]
IoT–ML architecture for greenhouses	Distributed IoT, predictive ML	The web-mobile IoT platform with adaptive control achieved 97.27% in crop recommendations and 97.50% in disease detection, optimizing temperature, humidity, light, and water, reducing resource use, temperature control, humidity, system stability, and operational efficiency.	[31]

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Sensor-based IoT framework	Environmental sensors, modular IoT	The IoT system with sensors and cloud computing enabled real-time automatic monitoring and control of temperature, humidity, soil moisture, and CO_2, improving water and energy efficiency in greenhouses, achieving monitoring accuracy, and reducing infrastructure costs.	[22]
Agricultural data privacy	IoT integrated with blockchain	The multi-level Edge–Fog–Cloud BCT architecture with QNN+BO reduced encryption by 46.7%, decryption by 54.6%, memory by 33%, and achieved MAPE of 19.3% in secure and efficient Agri-IoT, achieving data security, attack resistance, and validation times.	[32]
Sensor networks for digital twins	IoT, digital twin, continuous analysis	The co-created Agri-IoT Living Lab enabled continuous real-time monitoring; 73.2% preferred digital access; sensors validated edaphic-climatic ranges, establishing operational bases for agricultural digital twins, data-model synchronization, and simulation error.	[33]
Chemical sensors for macronutrients	Low-cost electrochemical sensors	The colorimetric M-CSS quantified N-NO_3, P-PO_4, and K via smartphone with $R^2 \geq 0.996$, ranges of 0–30 μg/mL, recoveries of 80–115%, and DER<11%, complying with AOAC, achieving NPK detection accuracy and measurement repeatability.	[23]
Smart irrigation system	ML, humidity sensors	The IoTML-SIS achieved an accuracy of 0.938, surpassing KNN (0.480–0.590), SVM (0.629), LR (0.721), MLP (0.842), and ELM (0.876), demonstrating greater reliability in agricultural classification, water saving, irrigation accuracy, and crop response.	[25]
Autonomous planting vehicle	Terrestrial robotics, automatic control	The robotic planter achieved 1% deviation in spacing, 94% accuracy in seed delivery, and 66.67% in dosage, demonstrating high spatial accuracy with limitations in metering, achieving planting precision, spatial uniformity, and labor reduction.	[34]
Embedded transplant system	Mechatronics, embedded control	The automatic transplanter achieved optimal performance at 2.0 km/h and 30°, achieving 600 mm spacing, 91.7% efficiency, 90.3% furrow closure, and only 2.1% failures, achieving a transplant success rate and operational efficiency.	[35]
Smart irrigation for soilless crops	Water demand sensors, IoT	Gravimetric irrigation mitigated salt stress, reducing non-commercial fruit; salinity decreased commercial yield by 68% and increased non-commercial yield by >20%, with significant interaction ($p<0.01$), resulting in dynamic irrigation adjustment and water use efficiency.	[36]

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Agricultural edge–AI architecture	Edge computing, lightweight deep learning	Models based on the MiT-B0 Vision Transformer architecture on edge (128×128) achieved 88% accuracy for climate (11 classes) and 93% for crops (5 classes), with high F1 and low MAE, κ, and Hamming.	[37]
LoRaWAN IoT Architecture	Long-range IoT, LPWAN communication	The IoT network achieved success rates >80% in most nodes; SN-G1 recorded ~70% due to solar limitations, while nodes in the vineyard maintained variation <1% despite different intervals, demonstrating network range, transmission stability, and scalability.	[19]
Non-invasive bioelectrical sensors	Multimodal sensors, multiscale analysis	The integrated bioelectrical system achieved non-invasive multi-organ evaluation with 98.3% accuracy in fruit, 95.8% in leaves, and tomographic resolution up to 2.6 mm, detecting physiological stress before visible symptoms, demonstrating early stress detection and bioelectrical-physiological correlation.	[38]
IoT system for agrivoltaics	IoT, PLC, solar energy	The photovoltaic system with solar tracking and LoRaWAN increased efficiency by up to 28%, stabilized the charge (12.79–13.05 V; 0.49–0.39 A), and reduced charging times for lead-acid batteries, providing energy efficiency and integrated crop-energy control.	[39]
Decentralized agricultural blockchain	Blockchain + ML + IoAT	The Edge–IoT model with ML and blockchain increased packet delivery rates by 16–17%, reduced network overhead by 18–21%, and maintained secure transmission in the face of faulty nodes, demonstrating the system's reliability, latency, and data security.	[40]
Wireless fertilizer sensor	Wireless power, smart sensors	The wireless resonant sensor (36.5 MHz) converted soil moisture into a thermal signal, reaching ≈75 °C at 5% VWC in 1 min, with thermal response inversely proportional to water content, controlled nutrient release, and real-time monitoring.	[41]

Note. The studies summarized in the table show the digital technologies developed between 2020 and 2025, highlighting their architecture, approach, and key technical contribution, including data acquisition systems, IoT, machine learning, and integration platforms for precision agriculture. Abbreviations: RFID, Radio Frequency Identification; UHF, Ultra High Frequency; VWC, Volumetric Water Content; RMSE, Root Mean Square Error; MAE, Mean Absolute error; ANN, Artificial Neural Network; SVM, Support Vector Machine; LSTM, Long Short-Term Memory; IoT, Internet of Things; AI, Artificial Intelligence; HCS, Chameleon Heuristic Search; DBN, Deep Belief Network; SPOP, Supervised Proof of Proposal; PBFT, Practical Byzantine Fault Tolerance; RPCA, Robust Principal Component Analysis–based consensus; ML, Machine Learning; MPa, Megapascal; W, Watt; SAX, Symbolic Aggregate approximation; BCT, Blockchain Technology; QNN, Quantum Neural Network; BO, Bayesian Optimization; M-CSS, Multi-Chemical Sensing System; $N\text{-}NO_3$, Nitrate-N; $P\text{-}PO_4$, Phosphate-P; K, Potassium; AOAC, Association of Official Analytical Chemists; DER, Relative Standard Deviation; IoTML-SIS, Internet of Things and Machine Learning–based Smart Irrigation System; KNN, K-Nearest Neighbors; LR, Logistic Regression; MLP, Multilayer Perceptron; ELM, Extreme Learning Machine; MiT-B0, Mix Transformer Base-0; F1, F1-score; κ (Kappa), Coefficient of Agreement; SN-G1, Sensor Node–Greenhouse; LoRaWAN, Long Range Wide Area Network; VWC, Volumetric Water Content.

 doi:10.20944/preprints202602.0211.v1

3.3. Precision Agriculture

Precision agriculture relies fundamentally on remote sensing systems, as they allow the characterization of crop and soil conditions with high spatial and temporal resolution, without direct contact and under variable operational conditions [42]. In this context, approaches based on computer vision enhance the interpretation of images acquired by remote platforms, improving early detection of agronomic anomalies. For instance, the KGDL-AOD model (knowledge-assisted agricultural object detection) demonstrated high robustness under heterogeneous scenarios, achieving mAP = 0.85, IoU = 0.82, and F1 = 0.80, outperforming reference models such as R-CNN, YOLO, and ECTB with improvements of 6%, 2%, and 1%, respectively [28]. The integration of data captured through IoT platforms and machine learning enables the transformation of remote information into management actions, as observed in web–mobile IoT architectures for greenhouses, which achieved 97.27% in crop recommendation and 97.50% in disease detection, optimizing environmental variables and reducing resource use. These technologies therefore enhance spatial diagnosis of stress and facilitate site-specific interventions to optimize inputs and minimize environmental impacts [31].

Drones and satellite imagery complement this approach by providing high temporal and spatial resolution data, which are essential for precise agricultural monitoring and for generating actionable information at the plot scale. The value of these platforms is particularly enhanced when images are integrated with real-time intelligent analysis architectures, such as edge–AI schemes, where lightweight models allow the classification of production scenarios without full dependence on the cloud. An agricultural edge computing architecture with lightweight deep learning, using the Vision Transformer MiT-B0 (128×128), achieved 88% accuracy in climate classification (11 classes) and 93% in crop classification (5 classes), with robust performance metrics (high F1 and low MAE, κ, and Hamming) [37]. Moreover, the combination of computer vision and autonomous robotics enhances site-specific management derived from prescription maps, as evidenced by intelligent spraying robotic systems achieving spatial precision <0.4 mm and 73.3% of impacts within ±1σ, with an average power consumption of 61–63 W. These results demonstrate that drones, satellites, and intelligent analytics consolidate precision agriculture as a key approach to improving productivity and sustainability through data-driven decision-making [30].

Soil mapping constitutes one of the most relevant applications of precision agriculture, as it enables detailed characterization of the physical, chemical, and biological properties of the soil, integrating spatial information to guide site-specific management decisions. In this context, the development of smart sensors enhances the capture of critical edaphic variables and their translation into operational indicators. For example, a wireless fertilizer sensor based on resonant energy (36.5 MHz) has been reported to convert soil moisture into a thermal signal, reaching approximately 75 °C at 5% VWC in 1 minute, with a thermal response inversely proportional to water content; additionally, it enables controlled nutrient release and real-time monitoring, contributing to improved fertilization efficiency in specific zones [41]. Complementarily, non-invasive bioelectric sensors expand agroecosystem diagnostics by capturing physiological signals associated with stress, achieving multi-organ assessments with 98.3% accuracy in fruit and 95.8% in leaves, as well as tomographic resolution up to 2.6 mm, detecting stress before visible symptoms. These technologies thus enhance productive zoning, prevent soil degradation, and support the sustainability of the production system [38].

Crop vigor analysis and the identification of spatial variability complement these efforts by providing a dynamic assessment of vegetative performance across different phenological stages, allowing timely and site-specific interventions. In intensive systems, for example, smart irrigation based on water-demand sensors and IoT has shown direct impacts on production uniformity. Gravimetric irrigation helped mitigate saline stress and reduce the proportion of non-commercial fruits; additionally, salinity was shown to decrease commercial yield by up to 68% and increase non-commercial yield above 20%, with a significant interaction ($p < 0.01$), demonstrating the need for dynamic irrigation adjustments to maintain water use efficiency and crop vigor [36]. Similarly, IoT platforms integrated into agrivoltaic schemes, controlled via PLC and LoRaWAN communication,

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increased energy efficiency by up to 28% through solar tracking, stabilizing system load (12.79–13.05 V; 0.49–0.39 A) and reducing charging times. This supports continuous monitoring and resource management at the spatial scale, demonstrating that these approaches strengthen smart agriculture by linking vigor diagnostics with more resilient irrigation and energy decisions [39].

3.4. Robotics and Automation in Agriculture

Robotics applied to agriculture has advanced rapidly, excelling not only in harvesting but also in critical tasks such as sowing and transplanting, where precision determines successful crop establishment. In this context, an autonomous ground-based sowing vehicle with automated control achieved only 1% deviation in spacing, 94% accuracy in seed delivery, and 66.67% in dosing, demonstrating high spatial accuracy and potential to reduce labor dependence, although limitations were observed in the metering system [34]. Complementarily, an embedded mechatronic transplanting system achieved optimal performance at 2.0 km/h and 30°, attaining 600 mm spacing, 91.7% efficiency, 90.3% furrow closure, and only 2.1% failure rate. These results confirm substantial improvements in operational continuity and transplant success rate, demonstrating that such operational advances in agricultural automation consolidate automation as a key factor for increasing uniformity, efficiency, and resilience in modern production systems [35].

3.5. Blockchain and Digital Traceability in Agriculture

The incorporation of blockchain in agriculture has strengthened digital traceability by ensuring distributed, immutable, and verifiable records of agricultural practices, logistics, and postharvest management, reducing the likelihood of tampering and fraud. In this context, a decentralized approach integrating Edge–IoT, machine learning, and blockchain increased package delivery rates by 16–17% and reduced network overhead by 18–21%, while maintaining secure transmission even in the presence of faulty nodes, demonstrating simultaneous improvements in reliability, latency, and data security for connected agricultural environments [40]. Additionally, a multi-level Edge–Fog–Cloud blockchain architecture oriented toward privacy, with QNN+BO optimization, decreased encryption times by 46.7% and decryption times by 54.6%, reduced memory usage by 33%, and achieved a MAPE of 19.3%, consolidating a more efficient and attack-resilient validation scheme in Agri-IoT applications. These advancements reinforce sustainability certification and market trust through transparency and robust information protection [32].

Moreover, the transparency provided by blockchain enhances postharvest quality control by enabling critical conservation variables—such as temperature, relative humidity, transport times, and sanitary conditions—to be recorded automatically, verifiably, and immutably during storage and transportation. This approach facilitates early detection of failures in the supply chain, as each event is audited and accessible to distributors, buyers, and certification entities, increasing confidence in product integrity. In this context, multiblockchain-based traceability schemes improve operational performance within the supply chain, as the SPOP algorithm reduces consensus rounds to a single effective stage, maintains 51% fault tolerance, and offers greater scalability compared to traditional approaches such as PBFT or RPCA, optimizing data integrity, validation time, and transaction transparency. These capabilities contribute to reducing postharvest losses, enhancing food security, and improving producer competitiveness in national and international markets through more open, efficient, and auditable supply chains [29].

3.6. Digital Twins and Agricultural Simulation

Digital twins applied to agriculture represent a strategic innovation by enabling the virtual replication of real-field behavior through the integration of sensor data, remote sensing, and agronomic models, creating dynamic environments to simulate crop growth and its interaction with soil and climate. This capability is enhanced when the digital twin is fed by IoT networks with continuous real-time monitoring, as demonstrated in the Agri-IoT Living Lab, where the validation of soil and climate ranges established operational bases for data–model synchronization and simulation error control, while also showing high acceptance of digital access (73.2%) [33]. In predictive terms, soil moisture–oriented digital twins have demonstrated high accuracy and stability; the use of random forest achieved 96.0% on real data and 94.9% on the digital twin, with variability ≤4.7% across textures, outperforming alternatives such as ANN and SVM in robustness. These results confirm that digital modeling allows the evaluation of irrigation or fertilization decisions before field implementation, reducing uncertainty, operational risks, and inefficient resource use [27].

