OPEN ACCESS

ORIGINAL ARTICLE

UNAH UNIVERSIDAD AGRARIA DE LA HABANA

Revista Ciencias Técnicas Agropecuarias 35
January-December 2026
ISSN 1010-2760, eISSN 2071-0054
Cu-ID: https://cu-id.com/2177/v35e22

Precision Agriculture Technologies for Irrigation and Agricultural Mechanization: Adaptability to the Cuban Context

Tecnologías de Agricultura de Precisión para Riego y Mecanización Agrícola: Adaptabilidad al Contexto Cubano

Calixto Domínguez Vento[1*], Ismelis Iglesias Núñez[2], Enrique Cisneros Zayas[1], Alexander Miranda Caballero[3], Pedro Paneque[4] and Amaury Rodríguez González[1]

[1]Instituto de Investigaciones de Ingeniería Agrícola (IAgric), Carretera de Fontanar, km 2 1/2, Reparto Abel Santamaría, Boyeros, La Habana, Cuba. Telef.: (53) (7) 645-1731; 645-1353. E-mail: enrique.cisneros@iagric.minag.gob.cu, amaury.rodriguez@iagric.minag.gob.cu
[2]Dirección, Cooperativa No Agropecuaria (CNA) denominada "CODE43W". No. 379. Tomo XX, Folio 191, Hoja 282, Sección Cooperativas "CNA". NIT 23004306721. La Habana, Cuba.
[3]Ministerio de la Agricultura, Director de Ciencia, Innovación y Extensión Agrícola, La Habana, Cuba.
[4]Universidad Agraria de La Habana, Investigador Titular, Centro de Mecanización Agropecuarias (CEMA), San José de las Lajas, Mayabeque, Cuba. E-mail: paneque@unah.edu.cu

[*]Author for correspondence: Calixto Domínguez-Vento, e-mail: calixtodominguez1986@gmail.com

ABSTRACT: Agriculture faces the challenge of increasing productivity to ensure global food security while adapting to climate change and reducing its environmental impact. This review analyzes the state of the art in smart irrigation and precision mechanization technologies and assesses their potential adaptation to the Cuban context. The most recent evidence confirms that smart irrigation systems based on IoT and predictive algorithms achieve water savings of 30-50%. Precision mechanization, including variable rate technology (VRT) and autonomous agricultural robotics, reduces fertilizer use by 15-30% and herbicide use by up to 90%. Early pest detection systems based on computer vision and deep learning achieve accuracies exceeding 95%. Farm management information systems (FMIS) act as the integrating core of these systems. Adaptation to the Cuban context is possible, but faces challenges such as high costs, connectivity limitations, and an obsolete machinery fleet. However, the existing skilled human capital and political will offer significant opportunities. A three-phase, phased implementation strategy is proposed, prioritizing low-cost technologies, shared machinery models, the use of mobile phones as navigation assistants, and the development of local capabilities, beginning with systems that operate both offline and online. The integration of these technologies can be a strategic pathway to increase food sovereignty and the resilience of Cuban agriculture in the face of climate change, resource scarcity, and the need for greater productive efficiency.
Keywords: AIoT, Precision Mechanization, Smart Irrigation, Agricultural Robotics, Agricultural Management Systems.

RESUMEN: La agricultura enfrenta el desafío de aumentar la productividad para garantizar la seguridad alimentaria global, mientras se adapta al cambio climático y reduce su impacto ambiental. Esta revisión analiza el estado del arte de las tecnologías de riego inteligente y mecanización de precisión, y evalúa su potencial adaptación al contexto cubano. La evidencia más reciente confirma que los sistemas de riego inteligente basados en IoT y algoritmos predictivos logran ahorros de agua del 30-50%. La mecanización de precisión, incluyendo la tecnología de tasa variable (VRT) y la robótica agrícola autónoma, reduce el uso de fertilizantes en un 15-30% y herbicidas hasta en un 90%. Los sistemas de detección temprana de plagas basados en visión por computador y aprendizaje profundo alcanzan precisiones superiores al 95%. Plataformas de gestión agrícola (FMIS) actúan como núcleo integrador de estos sistemas. La adaptación al contexto cubano es posible, pero enfrenta desafíos como altos costos, limitaciones de conectividad y obsolescencia del parque de maquinaria. Sin embargo, el capital humano calificado y la voluntad política existente ofrecen oportunidades significativas. Se propone una estrategia de implementación gradual en tres fases que prioriza tecnologías de bajo costo, modelos de maquinaria compartida, uso de telefonía móvil como asistente de navegación y desarrollo de capacidades locales, comenzando con sistemas que operan "offline/online". La integración de estas tecnologías puede ser una vía estratégica para aumentar la soberanía alimentaria y la resiliencia de la agricultura cubana frente al cambio climático, la escasez de recursos y la necesidad de una mayor eficiencia productiva.
Palabras clave: AIoT, mecanización de precisión, riego inteligente, robótica agrícola, sistemas de gestión agrícola.

Received: 02/12/2025
Accepted: 23/04/2026
Conflicts of interest: The authors declare that there are no conflicts of interest.
Author contributions: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Supervision, Validation, Writing - original draft, Writing - review & editing: Calixto Domínguez Vento. **Conceptualization, Investigation, Supervision:** Ismelis Iglesias Núñez. **Investigation, Supervision, Validation, Writing-original draft:** Enrique Cisneros Zayas, Alexander Miranda Caballero, Amaury Rodríguez González. **Investigation, Supervision, Validation, Writing-original draft, Writing-review & editing:** Pedro Paneque.
The mention of trademarks of specific equipment, instruments or materials is for identification purposes, there being no promotional commitment in relation to them, neither by the authors nor by the publisher.