4. Impact of These Technologies on Agricultural Sustainability

4.1. Optimizing Water Use

Water optimization through digital technologies is based on the integration of spectral information, physiological measurements, and edaphoclimatic modeling to support evidence-based irrigation decisions. The combined use of vegetation indices (NDVI/SAVI) with stem water potential (Ψ_stem) enables precise diagnosis of severe deficit conditions, reflected in reductions of 13% in VI, 23% in Ψ_stem, and 14% in crop size, facilitating the definition of operational thresholds to adjust irrigation scheduling and prevent yield losses. Additionally, the incorporation of ground cover increases observed vigor by 19–42% and reduces soil structural degradation by 7–8%, contributing to improved water retention and applied water use efficiency [43]. Likewise, water savings are enhanced through quantification of actual demand via lysimetry and the calculation of peak ETc at 7.41 mm d^{-1}, with cumulative requirements of 228.82 mm and Kc values of 0.75–0.98–0.76, allowing models to be calibrated under climate variability and ENSO events to optimize management strategies [44].

Georeferenced soil moisture maps, infiltration simulations, and evapotranspiration estimates allow the identification of microzones with deficits, saturation, or limited drainage, enabling sub-plot scale irrigation adjustments and reducing losses due to percolation or runoff. The incorporation of drones and satellite imagery enhances diagnostic (Figure 4) sensitivity by detecting water stress patterns not perceptible in the field, allowing for early and targeted interventions. In this context, the integration of stomatal conductance with remote sensing (Landsat) has enabled robust estimation of GPP (0.5–11.5 g C m^{-2} d^{-1}), ET (0.5–7.5 mm d^{-1}), and mean water use efficiency (WUE) of 2.14 g C kg^{-1} H_2O, with high agreement ($R^2 \approx 0.87$–0.88), strengthening joint water–carbon assessments [45]. Furthermore, monitoring precision depends on instrumental stability: sensors such as ML3, SM150T, and EC-5, combined with amendments (2.5–5%) and specific soil+amendment calibration, corrected deviations (<0.14 m^3 m^{-3}) in volumetric water content ranges of θ_v = 0.14–0.33 m^3 m^{-3}, enhancing operational reliability [46].

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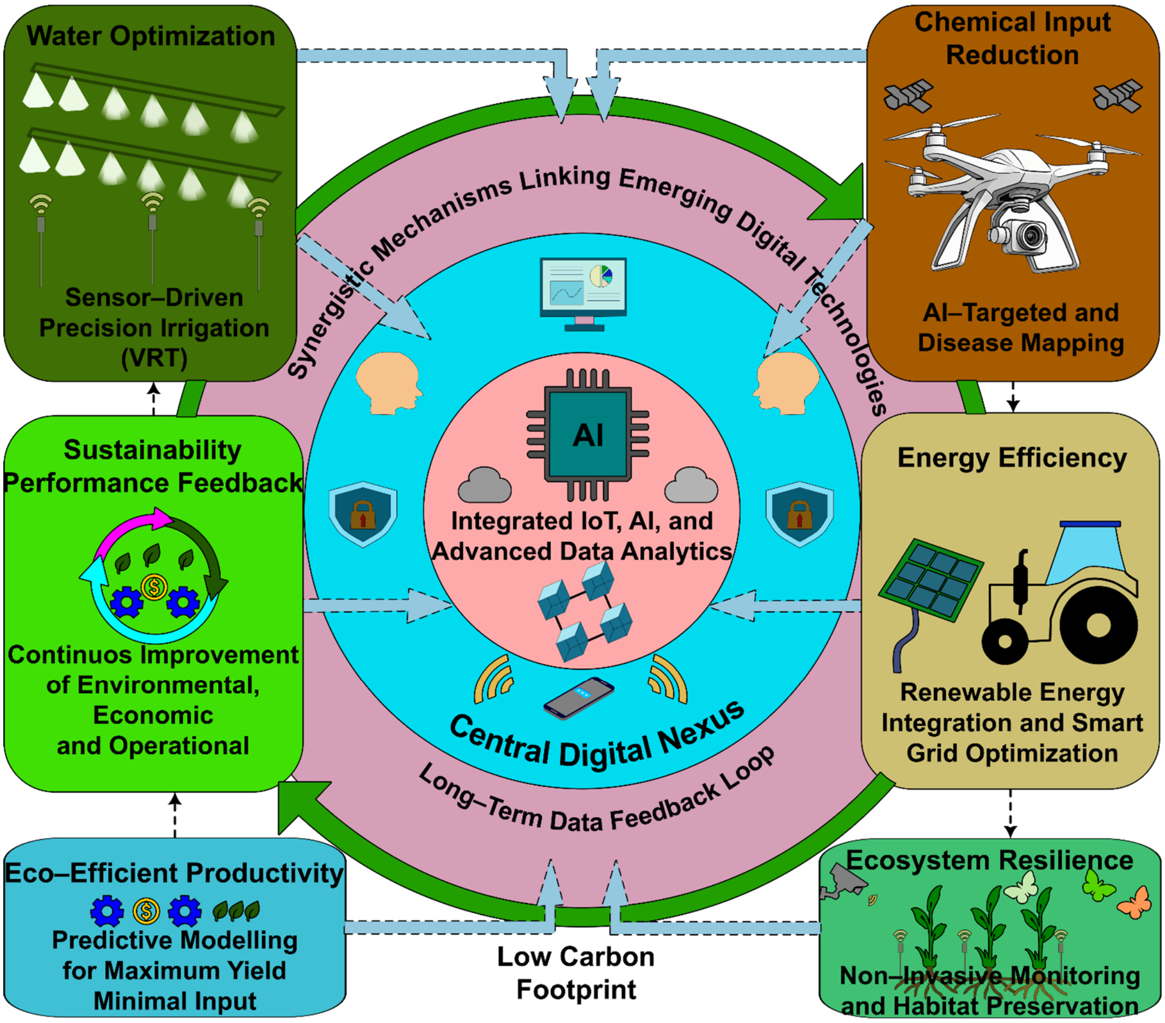

Figure 4. Schematic representation of the synergistic mechanisms linking emerging digital technologies to key agricultural sustainability goals. The central hub (Digital Nexus) integrates real-time data streams to drive five actionable pathways: (1) Water Optimization: Utilizes soil moisture sensors to trigger Variable Rate Technology (VRT) irrigation, reducing water footprints. (2) Chemical Input Reduction: Employs computer vision and AI to detect pests/diseases for ultra-precise, spot-specific agrochemical application. (3) Energy Efficiency: Optimizes machinery routes via GPS and integrates renewable energy sources into farm operations. (4) Ecosystem Resilience: Uses non-invasive remote sensing to monitor biodiversity corridors without disrupting habitats. (5) Eco-Efficient Productivity: Leverages predictive modeling to decouple yield maximization from environmental degradation. The outer dashed ring illustrates the continuous feedback loop, where improved environmental conditions generate higher-quality data, further refining the central AI models over time.

4.2. Reduction of Chemical Inputs.

The reduction of chemical inputs through digital technologies is based on the ability to monitor, predict, and act locally on the actual needs of the crop, replacing uniform application schemes with precision interventions (Table 3). The combination of soil and plant sensors with predictive models and artificial intelligence enables early identification of nutritional deficiencies, microenvironmental variations, and emerging pest or weed hotspots, allowing targeted applications at optimal doses and only where agronomic demand exists. In this context, machine learning and deep neural network approaches have demonstrated high predictive capacity for estimating plant growth (~86% accuracy) by integrating variables such as salinity (NaCl), pH, moisture, temperature, and radiation, facilitating the design of personalized and efficient production systems with reduced reliance on corrective fertilization [47]. Complementarily, computer vision applied to weed management enables progress toward selective control: lightweight architectures such as HGNetv2–YOLOv8 achieved 82.9% mAP

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at 208.3 FPS, while HSG-Net reached 84.1% mAP with low computational complexity, optimizing detection for site-specific applications in wheat [48].

Table 3. Resource efficiency and ecosystem resilience.

Sustainability dimension	Agricultural variable evaluated	Technology and the reported impact	Ref.
Efficient use of water	Vegetation indices, water status, response to irrigation	The NDVI/SAVI and stem Ψ technology showed severe RDS: −13% VI, −23% stem Ψ and −14% size; vegetation cover increased IV 19–42% and reduced structure 7–8%, allowing evaluation of the crop's response to irrigation and optimization of water scheduling.	[43]
Efficient water use / climate resilience	Evapotranspiration, soil and climate variability, ENSO	Lysimetry and edaphoclimatic analysis quantified peak ETc at 7.41 mm d^{-1}, demand at 228.82 mm, and Kc at 0.75–0.98–0.76; Tp 47.80% and PWP 21.99% conditioned water availability, where climate models and sensors allowed ETc to be quantified under ENSO events and water management strategies to be adjusted.	[44]
Resource optimization	Plant productivity, adaptation to the environment	Digital agriculture with ML and DNN predicted seablite growth with 86% accuracy, integrating salinity (NaCl), pH, humidity, temperature, and light as climate controllers for the crop, facilitating the design of customized and efficient production systems.	[47]
Environmental footprint	Water use, carbon efficiency	The CE–RS (Landsat) integration estimated GPP 0.5–11.5 gC m^{-2} d^{-1}, ET 0.5–7.5 mm d^{-1} and average WUE 2.14 gC kg^{-1} H_2O, with high concordance (R^2≈0.87–0.88), allowing for the evaluation of water–carbon ecosystem efficiency.	[45]
Monitoring accuracy	Soil moisture, sensor stability	The use of soil conditioners improved the accuracy and durability of the devices, where ML3, SM150T, and EC-5 sensors in sandy loam soil with amendments (2.5–5%) maintained greater accuracy at θv=0.14–0.33 m^3 m^{-3}; soil+amendment calibration corrected deviations <0.14 m^3 m^{-3}.	[46]
Efficient use of water	Field-scale soil moisture	The fusion of ground-penetrating radar and satellite data improved spatial moisture estimation, where GPR–SAR integration estimated soil moisture at 0–10 cm, with GPR reaching R^2=0.74 and Sentinel-1 R^2=0.32, improving spatial mapping for precision irrigation.	[49]
Crop resilience	Plant stress, physiological indicators	The HARPS hybrid model achieved 96.6% accuracy, ROC 0.970, and AUC 0.972 in 8 seconds, outperforming DT, RF, SVM, GB, XGB, and LGBM on 8,525 samples, enabling robust and early detection of plant stress.	[50]

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Sustainable agricultural production	Detection of small objects, pest wildlife.	AI-powered remote sensing supported sustainable management and compliance with SDG 2, where YOLOv3 architecture with multimodal UAS data achieved robust detection of small objects, reaching mAP 0.86 and F1 93.39%, optimizing precision agricultural management and reducing environmental impacts.	[51]
Energy efficiency	Energy consumption in greenhouses	Multi-objective predictive MPC control in greenhouses with GCHP reduced electricity consumption by ≈30% in 20 hours, maintaining a stable indoor temperature compared to reactive control.	[52]
Reduction of chemical inputs	Weeds, crop cover.	The HGNetv2–YOLOv8 model achieved 82.9% mAP with 2.4 million parameters, 6.9 GFLOPs, and 208.3 FPS. HSG-Net achieved 84.1% mAP with 1.6 M parameters and 4.1 GFLOPs, demonstrating that lightweight computer vision models improved weed detection for selective wheat control.	[48]
Water resilience	Microbial response to water stress	The *Gradient Boosted Trees* model achieved 87% accuracy (σ=4%) and maximum gain (68.0), surpassing DL (80%) and GLM (69%), although with higher computational cost due to a total calculation time of 3,381,260 and a training time of 22,101.2 per 1,000 rows.	[53]
Soil health	Soil salinity	Hyperspectral UAV images enabled the monitoring of salinization processes, where the PSO-GPR model with FOD-0.7 and BOSS predicted soil salinity with R^2=0.92, RMSE=0.15 dS m^{-1} and RPD=3.54, optimizing irrigation and salt management in cotton.	[54]
Sustainable productivity	Non-destructive testing	UAV spectral metrics enabled yield prediction without affecting the crop, where TRAC–UAV–NDVI integration with PCA and Elastic Net explained 72% of bean yield (RMSE≈10.67 g), enabling early non-destructive estimation and site-specific management.	[55]
Efficient use of nutrients	Flavanol nitrogen index	UAV and ML estimated non-destructive NFI; RF achieved R^2 = 0.86 and RMSE = 0.32 at 75 DAP, outperforming GB (R^2 = 0.75) and SVR, with greater accuracy at 45–90 DAP.	[56]
Efficient use of water and fertilizers	Yield, inputs applied	Sentinel-1/2 and WLS estimated corn yield with R^2 = 0.89 and RMSE = 12.8%, reducing water use by 10.23–14.76% and N by 5.5–8.5% without loss of productivity, demonstrating that data-driven optimization reduced water and fertilizer use while maintaining yield.	[57]
Climate change mitigation	Soil organic carbon	Remote sensing and ML enabled monitoring of carbon dynamics in conservation systems, where Sentinel-1 SAR and Sentinel-2 MSI with XGBoost estimated COS with R^2	[58]

 doi:10.20944/preprints202602.0211.v1

		test = 0.91 and RMSE = 0.17 t C ha^{-1}, mapping spatial variability (0.9–3.8 t C ha^{-1}) for sustainable management.	
Integrated sustainable agriculture	Production and environmental indicators	The implementation of smart technologies improved the overall sustainability of the agricultural system, where the photovoltaic solar dryer with absorption dehumidification eliminated ~109 L/cycle in 23.5 hours, operating with 12 PV panels (6 kWp) and an electricity demand of 190 kWh/cycle.	[59]
Soil conservation	Soil compaction	The integration of soil vibrations and moisture with Random Forest and XGBoost allowed compaction to be estimated with 93.7–93.8% correlation, with no statistical differences, optimizing tillage and agricultural sustainability.	[60]
Efficient use of water	Water retention capacity	Irrigation zoning (23.4 ha) using GIS software, the Kriging method, and based on CRA (79–167 mm) allowed EID (34–110 mm) to be adjusted against CWR (260–667 mm), optimizing irrigation and crop sustainability.	[61]
Sustainability of the agri-food chain	Multi-criteria decision strategies	The fuzzy decision-making approach supported sustainable strategies in agri-food chains, where Multi-Criteria Decision Making (MCDM) found that carbon footprint (C12, 0.0416; 62.5%) and high water consumption (C1, 0.0405) dominated environmental prioritization; energy scarcity (C6, 0.0146) was marginal.	[62]
Energy efficiency and renewables	Energy consumption and productivity	The intelligent hydroorganic system powered by solar energy generated 288.73 W at 99,574 lux (85–95% η), reducing grid consumption and energy costs for small farmers and optimizing climate control in greenhouses.	[63]

Note. The studies synthesize the results on sustainable dimensions and agricultural variables published between 2020 and 2025, including digital and sensor technologies, as well as their reported impact on water optimization, fertilization, soil management, and biodiversity enhancement. Abbreviations: NDVI, Normalized Difference Vegetation Index; SAVI, Soil Adjusted Vegetation Index; VI, Vegetation index; Ψstem, Stem Water Potential; RDS, Sustained Deficit Irrigation; IV, Viscosity Index; ETc, Crop Evapotranspiration; Kc, Crop Coefficient; mm d^{-1}, Millimeters per day; Tp, Total Porosity; PWP, Permanent Wilting Point; ENSO, El Niño – Southern Oscillation; ML, Machine Learning; DNN, Deep Neural Networks; CE, Eddy Covariance; RS, Remote Sensing; GPP, Gross Primary Productivity; ET, Evapotranspiration; WUE, Water Use Efficiency; gC, Grams of Carbon; ML3, Soil Moisture Sensor (Delta-T); SM150T, Soil Moisture Sensor (Delta-T); EC-5, Soil Moisture Sensor (Meter); θv, Volumetric Water Content of the Soil; GPR, Ground Penetrating Radar; SAR, Synthetic Aperture Radar; HARPS, Hybrid Adaptive Risk Prediction System; DT, Decision Tree; RF, Random Forest; SVM, Support Vector Machine; GB, Gradient Boosting; XGB, Extreme Gradient Boosting; LGBM, Light Gradient Boosting Machine; ROC, Receiver Operating Characteristic; AUC, Area Under the Curve; UAS, Unmanned Aerial System; YOLOv3, You Only Look Once v3; mAP, mean Average Precision; F1, F1-score; MPC, Model Predictive Control; GCHP, Ground-Coupled Heat Pump; HGNetv2, Lightweight object detection model; GFLOPs, Giga Floating Point Operations; FPS, Frames Per Second; GLM/MLG, Generalized Linear Model; DL, Deep Learning; PSO, Particle Swarm Optimization; GPR, Gaussian Process Regression; FOD, Fractional Order Differentiation; BOSS, Bootstrap Soft Shrinkage; RPD, Ratio of Performance to Deviation; dS m^{-1}, deciSiemens per meter; TRAC,

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Tracing Radiation and Architecture of Canopies, UAV, Unmanned Aerial Vehicle; NDVI, Normalized Difference Vegetation Index; PCA, Principal Component Analysis; VIF, Variance Inflation Factor; RF, Random Forest; GB, Gradient Boosting; SVR, Support Vector Regression; NFI, Nitrogen Flavanols Index; RMSE, Root Mean Square Error; DAP, Days After Planting; WLS, Weighted Least Squares; N, Nitrogen; SAR, Synthetic Aperture Radar; MSI, Multispectral Instrument; XGBoost, eXtreme Gradient Boosting; COS, Soil Organic Carbon; ZGR, Irrigation Management Zone; CRA, Water Retention Capacity; EID, Estimated Irrigation Depth; CWR, Crop Water Requirement.

Remote sensing, precision agriculture, and digital twins enhance agrochemical reduction by characterizing spatial variability within crops and translating it into site-specific management prescriptions. Through multispectral imagery, vigor maps, and simulation models, it is possible to identify areas with localized stress, nutritional deficiencies, or early disease hotspots, replacing generalized applications with targeted, dosed interventions. In this context, the integration of Sentinel-1/2 with WLS algorithms enabled robust maize yield estimation ($R^2 = 0.89$; RMSE = 12.8%), demonstrating that data-driven optimization reduces water use by 10.23–14.76% and nitrogen fertilization by 5.5–8.5% without compromising productivity [57]. Additionally, the use of UAVs combined with machine learning facilitated non-destructive estimation of the flavanol nitrogen index, with Random Forest achieving $R^2 = 0.86$ and RMSE = 0.32 at 75 DAP, outperforming other approaches and improving precision during critical windows of 45–90 DAP for nutrition adjustment. These capabilities, together with robotic automation and mechanical control, consolidate cleaner and more sustainable production systems [56].

4.3. Energy Efficiency in Agriculture

The digitalization of agricultural systems has enabled progress toward more efficient energy management through automation, continuous monitoring, and predictive process control. The incorporation of sensors and optimization algorithms reduces unproductive time, prevents operational overlaps in mechanized tasks, and improves power allocation in electric equipment, decreasing energy consumption per unit of production. Specifically, intelligent irrigation schemes synchronize the operation of pumps and valves with actual soil water demand, avoiding unnecessary activation cycles and reducing associated electricity costs. In controlled environments, the impact is even more pronounced: a solar-powered intelligent hydro-organic system generated 288.73 W under 99,574 lux, achieving conversion efficiencies of 85–95%, thereby reducing dependence on the electrical grid and lowering energy costs in greenhouses for smallholders [63]. Additionally, the application of multi-objective predictive control (MPC) in greenhouses equipped with GCHP systems reduced electrical consumption by approximately 30% over 20 hours while maintaining superior thermal stability compared to reactive controls, demonstrating that these results directly contribute to emission reduction and improved profitability in the agricultural sector [52].

In this context, emerging technologies in precision agriculture provide an additional layer of energy optimization by enabling the planning of operations based on simulations and demand forecasts, integrating agronomic, edaphic, and environmental variables into dynamic models. This capability allows for the scheduling of mechanized tasks and irrigation during windows of higher operational efficiency, reducing consumption associated with frequent start-ups and redundant movements. Additionally, the availability of renewable energy, particularly photovoltaic systems in the field, can be incorporated as an operational constraint to shift activities toward periods of higher solar generation and lower dependence on fossil fuels. Concurrently, remote monitoring using drones and satellites reduces the need for on-site inspections and machinery use, decreasing fuel consumption and emissions. In this regard, the integration of ground-penetrating radar (GPR) with satellite remote sensing improved the spatial mapping of soil moisture at 0–10 cm depth, where GPR achieved $R^2 = 0.74$ compared to Sentinel-1 ($R^2 = 0.32$), strengthening decision-making for precision irrigation and avoiding energetically inefficient applications [49].

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4.4. Improvements in Biodiversity and Ecosystem Resilience

Agricultural digitalization enhances biodiversity conservation by enabling finer management of the agroecosystem through continuous monitoring and minimally invasive intervention decisions. The integration of sensors, drones, and remote sensing allows the detection of microenvironmental variations, pest pressure, and soil condition changes with high resolution, reducing intensive practices that degrade habitats and alter biological communities. In this context, machine learning tools provide evidence to minimize physical impacts: the combination of soil vibration and moisture signals with Random Forest and XGBoost models allowed compaction estimation with correlations of 93.7–93.8%, facilitating tillage adjustments and reducing structural soil disturbances [60]. Accordingly, the implementation of intelligent technologies in integrated systems has demonstrated improvements in overall sustainability, such as the use of photovoltaic solar dryers with absorption dehumidification, capable of removing ~109 L per cycle in 23.5 h using 12 PV panels (6 kWp), thereby reducing energy dependence and environmental pressure [59].

The integration of digital tools and spatial analysis enables a dynamic representation of soil–crop–environment interactions, providing quantitative foundations for designing resilience strategies against climatic disturbances [62]. By simulating extreme scenarios (droughts, floods, or interannual variability), these systems facilitate the selection of more tolerant cultivars, the planning of diversified rotations, and the adoption of data-supported regenerative practices. Intra-field zoning is a key component, as it allows decision-making adjustments according to edaphic and water heterogeneity: using GIS and Kriging, irrigation units were delineated across 23.4 ha with water retention capacities (CRA) ranging from 79–167 mm, enabling the adjustment of effective irrigation depth (EID, 34–110 mm) relative to crop water requirements (CWR, 260–667 mm), thus optimizing irrigation and reducing ecosystem pressure [61]. Accordingly, remote sensing combined with machine learning has enabled the monitoring of critical processes for climate mitigation, such as soil organic carbon (SOC); Sentinel-1 SAR and Sentinel-2 MSI integrated with XGBoost estimated SOC with $R^2 = 0.91$ and RMSE = 0.17 t C ha^{-1}, mapping spatial variability from 0.9 to 3.8 t C ha^{-1} to guide conservation-oriented management [58].

4.5. Increased Productivity with a Smaller Environmental Footprint.

The integration of digital technologies has demonstrated that it is possible to intensify agricultural productivity without proportionally increasing environmental pressure, by replacing generalized management practices with data- and spatial variability–driven decisions. Soil moisture and nutrient sensors, drones, and artificial intelligence enable real-time characterization of crop status and the application of inputs at optimal doses and timing, reducing waste, costs, and soil degradation risks. Additionally, automation and continuous monitoring facilitate early detection of water stress, nutritional deficiencies, or pest presence, preventing yield losses due to delayed responses. In this context, spectral metrics obtained via UAV have enabled non-destructive and early yield estimation: the TRAC–UAV–NDVI integration with PCA and Elastic Net explained 72% of yield variability in common bean (RMSE ≈ 10.67 g), enabling site-specific management aimed at maximizing productivity with minimal impact [55]. Consequently, remote sensing combined with AI enhances sustainable management by identifying small-scale relevant targets within the production system; using multimodal UAS data, YOLOv3 achieved mAP = 0.86 and F1 = 93.39%, strengthening precision agriculture and contributing to reduced environmental impacts [51].

In the same vein, climate scenario simulation, crop growth modeling, and the prediction of soil responses to various interventions enable the definition of optimal irrigation, fertilization, and phytosanitary control strategies, enhancing system efficiency without compromising product quality. In this context, advanced analytics provide early diagnostic capabilities: the hybrid HARPS model achieved 96.6% accuracy, ROC = 0.970, and AUC = 0.972 in 8 s over 8,525 samples, allowing robust detection of plant stress compared to traditional approaches [50]. Likewise, water resilience can be assessed by incorporating biological responses; Gradient Boosted Trees reached 87% accuracy (σ = 4%) when modeling microbial response to water stress, highlighting potential for anticipating

 doi:10.20944/preprints202602.0211.v1

functional soil impacts [53]. Additionally, soil health monitoring using UAV hyperspectral imagery and PSO-GPR predicted salinity with $R^2 = 0.92$ and RMSE = 0.15 dS m^{-1}, reinforcing irrigation management and salinization mitigation. Furthermore, technologies such as blockchain can ensure traceability and verification of sustainable practices along the value chain, promoting responsible adoption [54].

5. Practical Applications in Key Crops and Production Systems

The evolution from conventional agronomic practices toward data-driven cyber-physical ecosystems entails reconfiguring agricultural management around continuous flows of data acquisition, transmission, processing, and decision execution. In this context, high-frequency remote sensing, IoT, and advanced analytics enable the transformation of biological and environmental signals into prescriptive actions at the plot scale, optimizing interventions based on spatial and temporal variability. Web-integrated platforms with lightweight computer vision models have achieved real-time diagnostics with high accuracy, where MobileViTv2 reached 94% accuracy, F1 = 0.94, and AUC = 0.95–0.99, with web reliability of 85.3–90.2%, outperforming more complex alternatives [64]. Likewise, the integration of hyperspectral sensors with CNNs allowed the identification of six stress levels with 83.40% accuracy, while MLVI and H_VSI indices anticipated stress 10–15 days before visible symptoms ($r = 0.98$), enabling early interventions and reducing losses [65].

The performance of smart-agriculture systems is conditioned by comprehensive digital architectures capable of orchestrating the ingestion of multimodal data, its semantic standardization, and real-time processing to transform heterogeneous information into operational actions at the field level. Applied evidence supports this feasibility, where deep learning models with ensemble stacking and explainability (XAI) have classified diseases in *Lagenaria siceraria* with 99.52% accuracy, integrating into web platforms for real-time diagnostics and phytosanitary support [66]. Similarly, systems combining CNN architectures (DenseNet121, EfficientNetB0, InceptionV3, MobileNetV2, ResNet50, and Xception) achieved 99% accuracy in cucumber pest detection, demonstrating the scalability of automated analysis across diverse production contexts [67].