This is an open access article under terms of the license Creative Commons Attribution-NonCommercial (BY-NC 4.0).
https://creativecommons.org/licenses/by-nc/4.0/

INTRODUCTION

Agriculture faces the challenge of increasing production to feed a growing global population (Zain *et al*., 2023; Saha *et al*., 2025), in a context of climate change, water scarcity, and the need to reduce its environmental impact, which includes soil degradation, agrochemical pollution, and greenhouse gas emissions (Domínguez *et al*., 2024, 2025; Getahun *et al*., 2024). The answer to this challenge may lie in a profound digital transformation of the sector, moving towards a precision agriculture (PA) and smart farming model that allows for more with less (Guzmán *et al*., 2024; Elhoseny *et al*., 2026).

Two fundamental pillars of this transformation are efficient water management through smart irrigation and the optimization of agricultural tasks through precision mechanization. Smart irrigation, enabled by wireless sensor networks (WSNs), the Internet of Things (IoT), and Artificial Intelligence (AI) algorithms, allows irrigation to be scheduled based on the actual needs of the crop and real-time soil and climate conditions, replacing traditional practices based on fixed schedules (Abioye *et al*., 2020; Morchid *et al*., 2026).

Similarly, precision mechanization, which integrates variable rate technology (VRT), autonomous guidance systems, and autonomous agricultural robotics, optimizes the use of inputs such as fertilizers, herbicides, and fuels, while increasing operational efficiency and reducing soil compaction (Schimmelpfennig, 2016; Cortez et al., 2024). The convergence of IoT and AI, known as AIoT, is exponentially enhancing these capabilities, creating more autonomous and predictive systems capable of managing the inherent complexity of agroecosystems (Bayih *et al*., 2022; Adli *et al*., 2023).

In addition to water and nutrients, plant health is another critical factor for productivity. Traditionally, pest and disease detection has relied on visual inspection in the field, a laborious and subjective process that often detects the problem only when it is already advanced (Mahlein, 2016). Control, meanwhile, has historically been based on the uniform application of pesticides across the field, an approach that leads to inefficient use of chemicals, high economic costs, and serious environmental and human health impacts (Aktar *et al*., 2009; Nicolopoulou *et al*., 2016). The integration of AIoT systems offers a paradigm shift towards predictive and precision management, enabling early detection and localized action.

The Cuban agricultural sector is no stranger to these challenges and opportunities. It faces structural problems that limit its productivity, such as the technological obsolescence of agricultural machinery, with more than 80% of tractors being over 30 years old (estimated from data reported by Suárez & Ríos, (2019), and the low efficiency of irrigation systems, where 70% of the areas use surface irrigation with efficiencies below 50% (Tejeda *et al*., 2025). These inefficiencies result in water losses exceeding 1.2 billion cubic meters annually and inefficient fertilizer use, with losses exceeding 40% (MINAG, 2023). Given this reality, technological modernization has become a national strategic priority, recognized in the "Program for Technological and Business Modernization in the Agrochemical and Agricultural Machinery Production Sector" (ONUDI, 2024) and aligned with the objectives of the National Economic and Social Development Plan until 2030 (PNDES 2019).

The objective of this article is to analyze the state of the art of smart irrigation technologies, precision mechanization, and pest detection systems, and to evaluate the possibility of adapting these technologies to the Cuban context, identifying barriers and opportunities for successful implementation.

MATERIALS AND METHODS

A systematic literature review was conducted following the PRISMA 2020 principles (Page *et al*., 2021), adapted for agricultural sciences (Prado *et al*., 2025). The search was structured in four phases: planning, execution, synthesis, and analysis.

Search and Selection

Strategy The Scopus, Web of Science, and Google Scholar databases (2015-2026) were consulted using a search equation that combined terms related to precision agriculture, IoT, sensors, machine learning, water efficiency, and sustainability. Additionally, Cuban national sources were included to contextualize the local situation regarding machinery and irrigation.

The inclusion criteria were: (i) original articles or reviews; (ii) English/Spanish language; (iii) application of digital technologies to irrigation, mechanization, or pest detection; (iv) quantitative or qualitative results on water efficiency, yield, or sustainability. Editorials, studies without full text or direct empirical evidence (Prado *et al*., 2025) and articles for which only the abstract was accessible due to access limitations from Cuba were excluded.

The selection process included: screening by title/abstract, full-text evaluation, and data extraction. From 437 initial records, 82 international articles and 6 Cuban sources were selected, totaling 88 documents analyzed.

Extraction, Synthesis, and Contextual Analysis

A database was constructed with structured fields (author, technology, crop, quantitative results, barriers). For each technology, the information was synthesized in summary tables with the following fields: results obtained, country/region of study, bibliographic reference, feasibility of application in Cuba, and challenges/perspectives for its introduction.

The analysis was developed along two axes: (1) the global state of the art in precision irrigation technologies (IoT sensors, variable-rate irrigation, digital monitoring systems) and (2) a gap analysis for Cuba, considering barriers (technological obsolescence,

low irrigation efficiency, limited connectivity, high costs) and opportunities (political will, skilled human capital, low-cost technologies < USD 50, free satellite data).