In this regard, the architectural roadmap (Figure 5) organizes a sequential flow that coherently integrates data capture and its transformation into actionable agronomic decisions. The process begins with the acquisition of information through IoT sensors, UAV/satellite images, spectral signals, and agronomic records, ensuring multi-source and multi-scale data. These inputs are then consolidated into processing and storage layers in the cloud, where AI-based analytical modules are deployed for classification, prediction, and early detection of stress, pests, or spatial variability. Finally, the system converges in prescription and action modules, geared toward site-specific management of irrigation, fertilization, and phytosanitary control. This architecture allows predictive models to be synchronized with real-time decisions, increasing efficiency, traceability, and scalability in extensive implementations, and promoting inclusive digitization through frugal solutions for family farming.

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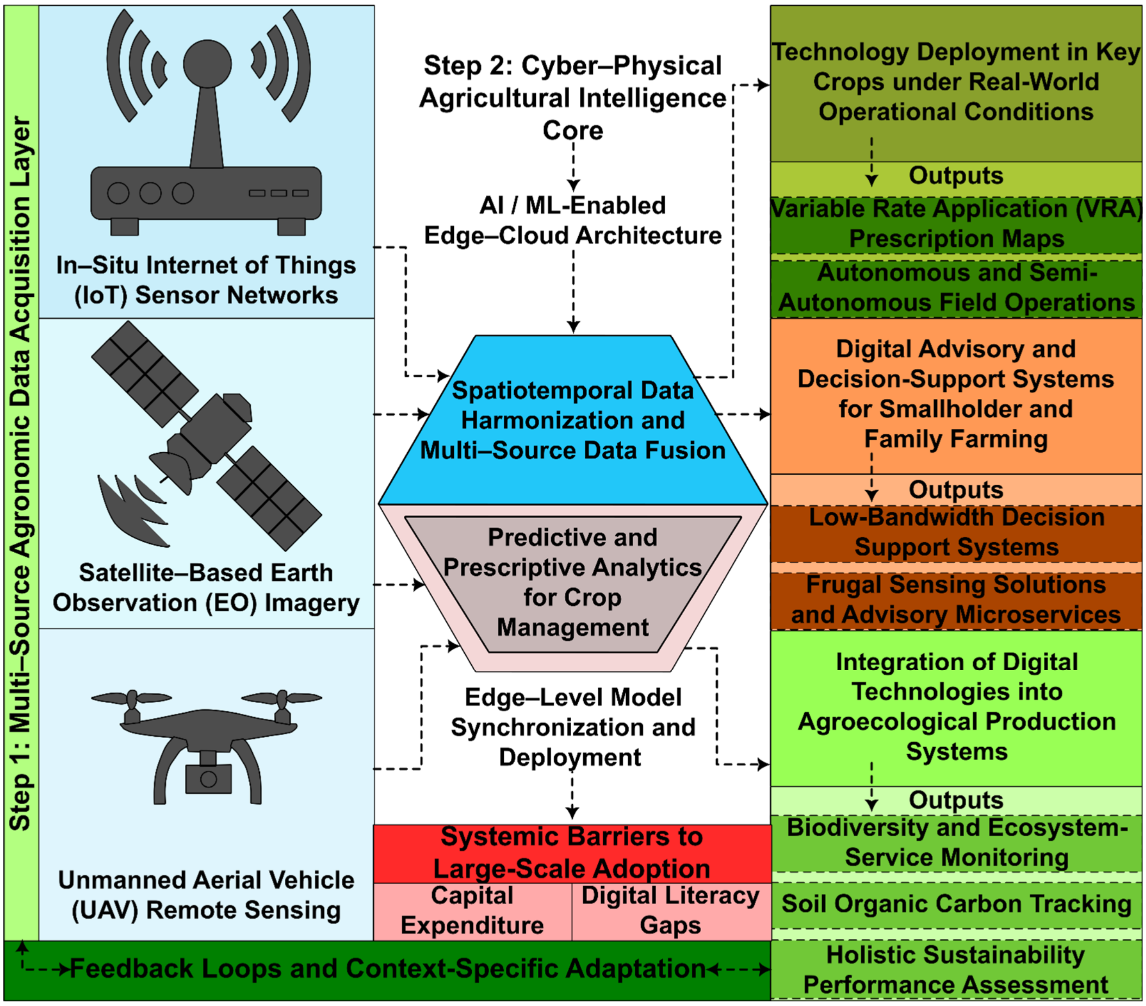

Figure 5. Idealized Integrated Digital Agriculture System Architecture (Topic 5). This schematic illustrates the theoretical optimal data flow for emerging technologies in sustainable agriculture. The process begins with Step 1: Multi-Source Data Ingestion, where diverse data streams from IoT sensors, satellite imagery, and UAVs are collected. This data flows into Step 2: Cyber-Physical Processing Core, a central hub for data fusion, AI/ML-driven predictive analytics, and edge synchronization. The processed intelligence is then disseminated to three distinct target applications: for industrial-scale operations (e.g., VRA), for smallholder inclusivity via frugal mobile services, and for holistic agroecological monitoring. The smooth, glowing blue pathways represent uninterrupted data interoperability and system integration.

5.1. Technical Incorporation of Technology in Specific Crops and Real-World Contexts

The adoption of emerging technologies is driving substantial improvements in the efficiency and stability of multiple production systems, with particular impact on Andean crops, fruit orchards, and export-oriented value chains. In high-Andean environments, where climatic variability strongly affects productivity, the integration of soil sensors, satellite remote sensing, and predictive models enables the optimization of sowing windows, adjustment of water management, and reduction of losses due to abiotic stress. Recent evidence confirms the potential of AI to reinforce these systems: in potato, CNN models with transfer learning (VGG16) classified field pests with 96.3% accuracy and inference times of 45 ms, enabling edge deployments for early response [68]. Similarly, in high-value fruit crops (avocado, blueberry, citrus, and grapevine), remote monitoring and automated irrigation support precise management of water and nutrient stress, increasing uniformity and fruit quality. In wheat, the combination of spectroscopy and machine learning allowed the detection of *Fusarium spp*. with metrics exceeding 0.89 and external validation achieving 100% predictive accuracy [69]. Additionally, multi-species approaches based on EfficientNetB0–MobileNetV2 ensembles reached

 doi:10.20944/preprints202602.0211.v1

99.77% accuracy across 38 classes, demonstrating feasibility for simultaneous diagnosis in multiple crops [70].

In vegetables, the convergence of precision agriculture, IoT networks, and greenhouse sensorization has enabled high-resolution environmental control, optimizing critical variables (temperature, humidity, radiation, and CO_2) to improve yield and energy efficiency (Table 4), while reducing phytosanitary pressure through early detection and localized management. In open-field conditions, computer vision applied to mechanized tasks shows direct sustainability impacts: deep learning–based systems were able to identify cabbage and perform intra-row weeding with up to 96.67% accuracy and ≤1.57% crop damage at low speeds, decreasing herbicide use and soil disturbance [9]. Similarly, real-time detection models have achieved near state-of-the-art performance; for example, YOLOv8 and CNN architectures with transfer learning detected diseases in chili with mAP@0.5=0.995 and mAP@0.5–0.95=0.941, exceeding 99% in both precision and recall [71]. Additionally, an improved YOLOv7 with BiFormer attention increased mAP by +2.5% and reached 94.2% accuracy for optimizing Chinese cabbage counting and establishment [72], while in tomato, an optimized YOLOv8 demonstrated robust performance for foliar diagnostics (mAP@0.5=79.8%; F1=78.6%), indicating that these capabilities, integrated with blockchain traceability, spectral analysis, and digital twins, strengthen more competitive and resilient agro-export chains [73].

Table 4. Digital applications for diagnosis, monitoring and early detection in crops.

Crop / production system	Digital application	Technology used and operational result	Ref.
Bottle gourd	Disease diagnosis	Deep learning with ensemble stacking and XAI classified diseases of *Lagenaria siceraria* with 99.52% accuracy, enabling real-time web diagnostics and support for phytosanitary decisions.	[66]
Sugar cane	Detection of rickets	Biosensors and molecular analysis enabled early detection of RSD, where the potential-induced electrochemical nanobiosensor detected Lxx DNA directly in cane sap, with a LOD of 10 cells/μL, r=0.99, and high concordance with qPCR (r=0.84).	[74]
Agricultural systems	Pest recognition	The IPRMEFP-HOFTL model integrated WF, CapsNet-Xception, and DAE-LSTM optimized with MOROA, achieving >98.22% accuracy in automatic pest detection on IP102, where computer vision and deep learning improved automatic insect identification.	[75]
Potato	Pest detection	CNN models detected pests with high accuracy in the field, where VGG16 with transfer learning classified potato pests with 96.3% accuracy, 95.8% precision, 96.1% recall,	[68]

doi:10.20944/preprints202602.0211.v1

		and 95.9% F1 score, achieving 45 ms inference and edge implementation.	
Cucumber	Pest detection	The combination of architectures such as CNN, DenseNet121, EfficientNetB0, InceptionV3, MobileNetV2, ResNet50, and Xception achieved an overall accuracy of 99%.	[67]
Cabbage	Weed control in open fields	Deep learning for computer vision and intelligent control enabled the identification of cabbage and avoidance of obstacles, achieving up to 96.67% weeding accuracy and ≤1.57% crop damage at low speeds, using experimental evaluation in intra-row weed control.	[9]
Red chili pepper	Diagnosis of diseases	Deep learning enabled accurate classification of pathologies, where the YOLOv8 architecture and CNNs with transfer learning detected chili diseases in real time, achieving mAP@0.5=0.995, mAP@0.5–0.95=0.941, and >99% precision and recall.	[71]
Rice	Classification of diseases	The CNN-ELM model achieved high accuracy in leaf disease detection, where the model achieved 99.18% accuracy, surpassing BPNN (95.83%), PCA-SVM (96.55%), CNN (94.0%), DNN-JOA (94.25%), SVM (93.33%), VGG16-CNN (92.89%), and KNN (70%).	[76]
Castor bean	Insect identification	CNN with data augmentation improved pest detection, where CNN models with VGG16, VGG19, and ResNet50, optimized with synthetic augmentation, increased validation accuracy from 71.23–74.85% to 82.18% (VGG16) and 76.71% (VGG19).	[77]
Agricultural systems	Automatic notification of diseases	AI and IoT generated early warnings for producers, where the IoT–YOLOv8 system with integrated cloud achieved macro accuracy of 0.56, weighted recall of 0.51, and F1 of 0.49, enabling remote disease diagnosis and real-time decision support.	[78]
Multi-crop systems	Multi-species classification	The EfficientNetB0–MobileNetV2 ensemble model on PlantVillage (54,305 images, 38 classes) achieved 99.77% accuracy, optimizing automated disease detection and support for	[70]

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		sustainable agriculture, enabling simultaneous diagnosis across multiple crops.	
Chinese cabbage	Seedling detection	The improved YOLOv7 model with decoupled head and BiFormer attention achieved +2.5% mAP, 94.2% accuracy in CCSB adjustment, and 91.3% identification, optimizing intelligent weeding of Chinese cabbage, as artificial vision optimized crop counting and establishment.	[72]
Tomato	Detection of leaf diseases	The optimized YOLOv8 model achieved 85.7% precision (P), 72.8% recall (R), 79.8% mAP@0.5, 51.6% mAP@0.5:0.95, and 78.6% F1, demonstrating efficient and robust detection in tomato leaves and its accuracy in diagnosing diseases.	[73]
Wheat	Fungus detection	Spectroscopy and DL detected Fusarium spp., where the XGBoost model achieved accuracy, precision, recall, and score (F1) >0.89, consistent five-fold cross-validation (0.82–1.00), and 100% predictive precision in external validation with 12 wheat ears.	[69]
Agricultural systems	Instant pest detection	The MobileNetV2–EfficientNetB0 fusion model achieved Acc 89.5%, P/R 95.68%, F1 95.67%, AUC 0.95, with <10 ms inference and superiority over the base CNN (81.25–83.10%).	[79]
Agricultural systems	Web diagnosis	The web platform facilitates access to diagnosis, where the MobileViTv2 model achieved Acc 94%, F1 0.94, and AUC 0.95–0.99, outperforming EfficientNet-B7 and hybrid, with web reliability of 85.3–90.2% in real-time diagnosis.	[64]
Interleaved systems	Disease detection	The hyperspectral model achieved 99.676% accuracy in corn-soybean and 99.538% in pea-cucumber, demonstrating robustness and applicability for smart and sustainable agriculture, improving disease diagnosis in polycultures.	[80]
Agricultural systems	Disease dataset	The standardized dataset strengthened model training, where the MobileNetV2 architecture achieved higher accuracy (92.5–93.8%), F1 (85–88%), and AUC (95–98%) in leaf disease detection, outperforming DenseNet121, InceptionV3, and ResNet50.	[81]

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Roses	UAV-assisted monitoring	The UAV detected stress and phenological anomalies, where the MambaIR-ROSE-YOLO approach achieved PSNR of 28.34 dB, SSIM 77.07%, mAP of 95.3% in high resolution and 94.4% in super-resolution images for roses in greenhouses.	[82]
Agricultural systems	Stress detection	Hyperspectral imaging enabled stress to be identified before visible symptoms appeared, with the CNN model achieving 83.40% accuracy, detecting six levels of stress in crops; the MLVI and H_VSI stress indices anticipate stress 10–15 days in advance with a correlation of r = 0.98.	[65]
Lettuce	Pigment phenotyping	Multispectral images quantified pigmentation, where the use of AIA with VIS-NIR-SWIR hyperspectroscopy classified 11 varieties of lettuce; the AdB, CN2, G-Boo, and NN models achieved R^2 and ROC > 0.99, highlighting exceptional accuracy.	[83]
Pearl millet	Disease prediction	The disease detection model for finger millet leaves, combining GNN, DynaNet, AE, and RNN, achieved 95.6% accuracy, >94% F1, and prediction in 0.035 s/im, anticipating the occurrence of crop diseases.	[84]
Tomato	Reduction in harvest time	The modified SSD model achieved 95% detection accuracy and 96.1% recall on organic tomatoes, outperforming the classic and self-service SSDs, with high robustness and operational efficiency.	[85]