Based on this analysis, and following the recommendations of Prado et al. (2025) on low-cost hybrid systems for small and medium-sized farms, a three-phase (short, medium, and long term) phased implementation strategy was designed, prioritizing affordable technologies, shared machinery, mobile phone use, and local capacity building.

RESULTS AND DISCUSSION

Analysis of the selected articles confirms exponential growth in research on precision agriculture (PA) applied to irrigation, fertilization, and crop protection, especially since 2017. This coincides with the increased availability of low-cost technologies, such as IoT sensors and drones, and the rise of artificial intelligence techniques (Wolfert *et al*., 2017; Liakos *et al*., 2018). Most studies focused on extensive crops such as maize, wheat, rice, and soybeans, which represent a large portion of the global agricultural area and have high input consumption.

State of the Art of Technologies

Smart Irrigation and Water Management

Smart irrigation systems have evolved from simple timer-based automation to complex, data-driven decision support systems (DSS). The fundamental component is soil moisture sensors, deployed on wireless network systems (WSNs) that use low-power protocols such as LoRaWAN, ZigBee, or NB-IoT to transmit data in real time (Ojha *et al*., 2015; Jawad *et al*., 2017). Alongside these, automatic weather stations provide essential data for calculating reference evapotranspiration (ETo), a key parameter in water balance models (Liu *et al*., 2025; Morchid *et al*., 2026). The integration of these sensors with cloud platforms and AI algorithms enables precise remote irrigation management (Morchid et al., 2026).

A significant advancement has been the integration of machine learning (ML) algorithms. Models such as Random Forest, Support Vector Machines (SVM), and especially Long Short-Term Memory (LSTM) recurrent neural networks are used to predict crop water requirements hours or days in advance, based on time series data from sensors and weather forecasts (Adeyemi *et al*., 2017; Goap *et al*., 2018). These predictive models outperform threshold-based methods because they can anticipate demand and optimize water use more dynamically (Chlingaryan *et al*., 2018). Zhang *et al*. (2020) demonstrated that LSTM models can predict soil water content with a root mean square error (RMSE) of less than 2-3%. Table 1 summarizes the most relevant findings in the area of smart irrigation and its potential for adaptation to the Cuban context.

Technologies for Precision Nutrient Management

Precision nutrient management aims to optimize fertilization by applying the correct dose at the right time and place, requiring a detailed understanding of the spatial and temporal variability of soil fertility and crop nutritional status. Sensors play a crucial role in this process. Soil nutrient sensors (for N, P, and K) allow for high-resolution spatial mapping of soil fertility (Islam *et al*., 2023). However, active optical sensors (such as the GreenSeeker or Crop Circle) are more common for real-time application and have become established as relatively low-cost, highly effective tools. These sensors, mounted on sprayers or drones, measure the reflectance of the crop canopy in specific spectral bands (red, red edge, near-infrared) to calculate vegetation indices such as the Normalized Difference Vegetation Index (NDVI) or the Normalized Difference Red Edge Vegetation Index (NDRE), which are correlated with chlorophyll content and crop vigor, and therefore with its nutrient requirements (Wolters *et al*., 2019; Karydas *et al*., 2023).

In addition to optical sensors, electrochemical and near-infrared (NIR) spectroscopy sensors are gaining ground for in-situ soil nutrient monitoring. Although their use is more complex, they offer the possibility of creating high-resolution fertility maps (Adamchuk *et al.*, 2004).

Variable rate technology (VRT) integrates real-time sensor data or prescription maps to adjust the amount of fertilizer applied to different areas of a field (Koch *et al*., 2004; Schimmelpfennig & Ebel, 2016). VRT systems for solid and liquid fertilizers are commercially available and connect to GPS-equipped tractors. Research shows that VRT can increase nitrogen use efficiency by more than 20% by applying fertilizer where it is most needed, reducing over-application in low-potential areas and under-application in high-potential areas (Karydas *et al*., 2023).

The reviewed studies consistently demonstrate that precision fertilization can reduce total nitrogen fertilizer use by 10% to 30% without compromising yield, and in many cases even slightly increasing it (Colaço & Bramley, 2018). This improved efficiency translates into significant economic and environmental savings by reducing nitrate leaching losses and greenhouse gas emissions (Diacono *et al*., 2013). The use of integrated platforms such as ifarma/PreFer, which combine sensor data, satellite imagery, and machine learning (ML) algorithms, allows for closing the precision fertilization loop by generating fertilizer prescription maps from multiple data sources, facilitating its implementation at the farm level (Karydas *et al*., 2023).

Precision Machining and Agricultural Robotics

In the field of mechanization, innovations are focused on autonomous robotics and unmanned vehicles. Ground-based (UGV) and aerial (UAV) robots are transforming field operations, from planting to harvesting, offering unprecedented precision and addressing the growing labor shortage (Comparetti *et al*., 2025). Table 2 summarizes the most significant advances in this area.

Table 1. Smart Irrigation Applications: Results and Potential for Adaptation to Cuba

Aplicación / Tecnología	Result Obtained	Country/Region	Reference	Possibility of applying in Cuba	Challenges and Perspectives for its Introduction in Cuba
Sistema de riego autónomo con IoT y control difuso	Significant improvement in water savings and in the lifespan of the sensor network. Water savings of 61% compared to average methods.	China (simulation)	(Liu *et al*., 2025)	High performance, especially the low-cost version. The system is scalable and adaptable to different environments.	Field validation with local crops. Adaptation of the fuzzy algorithm to Cuban soil and climate conditions.
Low-cost IoT + cloud precision irrigation system	Precise environmental monitoring and optimal irrigation scheduling with an implementation cost of only $44 USD	Morocco (prototype)	(Morchid *et al*., 2026)	Very high. Low cost is crucial in the Cuban context.	Field trials with local crops and calibration of sensors for Cuban soils. Evaluation of long-term durability and performance under tropical conditions.
IoT + cloud smart irrigation system	Automation and real-time data analysis for optimal water management.	Morocco	(Elhoseny *et al*., 2026)	High. The cloud platform enables remote monitoring and centralized decision-making.	Need to improve internet connectivity in rural areas. Adaptation of the platform to local crops and conditions.
Integrated system: satellite + ML + fuzzy logic	Water savings of approximately 70% compared to traditional methods. Crop prediction with ML (97.35% accuracy).	Bangladesh	(Saha *et al*., 2025)	High, but requires advanced technical capabilities. The combination of satellites, ML, and fuzzy logic is very promising.	Lack of data infrastructure and trained personnel in machine learning and remote sensing. High initial computational cost.
Meta-analysis of crop protection technologies	Reduction of herbicide use by up to 97% through selective application systems.	Global	(Anastasiou *et al*., 2023)	Potential for high-value crops. Input savings are very attractive, but the technology requires investment.	Cost of spot spraying equipment. Need to develop accurate prescription maps for local conditions.

AIoT Systems for Pest Detection and Management

The convergence of IoT and Deep Learning (AIoT) enables a shift from reactive, broad-spectrum pest management to predictive, precision management. IoT, through wireless sensor networks, weather stations, and smart traps, provides the layer for collecting massive amounts of real-time data on environmental conditions and pest presence (Elijah *et al*., 2018; Xu *et al*., 2022). AI, and in particular Deep Learning (DL), equips systems with the ability to analyze these enormous amounts of data (images, time series) to identify subtle patterns, classify diseases, and predict outbreaks with unprecedented accuracy (Kamilaris & Prenafeta-Boldú, 2018; Liakos *et al*., 2018). Table 3 summarizes the most relevant advances in this area.

Technology Integration: AIoT, Agricultural Management Systems (FMIS) and Digital Twins

The true potential of digital agriculture is realized through the integration of all technologies on unified platforms. Integrated Farm Management Systems (IFMS) act as the brain of the operation, integrating data from sensors, satellites, and machinery to generate precise recommendations. Modern IFMS have evolved from simple logging tools to comprehensive cloud-based platforms that offer a wide range of functionalities: field and crop management, integration of data from multiple sources, traceability, economic analysis, and prescription map generation (Paraforos *et al*., 2017; Comparetti *et al*., 2025).

Table 2. Precision Mechanization Applications: Results and Potential for Adaptation to Cuba

Aplicación / Tecnología	Result Obtained	Country / Region	Reference	Possibility of applying in Cuba	Challenges and Perspectives for its Introduction in Cuba
Field robots (UGVs) for precision agriculture	Classification of UGVs according to size and function. Their role in planting, crop protection, and fruit harvesting is noteworthy.	Global	(Comparetti *et al*., 2025)	Low in the short term, potential in the medium term. Advanced robotics requires high investment and maintenance.	High acquisition and maintenance costs. Obsolescence of current machinery. Lack of specialized technical personnel in robotics.
Autonomous driving in agricultural machinery	Review of key technologies: navigation, perception, control, and fault tolerance. Commercial adoption limited by cost and lack of standardization.	Global	(Liu *et al*., 2025)	Short-term decline. Autonomous machinery is still expensive and requires modern tractors with compatible electronic systems.	The Cuban machinery fleet is mostly obsolete (over 30 years old). A thorough fleet renewal is needed.
Autonomous robots for mechanical weeding	Intelligent robotic row weeding system that combines deep learning with a selective weeding mode. High efficiency in weed removal.	China	(Quan *et al*., 2022)	Potential for organic or high-value crops. Mechanical weeding reduces reliance on herbicides.	Robot cost. Validation of the technology in Cuban crops (e.g., vegetables, tobacco). Adaptation to different soil types and field conditions.
Autonomous harvesting robots	Harvesting robots for strawberries that address labor shortages, increasing productivity and accuracy.	USA	(McFadden *et al*., 2024)	Short-term price decrease. Technology still under development and with high costs, intended for high-value crops on large farms.	High-value Cuban crops (e.g., tobacco, fruits) could be niche applications, but the initial investment is prohibitive.
Unmanned aerial vehicles (UAVs/drones)	A consolidated tool for crop monitoring, creation of prescription maps (NDVI), and detection of water stress and diseases.	Global	(Tsouros *et al*., 2019; Velusamy *et al*., 2022)	High, especially for monitoring. Low-cost commercial drones are accessible and can be operated with basic training.	Flight regulations. Need to process and interpret images to generate actionable agronomic recommendations (requires training).

The synergy between IFMS and VRT is clear: IFMS acts as the "brain" that integrates and analyzes data and generates prescriptions, which VRT, like the "arm," then executes in the field. In turn, the data generated during the VRT application (e.g., real-world application maps) feeds back into the FMIS, closing the loop and enabling continuous learning and improvement (Paraforos *et al*., 2017; Karydas *et al*., 2023).