Note. The studies synthesize the digital applications reported in studies published between 2020 and 2025, focused on diagnosis, monitoring, and early detection in crops, including technologies such as UAVs, IoT sensors, vis-NIR, machine learning, and deep learning, describing their operational results in terms of accuracy, efficiency, and predictive capacity. Abreviaturas: XAI, Explainable Artificial Intelligence; RSD, Sustained deficit irrigation; Lxx, Leifsonia xyli subsp. xyli; LOD, Limit of Detection; qPCR, Quantitative Polymerase Chain Reaction; IPRMEFP-HOFTL, Insect Pest Recognition Model using Heuristic Optimizer and Fusion Transfer Learning; WF, Wiener Filter; DAE-LSTM, Denoising Autoencoder–Long Short-Term Memory; MOROA, Multi-Objective Remora Optimization Algorithm; IP102, Insect Pest 102 Dataset; CNN, Convolutional Neural Network; VGG16, Visual Geometry Group; YOLOv8, You Only Look Once v8; DNN-ELM, Deep Neural Network–Extreme Learning Machine; BPNN, Backpropagation Neural Network; PCA-SVM, Principal Component Analysis–Support Vector Machine; DNN-JOA, Deep Neural Network–Jaya Optimization Algorithm; SVM, Support Vector Machine; KNN, K-Nearest Neighbors; ResNet50, Residual Network; F1, F1-score; CCSB, Chinese Cabbage Seedling Belt; XGBoost, eXtreme Gradient Boosting; AUC, Area Under the Curve; PSNR, Peak Signal-to-Noise Ratio; SSIM, Structural Similarity Index; mAP, Mean average accuracy; UAV, Unmanned Aerial Vehicle; MLVI, Modified Vegetation Index; H_VSI, Water Stress Severity Index; AIA, Artificial Intelligence Algorithms; VIS, Visible; NIR, Near Infrared; SWIR, Shortwave Infrared; AdB, Adaptive

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Boosting; CN2, Classifier Rule Learner; GNN, Graph Neural Network; DynaNet, Red Dyna for time series; AE, Autoencoder; RNN, Recurrent Neural Network; im, imagen.

5.2. Emerging Technology in Small-Scale Agriculture

The incorporation of emerging technologies in small-scale agriculture represents an effective pathway to enhance productivity and sustainability without requiring complex infrastructure, particularly in rural contexts where capital, connectivity, and technical support are limited. Technological evidence shows that even advanced tools can be adapted to small-scale operations: electrochemical nanobiosensors induced by potential have enabled early detection of sugarcane rickets (Lxx DNA) directly in sap, with a detection limit of 10 cells/μL and high correlation (r=0.99), showing concordance with qPCR (r=0.84) [74]. The use of mobile applications, low-cost sensors, and climate alert platforms allows producers to record critical variables, interpret risks, and adjust management practices with greater precision, optimizing water, seeds, and fertilization according to actual field conditions. Furthermore, digitalization facilitates planting planning and anticipates adverse events such as frost, drought, or pest outbreaks, reducing losses and improving income stability. Notably, computer vision and deep learning models, such as the IPRMEFP-HOFTL framework, integrated hybrid architectures (WF, CapsNet-Xception, and DAE-LSTM) optimized for performance, achieving >98.22% accuracy in automatic pest recognition, strengthening accessible phytosanitary monitoring [75].

The incorporation of digital capabilities within producer organizations, associations, and cooperatives amplifies the benefits of smart agriculture by scaling access to information, services, and markets through shared infrastructures and collective data governance. Digital support enhances decision-making efficiency in the field and reduces critical times for tasks such as diagnosis, management, and harvesting. In this context, advanced analytics applied to phenotyping has demonstrated high precision: multispectral and VIS–NIR–SWIR hyperspectral imaging enabled the classification of 11 lettuce varieties, with models such as AdB, CN2, G-Boo, and NN achieving R^2 and ROC values above 0.99, highlighting their potential for quality control and commercial differentiation [83]. The deployment of community drones, cooperative weather stations, and collaborative monitoring platforms reduces individual costs, improves agronomic planning, and strengthens traceability required by commercial chains and certification processes. This approach also facilitates access to credit and contracts by providing verifiable records of productive practices, quality, and technical compliance. Accordingly, computer vision solutions for harvesting have improved efficiency: a modified SSD model achieved 95% detection precision and 96.1% recall in organic tomatoes, reducing operational time and enhancing productivity in associative schemes [85].

5.3. Integration into Agroecological Systems.

The integration of digitalization into agroecological systems enhances productive efficiency while maintaining the ecological logic of management, providing objective, high-resolution information on soil–plant–climate dynamics. In this context, AI models applied to crop diagnostics have demonstrated high performance: hybrid architectures combining GNN, DynaNet, autoencoders, and RNN achieved 95.6% accuracy and >94% F1-score in predicting foliar diseases in millet, with inference times of 0.035 s per image, enabling timely field monitoring [84]. The sonification of climatological factors such as humidity and temperature, combined with soil mapping and local weather stations, facilitates the adjustment of regenerative practices such as rotations, cover cropping, and crop associations, optimizing water use and reducing soil disturbance without reliance on synthetic inputs. Furthermore, advanced analytics contribute to the prevention of phytosanitary risks through early-warning alerts, aligning with the preventive approach of agroecology. Complementarily, UAV-assisted monitoring allows the detection of stress and phenological anomalies in protected environments; the MambaIR-ROSE-YOLO framework achieved a mAP of 95.3% at high resolution and 94.4% at super resolution for roses, with reconstruction quality metrics

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of PSNR 28.34 dB and SSIM 77.07%, supporting management decisions without compromising ecological principles [82].

The application of emerging technologies in phytosanitary diagnostics is consolidating as a key component of digital agriculture, enabling the identification of diseases and insect pests with high precision and facilitating early interventions that reduce losses and unnecessary agrochemical use. In rice, a hybrid CNN–ELM approach demonstrated outstanding performance in foliar disease classification, achieving 99.18% accuracy and outperforming conventional models such as BPNN, PCA-SVM, standard CNN, SVM, and deep architectures, highlighting its robustness for operational scenarios [76]. Similarly, in castor, pest detection was enhanced through data augmentation strategies, where CNNs based on VGG16, VGG19, and ResNet50 increased validation accuracy from 71.23–74.85% to 82.18% (VGG16) and 76.71% (VGG19), improving model generalization under field variability [77]. Furthermore, the convergence of AI and IoT is enabling automated alert systems for producers: an IoT–YOLOv8 framework with cloud integration generated early notifications and decision support in real time via remote diagnostics, achieving a macro-precision of 0.56, weighted recall of 0.51, and F1-score of 0.49, evidencing functional viability for continuous monitoring in distributed agricultural systems [78].

The integration of digital agriculture in experimental studies confirms that the performance of smart farming systems depends not only on data availability but also on optimized models capable of operating in real time (Table 5) with high precision under field conditions. In this context, instant pest detection has shown significant advances through fused architectures, where the MobileNetV2–EfficientNetB0 model achieved an accuracy of 89.5%, precision/recall of 95.68%, F1-score of 95.67%, and AUC of 0.95, also highlighting ultra-fast inference (<10 ms) and superiority over baseline CNNs (81.25–83.10%), making it suitable for edge deployment in continuous monitoring [79]. Complementarily, in intercropping and polyculture systems, hyperspectral imaging maintained exceptional precision in disease detection, reaching 99.676% in maize–soybean arrangements and 99.538% in pea–cucumber, demonstrating robustness against species heterogeneity and applicability in sustainable agriculture [80]. Furthermore, the development of standardized datasets is strengthening model generalization and comparability, where MobileNetV2 achieved higher accuracy (92.5–93.8%), F1-score (85–88%), and AUC (95–98%) in foliar disease detection, outperforming widely used architectures such as DenseNet121, InceptionV3, and ResNet50, consolidating a solid foundation for training and validating digital field solutions [81].

Table 5. Digital applications for prediction, productive management and resource optimization.

Crop / production system	Digital application	Tecnologia utilizada y resultado operativo	Ref.
Orange Tree	Digital platform	The IoT architecture integrated production data for decision support, where the AgriLink platform successfully monitored soil moisture, air temperature and relative humidity in orange trees, using DHT11 and soil sensors at 1 Hz, with an accuracy of ±2 °C and ±5%.	[86]
Agricultural systems	Fertilization recommendati on.	The Adaboost and Random Forest (RF) classifiers achieved accuracies of 0.99 and 0.98, surpassing KNN (0.95), Decision Tree (DT) (0.94), and SVM (0.91), minimizing false positives, as the Internet of Things and	[87]

		machine learning analyzed soil and crops for precise fertilization.	
General agriculture	Cognitive weather station	The AI improved local climate prediction, where the model with two hidden layers of 50 neurons, sigmoid and tanh activations, Adam optimizer, trained for 30 epochs in Google Colab, achieved MASE 0.0012, RMSE 0.0034, and Willmott index 0.988.	[88]
Olive tree	Water status	The multispectral UAV was able to predict water stress in olive trees with RWC R^2=0.80, Ψ_MD R^2=0.61, g_s R^2=0.72; chlorophyll ab R^2=0.64, chlorophyll a R^2=0.61, and chlorophyll b R^2=0.52 using CWSI, TVI, and MCARI.	[89]
Vid	Cluster detection	The YOLOv7x model applied to UAV images predicted the number of grape clusters with R^2=0.64 and RMSE=0.78 clusters·plant^{-1}, while Sentinel-2 and PlanetScope indices achieved R^2<0.23, enabling automatic counting and planning.	[90]
Agricultural systems	Pathogen prediction	The use of deep learning anticipated phytosanitary outbreaks, where NN and CNN models were able to predict the transmission of plant diseases: NN Model 1 accuracy 88.664%, CNN Model 2 accuracy 96.933%, and Model 3 AUC-ROC up to 99.767%, being sensitive to climate variability.	[91]
Agricultural land	Organic matter	The use of deep learning and smartphone + ML estimated MOS non-destructively, where the metric approach estimated MOS with RMSE=0.17 vs. 0.51 (RF), ΔRMSE<0.05 between textures, validated with 500 samples, 20–30 °C, and 45–75% RH.	[92]
Durum wheat	Yield estimation	The UAV-MS in Timilia and Ciclope (0–120 kg N ha^{-1}): RF, NN, and SVM achieved R^2>0.6 in yield (RMSE 0.56 t ha^{-1}; MAE 0.43) and R^2>0.7 in protein (RMSE 1.2%), successfully predicting grain yield and protein concentration in wheat.	[93]
Extensive farming	Performance prediction	The PEnsemble4 model integrated UAV and IoT, analyzed CIre and NDRE using ML with Huber-M estimators, achieved 91% accuracy,	[94]

		and advanced yield prediction from R6 to R2, improving agricultural planning.	
Polyculture	Predictability of performance	The component analysis showed that PC2 explained 12.65% of the variance; Nyield_kgha, PMN, and Fe were dominant variables, while C_soil and N_residues negatively conditioned PC1–PC2, affecting yield.	[95]
Rice	Yield estimation	The RFE–MIR selection optimized ML performance: k-NN led (R^2=0.61; RMSE=578.43 kg ha^{-1}), followed by ANN (R^2=0.58), RF (R^2=0.44), and XGBoost (R^2=0.34), where the satellite and ML predicted rice productivity.	[96]
Rice	Stubble yield	GF-1/GF-6 and NDVI data estimated rice yield with high accuracy (validation R^2 = 0.88; RMSE = 3.48%), identifying maximum yields (8.21–8.36 t·ha^{-1}) with 60–75% residual coverage.	[97]
Cotton	Soil salinity	The multispectral UAV estimated spatial salinity, where the SSA-SVM selection and the BPNN model improved the estimation of soil salinity with UAVs, increasing accuracy by 5% and 10.69%, respectively, and generating maps with a resolution of 5 cm.	[98]
Wheat	Stubble coverage mapping	The satellite quantified waste coverage, with Sentinel-2B estimating WSC more accurately than Landsat-8: NDTI R^2=0.85, accuracy 86.53% (κ=0.78), RMSD 6.88–12.04%, outperforming the Straw Tillage Index (STI) and Normalized Difference Tillage Index (NDRI).	[99]
Vegetables	Weed prescription maps	The use of low-cost UAVs reduced the treated area by between 2.18% and 18.92%; RNA showed greater efficiency compared to MLC and OBIA, validating prescription maps for sustainable weed management.	[100]
Agricultural systems	Optimization in weed detection	The HHOGCN-WD model achieved >99.13% accuracy in weed detection and classification, demonstrating high efficacy for localized control and potential reduction in herbicide use in precision agriculture, using networks optimized for weed segmentation.	[101]