Digital twins take this concept a step further, allowing for the simulation and optimization of scenarios before field implementation (Purcell & Neubauer, 2023; Escribà *et al*., 2024). Table 4 summarizes the most relevant advances in this area.

Analysis of Adaptability to the Cuban Context

The transfer of these technologies to Cuba faces significant barriers encompassing technical, economic, institutional, and social aspects. However, it also presents unique opportunities that can be leveraged for successful adaptation.

Barriers and Challenges

A key structural challenge is the obsolescence of the agricultural machinery fleet. It is estimated that more than 80% of tractors in Cuba are over 30 years old. This reality hinders the integration of automatic guidance systems, VRT, and sensors that require electronic compatibility and modern communication systems. The simple installation of an ISOBUS adaptation kit (international standard ISO 11783), for example, is not feasible on most of this equipment without a profound technological upgrade. This limitation is exacerbated by the lack of standardization and interoperability between different platforms and manufacturers, which generates isolated data repositories and hinders system integration (Gupta & Kumar, 2025).

Table 3. AIoT Applications for Pest Detection: Results and Potential for Adaptation to Cuba

Aplicación / Tecnología	Result Obtained	Country / Region	Reference	Possibility of applying in Cuba	Challenges and Perspectives for its Introduction in Cuba
Disease detection with hyperspectral imaging	Detection of wheat yellow rust with 90-95% accuracy before visible symptoms.	China	(Huang *et al*., 2007)	Medium. Requires specialized equipment (hyperspectral cameras) and trained personnel.	High cost of equipment. Need to develop spectral libraries for local crops and diseases.
IoT smart traps for monitoringinsectos	Automatic counting and classification of insects with 90-96% accuracy.	Greece	(Potamitis *et al*., 2014)	High. Relatively low-cost technology that can be replicated with local components.	Development of traps adapted to the main pests of Cuba. Field validation. Training for data interpretation.
Convolutional neural networks (CNNs) for disease classification.	CNN models (AlexNet, ResNet, YOLO) achieve >95% accuracy in foliar disease classification.	Global	(Singh & Gupta, 2018; Jiang *et al*., 2019)	High, as an extension support tool. CNN-based mobile applications can be used by technicians and farmers.	Development of local databases of disease images. Adaptation of pre-trained models to Cuban conditions. Training in the use of applications.
Selective application systems (spot spraying).	Reduction of herbicide use by up to 90% through localized spraying.	USA	(Partel *et al*., 2019)	Potential for high-value crops. Input savings may justify the investment.	Equipment costs. Need to develop accurate prescription maps. Validation under local conditions.
Autonomous mechanical weeding robots	Elimination of 80-90% of weeds in organic crops, reducing dependence on herbicides.	Europe	(Machleb *et al*., 2020)	Potential for urban and peri-urban agriculture, and for high-value organic crops.	Robot cost. Validation in Cuban crops (e.g., vegetables, tobacco). Adaptation to different soil types.
Release of biological control agents using drones.	Precise release of parasitoid wasps in affected areas, optimizing biological control.	USA	(Teske *et al*., 2019)	Medium potential. Requires coordination between biological control programs and drone technology.	Flight regulations. Staff training. Integration with existing biological control programs in Cuba.

In the water sector, the inefficiency of irrigation systems is another major problem. Seventy percent of cultivated areas use surface irrigation with efficiencies below 50%, representing an annual loss of more than 1.2 billion cubic meters of water (MINAG, 2023; Tejeda *et al*., 2025). This situation reflects not only a technological problem but also a lack of monitoring and control systems. The high investment costs for technologies such as precision sensors, high-end drones, and automated irrigation systems represent a significant economic barrier, especially for small and medium-sized farms (Pierpaoli *et al*., 2013). Munz & Schuele (2022) demonstrate, through a sensitivity analysis, that the profitability of precision technologies like VRT is strongly influenced by farm size, which poses an additional challenge in the context of small and medium-sized agriculture, such as that of Cuba.

Added to this are infrastructure limitations, such as poor internet connectivity in rural areas, which affects the real-time transmission of data from sensors and IoT systems (Elijah *et al*., 2018; Bayih *et al*., 2022). Finally, the technical complexity and the need for specialized training to manage and interpret the generated data limit adoption (Aubert *et al*., 2012). Simply acquiring a sensor is not enough; trained personnel are required to calibrate it, interpret its data, and integrate it into a decision-making system. The lack of this specialized human capital is a barrier common to all the technologies analyzed.

In the specific case of AIoT systems for pest detection, the generalizability of AI models remains a problem. A model trained in one geographic region or with a specific crop variety may not function correctly under other conditions (Anastasiou *et al*., 2023). The need for large amounts of labeled data for training is another limitation, although techniques such as semi-supervised and transfer learning are emerging to mitigate it (Li *et al*., 2021; Benchallal *et al*., 2024). Integrating heterogeneous data (images, weather, soil) remains a technical and computational challenge (Cravero & Sepúlveda, 2021).