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Agricultural systems	Smart water control	Internet of Things (IoT) monitoring reduced water consumption, where the AIoT-based IWRC system achieved highly accurate water control in hydroponics, highlighting MLR-PSO-ANFIS444 with RMSE = 2.35×10^{-4} and R^2 = 0.99.	[102]
Cotton	Performance prediction	The UAV-based scale-sensitive CNN model outperformed conventional architectures, achieving $R^2 > 0.90$; MAE = 3.08 lb/row and 0.05 lb/grid; MAPE = 7.76–10%, successfully predicting productivity with RGB images.	[1]
Agricultural systems	Water requirement	The use of data-assisted hydrological models improves water efficiency, where CWSI calibration showed r^2 = 0.613; lower baseline Tc–Ta = −1.74·VPD − 1.23 and upper = 2.32 °C, adequately estimating water stress and soil water loss.	[103]
Agricultural systems	Environmental monitoring	The use of multisensory integration improved agricultural control and development, where XGBoost outperformed Random Forest in classifying tomato diseases using VGG16 features, achieving 93% accuracy, F1 = 0.93, precision ≥ 0.85, and recall ≥ 0.75, compared to 76% and F1 = 0.76 for Random Forest, with critical failures in early blight.	[104]
Agricultural systems	Low-cost digital tools	The use of accessible technologies facilitated adoption in crops, where digital image processing with color, shape, and texture extraction achieved 89.6% accuracy in shape and 94% in texture; round and rotten tomatoes showed confusion.	[105]
Greenhouses (potatoes)	Stress management	The DARY system, based on sensors, microcontrollers, MQTT, and a web application, increased pre-basic potato production by 22%, saved 27% water, reduced energy consumption by 12%, and cut costs by 35%, demonstrating that automated systems optimized production.	[106]
Agricultural systems	Smart irrigation	Digital systems reduced water consumption, where IoT architecture with environmental sensors monitored T = 22.1–28 °C, RH = 39–49.1%, soil moisture = 62.5–65%, and water	[107]

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		level = 60–62%, validating real-time smart irrigation.	
Olive tree	Cloud–fog monitoring	Distributed architecture improved latency in olive cultivation, where the ZigBee/CSMA-based WSN system achieved an average performance of ≈95% (72–100%) in packet delivery, maintaining high reliability despite congestion and physical obstacles.	[108]
Agricultural systems	Irrigation and fertigation	IoT technology optimized water and nutrient use, where synergistic agriculture with automated irrigation and fertigation allowed for complete phenological development and expected yields (cherry tomatoes 2.5–3.2 kg/plant), demonstrating productive efficiency without phytosanitary control.	[109]
Rice	Acame estimate	The use of UAV and DL technology quantified damage, where the SWRD-YOLO model with UAV images segmented rice beds with 94.8% accuracy, 88.2% recall, 93.3% mAP@0.5, 91.4% F1, and 16.15 FPS, surpassing YOLOv8n-seg.	[110]
Wheat	Performance prediction	UAV hyperspectral remote sensing with machine learning predicted wheat yield; SVM achieved R^2 = 0.62–0.73 and the Boruta ensemble model achieved R^2 = 0.78 in grain filling, improving estimates in wheat cultivation.	[111]
Sugar cane	Response to nitrogen	Spectral sensors evaluated nitrogen efficiency in sugarcane, where N–yield regression showed linear and quadratic adjustments; optimal N doses varied between 109.3–185.7 kg ha^{-1} depending on plot, area, and sugarcane stump cycle.	[112]
Agricultural systems	Agricultural big data	Deep learning integrated with IoT, BDA, and neural systems optimized monitoring, nutrition, and agricultural management, enabling Agriculture 3.0, with greater production efficiency and requirements for qualified personnel.	[113]
Agricultural systems	Smart prediction	The CNN–LSTM models integrated sensors and prediction, with AgriCNN-LSTMFusion achieving 98.5% accuracy, outperforming	[114]

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		CNN (95.4%), LSTM (94.1%), RF (92.3%), SVM (81.2%), and FNN (80.7%) in crop suitability.	
Agricultural systems	Climate management	The integration of digital platforms improved the management of agricultural inputs, where the system achieved R^2=0.96 (RMSE=0.04) in temperature and R^2=0.97 (RMSE=0.07) in ET_0 with XGBoost, validating its accuracy for smart irrigation.	[115]
Weeds	Precise segmentation	Deep network models optimize weed selection, with SWFormer achieving mAP=76.54% and accuracy=83.95% in crop-weed mixtures, and mAP=61.24% with accuracy=79.47% in SB20, outperforming conventional models.	[10]
Rice	Disease detection	The selection of deep learning algorithms improved disease diagnosis and prediction, with RDRM-YOLO achieving accuracy=94.3%, recall=89.6%, and mAP=93.5% with 7.9 MB, surpassing Faster R-CNN and YOLOv6–v8 in convergence, accuracy, and speed.	[116]
Sistemas agrícolas	Leaf spectroscopy	The use of NIR technology allowed for the estimation of foliar nitrogen, where vis-NIR with PLSR estimated foliar N in high-performance potatoes ($R^2 > 0.8$; RPD > 2), validated across multiple sites and varieties, although it underestimated leaves with N > 6%.	[117]

Note. The studies synthesize the digital applications reported in scientific studies published between 2020 and 2025, including IoT, remote sensing, vis-NIR, machine learning, and deep learning. Operational results are described according to performance metrics, productive efficiency, and resource optimization, in accordance with the literature of the analyzed period. Abbreviations: DHT11, Low-Cost Temperature and Relative Humidity Sensor; KNN, K-Nearest Neighbors; SVM, Support Vector Machine; MASE, Mean Absolute Scaled Error; RMSE, Root Mean Square Error; UAV, Unmanned Aerial Vehicle; RWC, Relative Water Content; Ψ_MD, Leaf Water Potential at Midday; g_s, Stomatal Conductance; CWSI, Crop Water Stress Index; TVI, Triangular Vegetation Index; MCARI, Modified Chlorophyll Absorption-Reflectance Index; YOLOv7, You Only Lookv7; NN, Neural Networks; CNN, Convolutional Neural Networks; AUC-ROC, Area Under the Receiver Operating Characteristic Curve; MOS, Soil Organic Matter; RF, Random Forest; HR, relative humidity; ML, Machine Learning; RF, Random Forest; NN, Neural Network; SVM, Support Vector Machine; IV, Vegetation Indices; Cire, Chlorophyll Index in red Border; NDRE, Normalized Difference Index of the red Border; R2/R6, Phenological Stages of Maize; PC, Main Component; Nyield_kgha, N yield (kg ha^{-1}); PMN, Potentially Mineralizable N; Fe, Iron; C_soil, Soil Organic Carbon; N_residue, N in Residues (%); RFE, Recursive Feature Elimination; MIR, Mutual Information Regression; ML, Machine Learning; k-NN, k-Nearest Neighbors; ANN, Artificial Neural Network; XGBoost, Extreme Gradient Boosting; GF-1/GF-6, Satélites Gaofen-1/Gaofen-6; WRC, Wheat Residue Cover; RS, Remote Sensing; VI, Vegetation Index; EVI, Enhanced Vegetation Index; NDVI, Normalized Difference Vegetation Index; GNDVI, Green NDVI; LULC, Land Use/Land Cover; UAV, Unmanned Aerial

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Vehicle; SSA-SVM, Sparrow Search Algorithm–Support Vector Machine; RFE, Recursive Feature Elimination; BPNN, Backpropagation Neural Network; WSC, Wheat Straw Cover; MSI, Multispectral Instrument; OLI-TIRS, Operational Land Imager–Thermal Infrared Sensor; IRC, Crop Residue Indices; NDTI, Normalized Difference Tillage Index; STI, Straw Tillage Index; NDRI, Normalized Difference Residue Index; RMSD: Root Mean Square Deviation; κ: Kappa Coefficient; MLC, Maximum Likelihood Classifier; OBIA, Object-Based Image Analysis; HHOGCN-WD, Harris Hawks Optimization–Graph Convolutional Network Weed Detection; IWRC, Intelligent Water Resources Control; MLR, Multiple Linear Regression; PSO, Particle Swarm Optimization; ANFIS, Adaptive Neuro-Fuzzy Inference System; CWSI, Crop Water Stress Index; Tc, Canopy temperature; Ta, Air temperature; VPD, Vapor Pressure Deficit; DARY, Digital Agriculture System for Controlled Irrigation and Thermal Regulation; MQTT, Message Queuing Telemetry Transport; WSN, Wireless Sensor Network; ZigBee, Communication Protocol; CSMA, Carrier Sense Multiple Access.

In this context, the convergence of high-resolution remote sensing, machine learning, and agronomic analytics is expanding the capacity of agroecological systems to anticipate risks and optimize decisions without intensifying interventions on the agroecosystem. Specifically, the use of UAVs equipped with hyperspectral sensors has shown potential to estimate key productive variables, where SVM-based models achieved coefficients of determination ranging from $R^2 = 0.62$ to 0.73, and an ensemble approach with Boruta variable selection increased performance up to $R^2 = 0.78$ during the grain-filling stage in wheat, improving yield prediction accuracy under real field conditions [111]. Similarly, the assessment of critical events associated with mechanical stress and harvest losses, such as lodging in rice, has been strengthened through deep learning applied to UAV imagery. Notably, the SWRD-YOLO model segmented lodged areas with 94.8% precision, 88.2% recall, mAP@0.5 of 93.3%, F1-score of 91.4%, and a processing speed of 16.15 FPS, outperforming baseline architectures such as YOLOv8n-seg. These results confirm that digital instrumentation not only enables timely environmental and productive monitoring but also facilitates early warning generation and preventive strategies aligned with resilience and sustainability principles inherent to agroecology [110].

6. Limitations, Challenges and Technological Gaps

In this context, one of the main barriers to large-scale adoption of digital agriculture lies in the mismatch between algorithmic performance reported under experimental conditions and operational realities in rural territories. Although deep learning approaches have demonstrated outstanding results in critical tasks—such as weed segmentation and phytosanitary diagnosis—their large-scale deployment faces constraints related to limited connectivity, energy availability, data heterogeneity, and lack of local capabilities for maintenance and calibration. For instance, advanced models like SWFormer achieved mAP = 76.54% and precision = 83.95% in crop–weed scenarios, demonstrating high spatial discrimination accuracy; however, these results rely on stable acquisition conditions and representative datasets, which are not always achievable in open fields and smallholder farms [10]. Similarly, compact architectures designed for efficiency, such as RDRM-YOLO, reached precision = 94.3%, recall = 89.6%, and mAP = 93.5% with a model size of 7.9 MB, suggesting feasibility for edge computing. Nevertheless, challenges in interoperability, model updating, and generalization under agroclimatic and phenological variability persist, limiting their direct transferability to heterogeneous rural systems [116].

Evidence reinforces that the gap is not merely technological but also socio-technical: the bottleneck lies in infrastructure, data governance, and the human appropriation necessary to democratize precision agriculture. This phenomenon aligns with integrated IoT–Big Data–deep learning approaches, which have demonstrated the capacity to optimize monitoring, nutrition, and productive management under the agriculture 3.0 paradigm, yet their performance critically depends on robust data infrastructure and skilled personnel for continuous operation and maintenance [113]. Similarly, hybrid models aimed at intelligent prediction, such as AgriCNN-LSTMFusion, achieved 98.5% accuracy by integrating sensors and deep learning, outperforming classical approaches;

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however, their transfer to real-world contexts requires high-quality data, persistent connectivity, and local technical capabilities to ensure calibration, updates, and operational reliability [114].

The Socio-Technical Friction Matrix (Figure 6) provides a critical counterpoint to the idealized architecture described above, showing that agricultural digitization fails not because of a lack of technology, but because of cumulative friction between social, organizational, and territorial conditions. The matrix identifies points where digital systems degrade or collapse when moving from controlled scenarios to rural areas with high biophysical heterogeneity, spatial dispersion, and structural constraints. In this context, soil and climate variability, land fragmentation, and limited connectivity reduce data quality and continuity, affecting model calibration, platform interoperability, and the reliability of recommendations. At the same time, capacity gaps, adoption costs, data governance, and institutional misalignment limit maintenance, scaling, and local appropriation. Thus, the matrix allows for prioritizing interventions and designing robust, adaptive, and contextualized solutions.

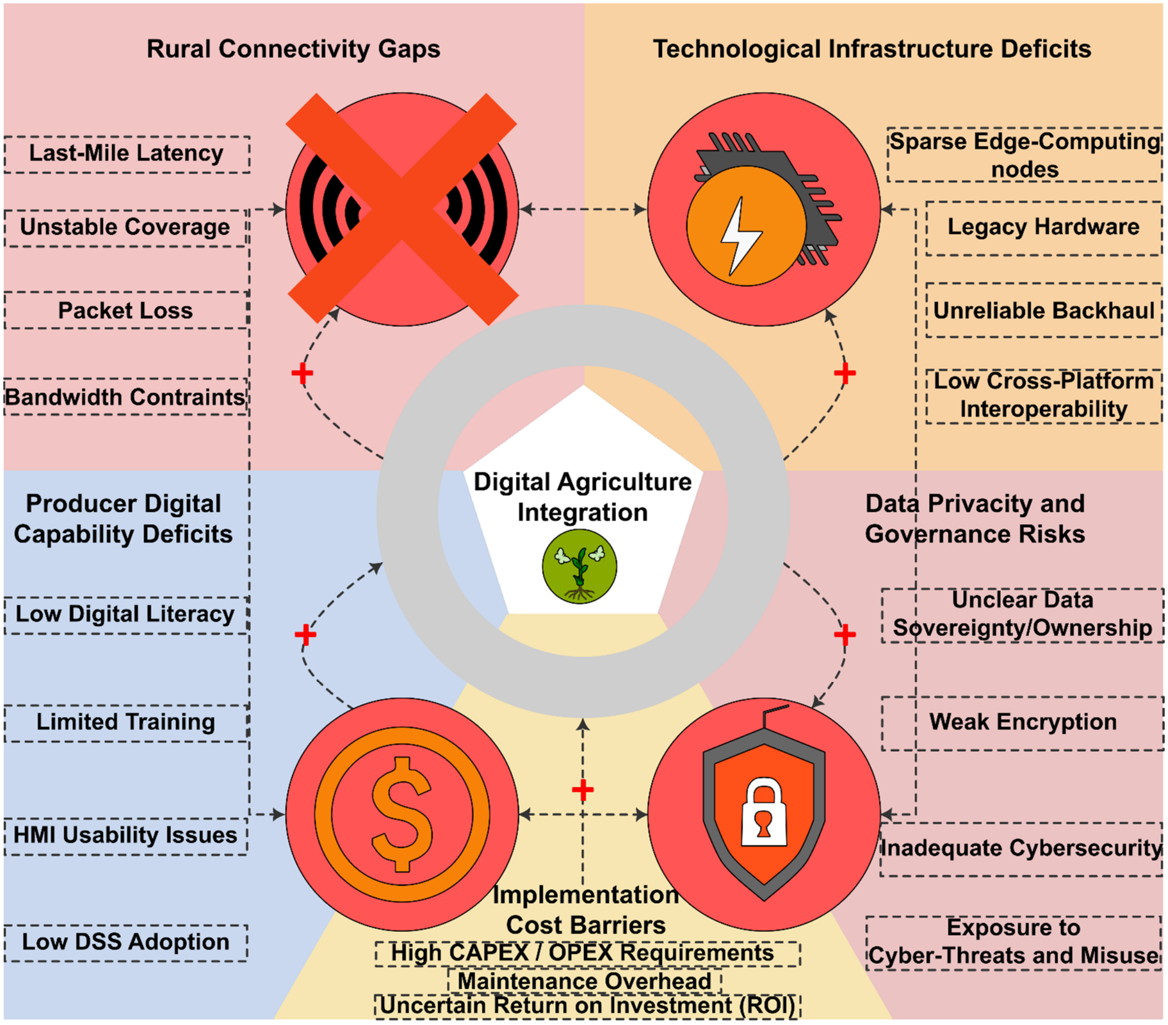

Figure 6. Socio-Technical Friction Matrix & Identified Barriers (Topic 6). A mirror image of Figure A, this diagram visualizes the systemic failure points identified in Topic 6 that disrupt the idealized flow. The ingestion layer is compromised by representing a rural connectivity void and infrastructure deficit (high latency, no edge nodes), preventing reliable data collection. The processing core is rendered vulnerable by highlighting data privacy and sovereignty hazards caused by unsecured protocols. The pipelines to the target applications are severed by key bottlenecks: shows the economic viability gap hindering scalable implementation, and illustrates the critical digital capability and literacy void impeding adoption by end-users, particularly in smallholder and agroecological contexts.

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6.1. Access to Rural Connectivity.

Limited access to connectivity in rural areas constitutes one of the main obstacles to the effective adoption of emerging digital technologies for sustainable agriculture, as most smart-agriculture solutions rely on continuous data flows, real-time synchronization, and machine-to-machine communication. Evidence from controlled systems highlights the productive potential of these technologies: the DARY system, based on sensors, microcontrollers, MQTT protocol, and a web application, increased pre-basic potato production by 22%, saved 27% of water, reduced energy consumption by 12%, and decreased costs by 35%, demonstrating that digital automation can simultaneously improve efficiency and sustainability [106]. In territories characterized by complex geography, low population density, and dispersed production units, internet infrastructure is often insufficient, unstable, or economically unviable, compromising the operation of sensors, monitoring platforms, mobile applications, and AI-based decision-support systems. Nevertheless, these solutions require functional connectivity to ensure telemetry, traceability, and continuous operation. In response to this limitation, distributed cloud–fog architectures have been proposed to reduce dependence on the cloud; for instance, a WSN system in olive orchards using ZigBee/CSMA maintained ≈95% packet delivery (72–100%) despite physical obstacles and low congestion, demonstrating that localized communication strategies can sustain reliability in adverse rural environments [108].

This connectivity gap restricts the deployment of sensor networks, the timely transmission of data, and operational access to critical services such as satellite imagery, predictive models, and dashboards, degrading the precision and utility of agronomic recommendations. Furthermore, the lack of coverage limits coordination among producers, technicians, and markets, reducing the capacity to respond to climatic events, pest outbreaks, or price fluctuations, with direct impacts on competitiveness and resilience. The expansion of rural connectivity faces economic and logistical barriers, including low population density, high deployment costs (fiber, towers, maintenance), and limited institutional capacity to support IoT operations [109]. Although LPWAN, low-Earth orbit satellites, and hybrid schemes offer alternatives, adoption remains uneven and dependent on public policy. When minimal operational connectivity exists, benefits are immediate: in smart irrigation systems, an IoT architecture with environmental sensors enabled real-time monitoring of critical variables (T = 22.1–28 °C; RH = 39–49.1%; soil moisture = 62.5–65%; water level = 60–62%), validating the ability for digital water control and consumption reduction under real operational conditions. High-quality rural connectivity is therefore not an ancillary component but an enabling condition for equitable agricultural digitalization, allowing small and medium producers to fully benefit from these innovations [107].

6.2. Insufficient Technological Infrastructure

The insufficiency of technological infrastructure constitutes a critical limitation for scaling digital agriculture in rural contexts, as many areas lack operational weather stations, communication nodes, stable power supply, local servers, and management platforms capable of ensuring continuous data capture, storage, and transmission. Evidence indicates that when integrated platforms are available, high accuracy can be achieved for critical variables in smart irrigation, reaching R^2 = 0.96 for temperature and R^2 = 0.97 for ET_0 using XGBoost models [115]. However, the scarcity of technological resources limits the effective functionality of sensors, drones, remote sensing, and AI-based models, all of which require minimal operational support to function reliably. Furthermore, the lack of maintenance services, spare parts, and specialized technical assistance increases system failures, downtime, and operational costs, discouraging adoption. Nevertheless, low-cost IoT architectures such as AgriLink have demonstrated field feasibility, monitoring soil moisture and environmental variables in orange orchards using DHT11 and soil sensors at 1 Hz, achieving accuracies of ±2 °C and ±5%, respectively [86].

On the other hand, inadequate energy infrastructure amplifies technological gaps in digital agriculture, as in many rural areas the electricity supply is unstable or nonexistent, disrupting the

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continuous operation of sensors, monitoring stations, IoT gateways, and communication equipment required for data transmission. In this context, even highly accurate models for agronomic recommendations—such as IoT- and machine learning–based approaches achieving 0.99 precision with AdaBoost and 0.98 with Random Forest for fertilization—critically depend on stable power and connectivity to operate at scale [87]. Interruptions in real-time monitoring degrade data quality, limit timely processing, and reduce the reliability of decision support systems. Although alternatives such as solar panels, long-life batteries, or hybrid schemes exist, their adoption remains constrained by initial costs, spare parts availability, and limited local technical expertise. It should be noted that advanced solutions, such as multispectral UAVs for estimating water stress in olive orchards (RWC $R^2 = 0.80$), require energy and logistical infrastructure that is not always available [89].

6.3. Implementation Costs.

Implementation costs constitute a structural barrier to scaling digital technologies in agriculture, particularly in small- and medium-sized farms where investment capacity and access to financing are limited. In practice, even proven solutions—such as automated grape cluster counting using YOLOv7x with UAV imagery ($R^2 = 0.64$)—require equipment, processing, and logistics that increase the cost of sustained adoption [90]. The acquisition of hardware (sensors, drones, weather stations), connectivity, software licenses, and automated machinery entails a high initial expenditure, to which recurring costs for installation, calibration, maintenance, component replacement, and platform updates are added, increasing perceived risk and delaying return on investment. This financial burden is further intensified when the technology requires complementary infrastructure (stable energy supply, storage, and processing) or specialized personnel to operate and translate data into agronomic decisions. Similarly, AI-based “cognitive” weather stations, despite their high predictive accuracy (RMSE = 0.0034; Willmott index = 0.988), require investment in sensors, training, and continuous technical support [88].

The absence of flexible financial models limits the sustained adoption of digital technologies, even when their agronomic performance is well documented. In many rural contexts, producers lack credit lines aligned with the agricultural cycle, subsidies for innovation, or co-financing schemes that allow them to amortize investments in sensors, UAVs, connectivity, and analytical software. Although deep learning models for pathogen prediction achieve high accuracy (CNN up to 96.933% and AUC-ROC 99.767%), their operational utility is sensitive to climatic dynamics and requires consistent data, which constrains their real economic benefit [91]. This financial gap prevents gradual adoption through mechanisms such as equipment rental, pay-per-use, technological “servitization,” or scalable modular packages, forcing producers to bear high upfront costs and increasing perceived risk. This perception is further heightened because the profitability of these solutions depends on exogenous factors—climatic variability, digital infrastructure, and local technical capacities—creating uncertainty about return on investment. For instance, yield and protein estimation in durum wheat using multispectral UAVs with RF/NN/SVM ($R^2 > 0.6$ for yield; $R^2 > 0.7$ for protein) requires monitoring campaigns, data processing, and technical support, which increase recurrent costs [93].

6.4. Lack of Digital Skills in Producers.

The lack of digital skills among producers represents a structural limitation to the effective adoption of emerging technologies, as it shifts the challenge from technological availability to operational knowledge appropriation. This is particularly relevant for low-cost, user-driven solutions, such as non-destructive soil organic matter estimation using smartphone-based deep learning (RMSE = 0.17 with 500 samples), whose performance relies on proper field capture and validation protocols [92]. In rural contexts, many farmers exhibit low digital literacy and limited experience with apps, dashboards, IoT platforms, or AI-based tools, complicating the configuration, calibration, and basic maintenance of sensors and monitoring systems. Consequently, the gap extends further, affecting the agronomic interpretation of data: without the competencies to translate analytical outputs (spectral indices, predictive alerts, risk thresholds) into management decisions, the

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information loses value and the likelihood of errors or technological abandonment increases. For instance, integrated UAV–IoT models for early yield prediction (PEnsemble4 with 91% accuracy, using CIre and NDRE) require minimal skills in indicator interpretation, data synchronization, and evidence-based decision-making [94].

Insufficient and fragmented technical training represents a critical gap that limits the effective appropriation of digital technologies by producers, even when such tools are available. As a result, technologies based on remote sensing, data analytics, and decision-support systems remain underutilized despite their high agronomic potential. For instance, satellite-based mapping of wheat residue cover using Sentinel-2B (NDTI, R^2 = 0.85; accuracy = 86.53%) requires an adequate understanding of spectral indices and interpretation criteria to guide management practices [99]. In many territories, training programs are designed using standardized approaches, without adaptation to heterogeneous educational levels, local languages, connectivity constraints, or traditional farming practices, which reduces their effectiveness and may generate resistance to innovation. This weakness becomes more pronounced when training is limited to isolated sessions, without continuous field-based support to troubleshoot operational failures, validate recommendations, and consolidate routines of use. For example, rice yield estimation using GF-1/GF-6 imagery and NDVI (R^2 = 0.88; RMSE = 3.48%) requires competencies to integrate spatial information into fertilization, irrigation, and residue management decisions [97].

7. Future Perspectives and Lines of Research

Regarding future perspectives and research directions, sustainable agriculture is expected to evolve toward more integrated digital ecosystems, where multisensor data fusion, predictive analytics, and intelligent automation enable risk anticipation and real-time decision optimization. In this context, the integration of environmental data with machine learning models has shown promising outcomes, as algorithms such as XGBoost have demonstrated superior capability for tomato disease classification when combined with deep features extracted from VGG16, achieving 93% accuracy and F1 = 0.93, and clearly outperforming traditional approaches such as Random Forest (76% accuracy and F1 = 0.76), particularly for critical failures such as early blight [104]. In this sense, a key research line will be the development of low-cost digital tools aimed at reducing technological gaps and facilitating field adoption. For instance, digital image processing with the extraction of color, shape, and texture attributes achieved relevant accuracies (89.6% for shape and 94% for texture), although challenges remain due to misclassification in categories such as round or rotten tomatoes. Overall, this evidence suggests that the future of the sector will depend on robust, affordable, and scalable solutions capable of combining technical precision with operational feasibility for large-scale implementation [105].

7.1. Integration of Generative AI in Agriculture

The integration of generative artificial intelligence (GenAI) into agriculture is emerging as a strategic research line due to its ability to transform heterogeneous data into actionable operational knowledge (Figure 7), thereby increasing the level of automation and precision in agricultural management. In this context, advances in proximal spectroscopy and smart sensing technologies represent a critical foundation to feed generative models. Evidence indicates that vis–NIR spectroscopy integrated with PLSR achieved strong predictive performance for estimating foliar nitrogen in potato (R^2 > 0.8; RPD > 2) under multi-site and multi-variety conditions, although underestimation was observed in leaves with N > 6% [117]. Unlike conventional predictive approaches, generative AI can integrate climatic, edaphic, physiological, and productivity-related information to construct simulated scenarios, adaptive recommendations, and plot-specific management plans while explicitly accounting for climatic uncertainty and spatial variability. This capability is particularly relevant for optimizing fertilization, irrigation scheduling, and phytosanitary control, where the automated generation of yield maps, variable-rate prescriptions, and technical protocols can reduce analytical time and improve input-use efficiency.

Complementarily, in sugarcane, spectral analysis enabled the characterization of yield response to nitrogen through linear and quadratic fittings, identifying variable optimal doses (109.3–185.7 kg ha^{-1}) depending on plot and cropping cycle, reinforcing the need for intelligent systems capable of producing differentiated and context-aware recommendations [112].