Table 4. Technology Integration Applications (AIoT, FMIS, Digital Twins): Results and Potential for Adaptation to Cuba

Aplicación / Tecnología	Result Obtained	Country / Region	Reference	Possibility of applying in Cuba	Challenges and Perspectives for its Introduction in Cuba
Precision fertilization service (PreFer) integrated into FMIS (ifarma)	A system that combines sensor data, satellite imagery, and machine learning to generate fertilizer prescription maps. It demonstrates how data integration can close the precision agriculture cycle.	Greece	(Karydas *et al*., 2023)	Alta, as a model to follow. A similar system could be developed for Cuba, integrating local data.	Need for a national or regional FMIS. Requires data infrastructure and personnel trained in machine learning and remote sensing. Inter-institutional coordination.
Integrated systems architecture for smart agriculture	Integration of IoT sensors, cloud computing and AI/ML algorithms to optimize operations (irrigation, fertilization, spraying).	Global	(Padhiary *et al*., 2025)	Media, as a long-term vision. The proposed architecture is complex and requires advanced technological infrastructure.	Develop a simplified architecture adapted to Cuban conditions. Prioritize interoperability and the use of open standards.
Digital twins in agriculture	Virtual replicas of farms that allow simulating the impact of different management strategies (irrigation, fertilization, rotation) before implementing them.	Global	(Purcell & Neubauer, 2023; Escribà *et al*., 2024)	Low short-term price, long-term potential. Emerging technology that requires large volumes of data and high computing power.	Develop digital twins for strategic crops (e.g., sugarcane, rice, tobacco) in collaboration with research centers. Training staff in modeling and simulation is key.
Conversational assistants based on generative AI	They provide personalized agronomic advice to farmers, adapted to their specific conditions and in natural language.	Global (conceptual)	(Boscán & Boscán, 2025)	High potential in the medium term. Once the Cuban agronomic knowledge base is developed, this technology could be very useful for agricultural extension.	Create a digital knowledge base with local agronomic information (soils, crops, climate, practices). Train specialists in the use and development of these tools.

Needs and Opportunities

Despite the barriers, there are key opportunities that can be leveraged. First, there is the political will for modernization, as evidenced by the ONUDI (2024) and its alignment with the National Sustainable Development Plan 2030. Cuba has a qualified human capital in institutions such as the Institute of Agricultural Engineering Research (IAgric), the Agrarian University of Havana (UNAH), the National Institute of Agricultural Sciences (INCA), the University of Havana (UH), the Comprehensive Automation Company (CEDAI), etc., which possess extensive experience in agricultural engineering, irrigation (design, evaluation, and management of irrigation systems), and mechanization, necessary for the implementation of smart irrigation and precision agriculture (Kushwaha *et al*., 2024). This knowledge base can serve as the foundation for building local capacity in digital agriculture.

The availability of low-cost technologies is another crucial opportunity. The study by Elhoseny *et al*. (2026) demonstrates that it is possible to implement smart irrigation systems at a cost of only US$44, making them potentially accessible to producers with small farms. Likewise, access to free satellite data (such as that from the Sentinel-2 mission) allows for the generation of NDVI maps and the estimation of water requirements without a significant initial investment (Marques *et al*., 2020; Saha *et al*., 2025). International cooperation, such as that established through UNIDO and other agencies (FAO, UNDP), can provide a channel for technology and knowledge transfer, which should be leveraged to adapt global solutions to the local context.

For successful adaptation, the following prioritized needs are identified, with an emphasis on precision irrigation. Transition from inefficient irrigation systems to more efficient ones:

1. Diagnosis and basic modernization of irrigation systems: Evaluate the current state of irrigation systems to identify losses and opportunities for improvement, with an emphasis on the transition from surface irrigation to more efficient pressurized systems.
2. Introduction of low-cost soil moisture sensors with intermittent connectivity (offline/online): Implement low-cost sensors (Elhoseny *et al*., 2026) in pilot areas. Given the connectivity limitations in rural areas, a practical first step is the use of sensors that operate with intermittent connectivity (local data recording with periodic download), subsequently progressing to hybrid systems that combine local storage with intermittent transmission, until real-time monitoring (continuous connection) is achieved. A complementary option is the development of robust, easy-to-use, and replaceable sensors for the spot and semi-instantaneous determination of soil moisture, linked to cell phones to allow farmers or technicians to make on-site decisions.
3. Training in efficient water management: Train technicians and farmers in irrigation scheduling based on reference evapotranspiration (ETo) and the interpretation of sensor data, even under conditions of limited connectivity.
4. Development of IoT-based automated irrigation systems: Implement systems that integrate sensors, weather stations, and fuzzy logic control algorithms (Liu *et al*., 2025) to automate irrigation, prioritizing solutions that function with intermittent connectivity.
5. Strengthening FMIS platforms for integrated water management: Develop local platforms that integrate sensor data, soil moisture maps, and water requirements (Karydas *et al*., 2023), with the capacity to operate offline/online and with periodic synchronization.
6. Training specialists in water requirements modeling: Train professionals in the use of water balance and evapotranspiration models, adapted to locally available data.
7. Developing irrigation prescription maps: Generate prescription maps based on satellite data, soil sensors, and crop models (Saha *et al*., 2025), using tools that do not require continuous connectivity.
8. Implementing autonomous irrigation systems with AI: Introduce systems that integrate sensor data, climate forecasts, and satellite imagery (Liu *et al*., 2025) in pilot projects, considering architectures that allow for local processing in case of disconnection.
9. Development of digital twins for irrigation optimization: Creating virtual replicas of irrigation systems to simulate climate scenarios and evaluate management strategies (Purcell & Neubauer, 2023), leveraging centralized computing centers.
10. Integration of renewable energies: Incorporating solar and wind pumping systems to reduce energy dependence and irrigation operating costs.
11. Automation of fertigation: Developing automated systems that integrate variable-rate application of water and fertilizers, optimizing both resources simultaneously.
12. Gradual implementation of automatic guidance systems: Adapting automatic guidance systems to existing machinery to reduce overlaps, improve application uniformity, and optimize fuel consumption (Vrchota *et al*., 2022; McFadden *et al*., 2023). Given the obsolescence of the machinery fleet (more than 80% of tractors are over 30 years old), a phased implementation strategy is proposed.