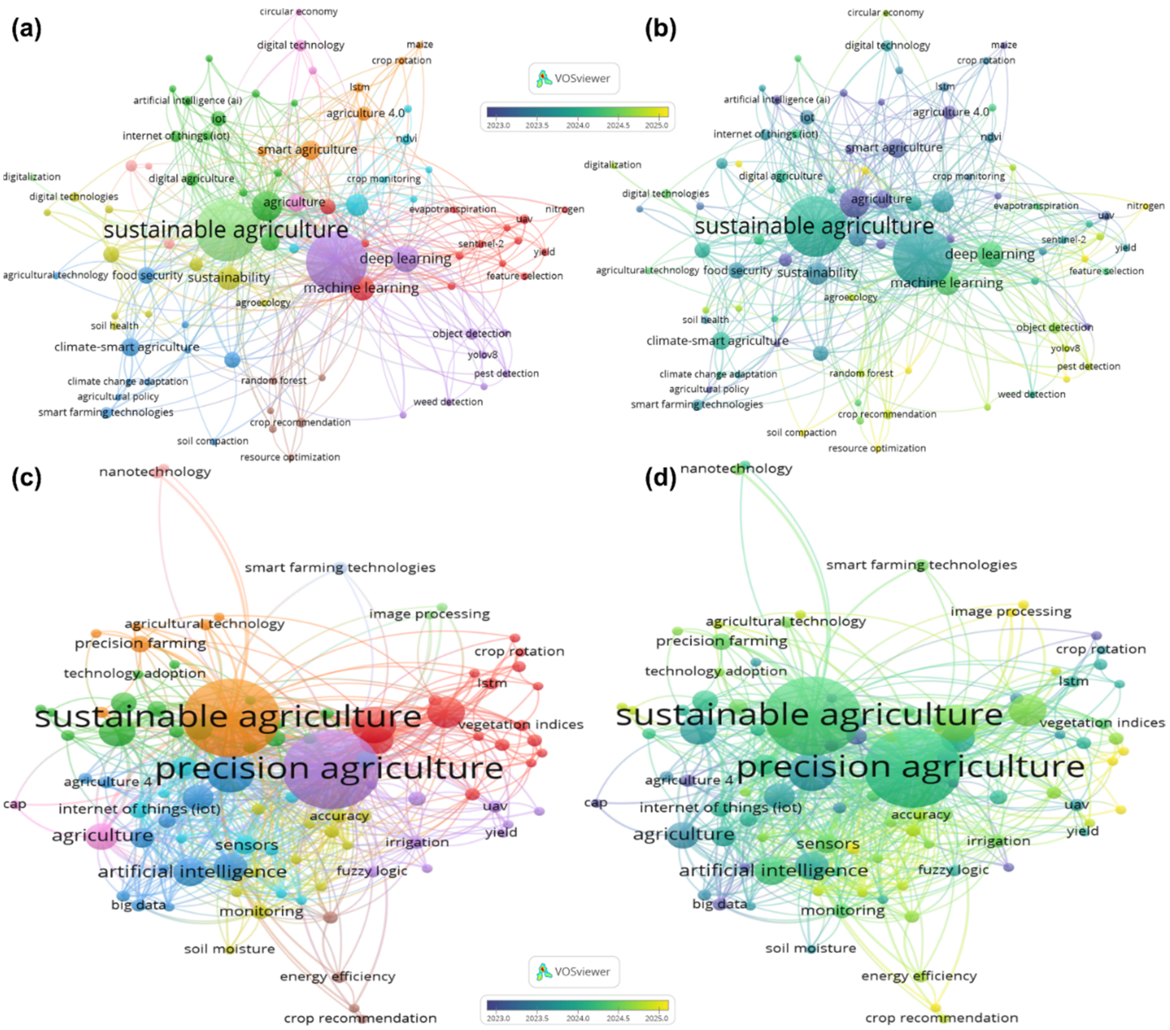

Figure 7. The thematic map shows that the field is structured around two dominant axes: "sustainable agriculture" and "precision agriculture," which act as central nodes of thematic articulation. The clusters reflect interconnected lines of research, where digital technologies are the main bridge between sustainability, productivity, and efficient resource management: (a) network visualization, where the dominant node "sustainable agriculture" (green) articulates sustainability and digitalization; (b) temporal overlap, showing the transition to recent approaches such as "deep learning" (green/blue) and "smart agriculture" (blue); (c) thematic clusters, highlighting "precision agriculture" (purple) linked to UAVs and vegetation indices (red), as well as "artificial intelligence" (light blue) connected with sensors and IoT; and (d) density, confirming a greater concentration around sustainability and precision agriculture.

7.2. Interoperable Digital Ecosystems.

The development of interoperable digital ecosystems is emerging as a critical pillar to consolidate the technological transformation of the agricultural sector, as it enables overcoming the current fragmentation of digital solutions, which often operate as isolated "technology islands" without effective communication. From an operational perspective, interoperability makes it possible to integrate field sensors, IoT platforms, drones, remote sensing, and agronomic management systems into a unified infrastructure, ensuring standardized data exchange and real-time information traceability. Within this framework, advances in data-driven water modeling highlight the value of integrating heterogeneous sources: the calibration of the Crop Water Stress Index (CWSI) enabled the estimation of water stress with $r^2 = 0.613$, using lower ($-1.74 \cdot VPD - 1.23$) and upper (2.32 °C) Tc–Ta baselines, thereby supporting the characterization of soil water loss and irrigation requirements [103]. This not only improves analytical quality but also enables more robust predictive models and automated control systems by providing integrated time series of climatic, edaphic, and productivity variables. Complementarily, intelligent water control based on IoT and AIoT demonstrated high accuracy in hydroponic systems, where the IWRC approach achieved outstanding performance using the MLR-PSO-ANFIS444 model ($RMSE = 2.35 \times 10^{-4}$; $R^2 = 0.99$), confirming that the integration of data and algorithms within interoperable platforms is decisive to reduce water consumption and optimize water-use efficiency [102].

Interoperable ecosystems foster collaboration among institutions, technology companies, research centers, and producer organizations by creating environments in which agricultural data can be shared, validated, and reused under standardized formats. In terms of outcomes, multi-source data integration has demonstrated significant improvements in agronomic prediction and control: in cotton, a scale-sensitive CNN model based on UAV imagery outperformed conventional architectures, achieving $R^2 > 0.90$ and low errors (MAE = 3.08 lb/row; MAPE = 7.76–10%), highlighting the potential of connected platforms to estimate productivity using RGB images [1]. This connectivity reduces duplication of efforts, accelerates solution development, and strengthens applied knowledge networks that particularly benefit small and medium-scale farmers through access to shared platforms, digital advisory services, and scalable recommendation models. Interoperability also facilitates the effective integration of emerging technologies—such as digital twins, generative AI, or blockchain—by enabling secure and continuous connections between devices, databases, and analytical systems, thereby maximizing their field-level impact. Complementarily, in precision agriculture, the HHOGCN-WD model achieved >99.13% accuracy in weed detection and classification, enabling site-specific control and reducing herbicide use through optimized segmentation. Overall, these advances indicate that interoperability not only increases efficiency, but also strengthens traceability, transparency, and environmental sustainability, supporting the transition toward intelligent, resilient, and competitive agricultural systems [101].

7.3. Fully Autonomous Systems.

The transition toward fully autonomous agricultural systems represents one of the most ambitious transformations in digital agriculture, as it integrates advanced robotics, artificial intelligence, high-precision sensors, and farm management platforms to execute operations without direct human intervention. Under this approach, autonomous tractors, harvesting robots, and intelligent drones operate as coordinated units capable of interpreting environmental data, planning routes, adjusting decisions in real time, and working continuously, thereby increasing efficiency and reducing costs in critical tasks such as irrigation, fertilization, weed control, and plant health monitoring. From a technological evidence perspective, autonomy is strengthened when systems incorporate remote sensing and high-resolution spatial analytics: in cotton, the use of multispectral UAV imagery enabled soil salinity estimation at detailed spatial scales, where SSA-SVM and BPNN models improved estimation accuracy by 5% and 10.69%, respectively, generating maps with 5 cm resolution, which supports localized autonomous interventions to mitigate salinity-induced stress [98]. Complementarily, in vegetable crops, low-cost UAVs were used to develop weed prescription maps, reducing the treated area by 2.18% to 18.92%; moreover, the artificial neural network (ANN) approach showed higher efficiency than methods such as MLC and OBIA, confirming the potential to automate sustainable management decisions and minimize generalized herbicide applications. Overall, these findings demonstrate that full autonomy depends not only on robotic machinery, but also on the integration of remote perception, predictive modeling, and interoperable connectivity, enabling intelligent agricultural systems capable of precise, adaptive, and sustainable actions [100].

At the research level, autonomous agricultural systems create decisive opportunities to design more resilient and sustainable agroecosystems, as crop management can be driven by dynamic and highly localized decision-making. One of the most promising directions is the development of collaborative robot swarms, in which multiple small units perform complementary tasks (monitoring, weeding, site-specific fertilization, or selective harvesting) while minimizing soil compaction and improving adaptation to spatial variability within the field [72]. In parallel, the integration of deep learning algorithms will allow these systems to evolve continuously by incorporating feedback from previous campaigns to optimize navigation routes, reduce energy consumption, and improve intervention accuracy [79]. In this context, UAV-based remote sensing represents a key enabler of autonomy, as it provides detailed spatial information to guide management actions; for instance, in cotton, multispectral UAV imagery enabled high-resolution soil salinity estimation, where SSA-SVM feature selection and the BPNN model improved prediction accuracy by 5% and 10.69%, respectively, generating 5 cm resolution maps, which supports targeted corrections in field microzones [98].

7.4. Data-Driven Regenerative Agriculture.

Data-assisted regenerative agriculture is emerging as an innovative perspective that integrates ecological principles with digital technologies to restore soil functionality, enhance biodiversity, and strengthen productive resilience under climate change. Within this approach, agroecosystem instrumentation through in situ sensors, satellite remote sensing, UAVs, and analytical platforms enables continuous monitoring of critical variables such as soil structure and moisture, vegetation cover dynamics, biological activity, and carbon accumulation, thereby generating quantifiable evidence of the impacts of regenerative practices (no-tillage, cover crops, diversified rotations, and organic matter incorporation) [87]. Furthermore, predictive models support the anticipation of system trajectories under alternative management scenarios, reducing uncertainty and improving long-term decision-making. In polycropping systems, for instance, multivariate analysis revealed key relationships between soil properties, nutrients, and productivity: the principal component PC2 explained 12.65% of the variance, with Nyield_kgha, PMN, and Fe as dominant variables, whereas soil_C and residue_N negatively conditioned the PC1–PC2 relationship, ultimately influencing yield outcomes [95].

The integration of big data analytics and artificial intelligence further strengthens this regenerative approach by enabling the simultaneous correlation of edaphic, climatic, spectral, and productivity-related variables to generate field-specific, verifiable, and parcel-adapted recommendations. In particular, the combination of satellite data with machine learning models has demonstrated strong potential to estimate agricultural productivity and support management decisions with improved accuracy. In rice systems, the RFE–MIR variable selection strategy enhanced predictive performance, highlighting k-NN as the best-performing algorithm ($R^2 = 0.61$; RMSE = 578.43 kg ha^{-1}), followed by ANN ($R^2 = 0.58$), thereby evidencing the usefulness of these techniques to anticipate system responses under different conditions [96]. Likewise, spatial analytics applied to UAV imagery enables the development of prescription maps for site-specific interventions, reducing input use and promoting low-impact practices; in horticultural crops, low-cost UAV approaches reduced the treated area by 2.18–18.92%, with neural network-based methods outperforming conventional techniques. Overall, this convergence of AI, remote sensing, and data-driven management accelerates the transition toward measurable, self-sustaining regenerative systems oriented toward environmental restoration [100].

8. Conclusions

Emerging digital technologies are redefining sustainable agriculture by evolving from isolated tools into integrated ecosystems for monitoring, analytics, and decision-making. The reviewed findings confirm consistent progress in high-resolution data acquisition through IoT networks and proximal sensing, as well as in the use of UAV-based remote sensing and satellite imagery to characterize crop vigor, spatial variability, and edaphoclimatic conditions. Building on this foundation, artificial intelligence and machine learning models have made a decisive contribution to

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agronomic prediction by enabling earlier and more accurate forecasting of water stress, pest outbreaks, nutrient deficiencies, and potential yield, thereby strengthening planning and reducing losses. Likewise, automation through agricultural robotics and the deployment of edge–AI architectures consolidate a scenario in which critical field operations can be executed with high precision and reduced human intervention, increasing operational efficiency and optimizing input use. Nevertheless, relevant gaps persist, particularly related to technological fragmentation, limited interoperability across platforms, insufficient methodological standardization, and difficulties in generalizing models across diverse edaphoclimatic contexts. In this context, it can be concluded that the future of digital agriculture will depend on building interoperable ecosystems supported by open standards and robust data governance, integrating technologies such as digital twins, blockchain, and generative AI to enable simulation capabilities, reliable traceability, and contextualized recommendations. Overall, this technological evolution represents a strategic opportunity to accelerate the transition toward more resilient, efficient, and environmentally sustainable production systems aligned with food security demands and climate change adaptation.

Supplementary Materials: Not applicable.

Author Contributions: Conceptualization, C.D.R.-Y. and A.J.R.-Y methodology, W.A.C.-R., C.D.R.-Y., A.J.R.-Y., W.A.M.-V., C.M.-R. and I.M.O.-E.; formal analysis, W.A.C.-R., C.D.R.-Y., A.J.R.-Y., W.A.M.-V. and I.M.O.-E.; investigation, C.D.R.-Y., A.J.R.-Y., W.A.M.-V., C.M.-R. and I.M.O.-E.; resources, all authors; data curation, C.D.R.-Y. and collaborators; writing—original draft preparation, C.D.R.-Y., A.D.E.-H., J.V.S.-V., E.G.-V.; writing—review and editing, all authors; visualization, C.D.R.-Y., A.J.R.-Y., W.A.M.-V., A.R.L.-C. and I.M.O.-E.; supervision, W.A.M.-V.; project administration, W.A.M.-V. All authors have read and agreed to the published version of the manuscript.

Funding: Not applicable.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Acknowledgments: The authors have reviewed and edited the output and take full responsibility for the content of this publication.

Conflicts of Interest: The authors declare no conflicts of interest.

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