Gradual Implementation Strategy

Based on the identified needs, a three-phase, phased approach is proposed, prioritizing precision irrigation as a fundamental pillar and the introduction of low-cost, high-impact technologies.

Phase 1 (Immediate, 1 to 2 years): Introduction of low-cost, high-impact technologies

Prioritized actions

- The desired outcome is the implementation of low-cost soil moisture sensors (Elhoseny *et al*., 2026) in strategic crops (rice, corn, beans, vegetables, and tobacco) for real-time monitoring. However, a more practical first step in the current Cuban context is the use of sensors that operate with intermittent connectivity, subsequently progressing to hybrid systems that combine intermittent and continuous connectivity, ultimately achieving real-time monitoring (continuous connection).
- Development of robust, easy-to-use, and replaceable sensors for determining point, discrete, and semi-instantaneous soil moisture, linked to cell phones for on-site decision-making.
- Development of CNN-based mobile applications for disease diagnosis (Singh & Gupta, 2018) and irrigation management, capable of operating offline.
- Intensive training in efficient water management for IAgric technicians and extension agents on irrigation scheduling based on ETo and sensor data.
- Monitoring with drones equipped with multispectral and thermal cameras for detecting water stress and other crop problems (Tsouros *et al*., 2019; Velusamy *et al*., 2022).
- Creation of a national Agricultural Management System (FMIS), adapted to local conditions, to serve as an integrating platform for all data (low-cost sensors, free satellite imagery, local weather forecasts), with the capacity for periodic synchronization in areas with limited connectivity.

- Strengthening rural connectivity, prioritizing investments in connectivity infrastructure to progressively enable real-time data transmission.
- Widespread use of solar and wind pumping systems to reduce dependence on fossil fuels and operating costs.
- Gradual introduction of automated guidance systems for machinery (Vrchota *et al*., 2022; McFadden *et al*., 2023). As a first, very low-cost option, using the operator's mobile phone (with an appropriate app) as a navigation assistant to guide movement in the field, operating under intermittent connectivity conditions (without requiring a permanent internet connection, only a GPS signal). This solution allows for increased operating efficiency of aging machinery, reducing overlaps and fuel consumption.
- Building local capacity around these technologies, transforming our technicians and agronomists into the specialists who adapt, calibrate, and operate these systems.

Expected results

- Reduction in water consumption of 20-30% in pilot areas.
- Decreased operating costs due to lower fuel consumption and reduced overlaps through the use of mobile phones as navigation assistants.
- Building local capacity in sensor management (including offline/online operation), precision irrigation, basic mobile guidance, and drone monitoring.
- Implementation of a national FMIS platform that integrates basic field data.

Phase 2 (Short/Medium Term - 3-5 years): Development and implementation of more complex systems.
Prioritized actions

Prioritized actions

- Development of IoT-based automated irrigation systems that integrate sensors, weather stations, and fuzzy logic control algorithms (Liu *et al*., 2025), with the capacity to operate in hybrid mode (local + cloud).
- Implementation of drip irrigation with variable flow control in crops with high water demand.
- Strengthening an FMIS platform adapted to local conditions that integrates sensor data, soil moisture maps, and climate forecasts (Karydas et al., 2023).
- Development of irrigation prescription maps based on satellite data and soil sensors (Saha et al., 2025).
- Establishing partnerships with international centers for model validation.
- Advancing the installation of automatic guidance systems on existing modern equipment in the country's main agricultural hubs and as the fleet is renewed.
- Development and implementation of VRT systems for fertilization and pest control in high-value crops and in areas with high spatial variability of soils, based on prescription maps generated from free satellite data (such as Sentinel-2) and soil analysis, similar to the "PreFer" service (Karydas et al., 2023).
- Development of smart traps adapted to the main pests of Cuba (Potamitis *et al*., 2014). Development of image databases of local diseases and pests for training AI models.

Expected Results

- Water consumption reduced by 30-40% in pilot areas and energy consumption reduced by 15-25% for pumping in selected areas.
- Nitrogen fertilizer use decreased by 10-3.0% without affecting yield.
- Validation of early warning systems for pests using smart traps.
- Development of local capacities in modeling, remote sensing, and machine learning.

Phase 3 (Medium/Long Term - 5-10 years): Introduction of advanced technologies

Prioritized Actions

- Implementation of AI-powered autonomous irrigation systems that integrate sensor data, weather forecasts, satellite imagery, and growth models (Liu *et al*., 2025).
- Automation of fertigation, integrating water and fertilizers.
- Introduction of robotics and autonomous systems in pilot projects in cooperatives or larger-scale state-owned enterprises (Comparetti *et al*., 2025; Liu *et al*., 2025).
- Development of digital twins for strategic crops and integrated water resource management (Purcell & Neubauer, 2023).
- Implementation of conversational assistants for agricultural extension (Boscán & Boscán, 2025).
- Making AIoT technologies a common tool for increasing food sovereignty, optimizing water use, and improving the operation of agricultural machinery.

Expected results

- Rationalization of irrigation and fertigation with a 40-50% reduction in water consumption.
- Significant reduction of the energy and carbon footprint.
- Implementation of digital twins for the simulation and improvement of crop management.

- Positioning of Cuba as a regional leader in smart irrigation technologies.

Given the high costs, promoting collaborative business models, such as machinery cooperatives or "machinery-by-the-hour" rental services (Munz & Schuele, 2022), can be a mechanism to overcome the economic and scale barriers that limit access to high-cost technologies, allowing the benefits of precision agriculture to reach small and medium-sized producers as well. The key will be adapting global technologies to local conditions, providing ongoing training for human resources, fostering sustained international collaboration, and developing business models that enable equitable access to technology. Therefore, the implementation of this strategy must be accompanied by a continuous training program for technicians and farmers, ensuring long-term sustainability.

CONCLUSIONS

- The integration of smart irrigation and precision mechanization is an unavoidable global trend for sustainable agriculture, offering water savings of 30-50%, herbicide reductions of up to 90%, and fertilizer reductions of 15-30%, with >95% accuracy in early pest detection. For Cuba, its adoption is a strategic necessity given the obsolescence of machinery (>80% over 30 years old) and the low efficiency of irrigation (70% surface irrigation with <50% efficiency).
- It is possible to initiate the digital transformation of Cuban agriculture without waiting for a complete infrastructure overhaul, through a gradual, three-phase approach: (1) low-cost technologies that operate with intermittent connectivity and are based on mobile telephony (sensors with local data logging, mobile applications without continuous internet access, use of the operator's phone as a navigation assistant); (2) hybrid systems; (3) continuous connectivity and robotics. This strategy enables progress toward precision agriculture, overcoming the limitations of rural connectivity in Cuba and the economic barriers that restrict access to high-cost technologies.
- Precision irrigation stands as a fundamental pillar of the transition, given water scarcity and losses due to the low efficiency of current systems. A model is proposed that begins with the installation of low-cost (≤US$44) soil moisture sensors in strategic crops (rice, corn, beans, vegetables, tobacco), initially operating in a semi-offline mode with on-site decision-making via mobile phone. This approach, validated in environments with limited connectivity, can achieve water consumption savings of 30-40% from the first phase, without requiring continuous internet infrastructure, and lays the groundwork for subsequent automation based on IoT and fuzzy logic control algorithms.
- The integration of these technologies, with an emphasis on smart irrigation and precision mechanization adapted to local conditions of limited connectivity and aging machinery, can be a decisive way to increase food sovereignty and the resilience of Cuban agriculture in the face of climate change, resource scarcity and the need for greater productive efficiency.

REFERENCES

ABIOYE, E.A.; ABIDIN, M.S.Z.; MAHMUD, M.S.A.; BUYAMIN, S.; ISHAK, M.H.I.; ABD RAHMAN, M.K.I.; OTUOZE, A.O.; ONOTU, P.; RAMLI, M.S.A.: "A review on monitoring and advanced control strategies for precision irrigation", *Computers and Electronics in Agriculture*, 173: 105441, 2020, ISSN: 0168-1699.

ADAMCHUK, V.I.; HUMMEL, J.W.; MORGAN, M.T.; UPADHYAYA, S.K.: "On-the-go soil sensors for precision agriculture", *Computers and electronics in agriculture*, 44(1): 71-91, 2004, ISSN: 0168-1699.

ADEYEMI, O.; GROVE, I.; PEETS, S.; NORTON, T.: "Advanced monitoring and management systems for improving sustainability in precision irrigation", *Sustainability*, 9(3): 353, 2017, ISSN: 2071-1050, DOI: http://doi.org/10.3390/su9030353.

ADEYEMI, O.; GROVE, I.; PEETS, S.; NORTON, T.: "Advanced monitoring and management systems for improving sustainability in precision irrigation", *Sustainability*, 9(3): 353, 2017, ISSN: 2071-1050, DOI: http://doi.org/10.3390/su9030353.

ADLI, H.K.; REMLI, M.A.; SALIHIN, W.; ISMAIL, N.A.; GONZÁLEZ, A.; CORCHADO, J.M.; MOHAMAD, M.S.: "Recent Advancements and Challenges of AIoT Application in Smart Agriculture: A Review", *Sensors*, 23(7): 3752, 2023, ISSN: 1424-8220, DOI: http://doi.org/10.3390/s23073752.

AKTAR, M.W.; SENGUPTA, D.; CHOWDHURY, A.: "Impact of pesticides use in agriculture: their benefits and hazards", *Interdisciplinary Toxicology*, 2(1): 1-12, 2009, ISSN: 1337-6853, DOI: http://doi.org/10.2478/v10102-009-0001-7.

ANASTASIOU, E.; FOUNTAS, S.; VOULGARAKI, M.; PSIROUKIS, V.; KOUTSIARAS, M.; KRIEZI, O.; LAZAROU, E.; VATSANIDOU, A.; FU, L.; DI BARTOLO, F.; JESUS BARREIRO, J.; MANUEL GOMEZ, J.: "Precision farming technologies for crop protection: A meta-analysis", *Smart Agricultural Technology*, 5: 100323, 2023, ISSN: 2772-3755, DOI: http://doi.org/10.1016/j.atech.2023.100323.

AUBERT, B.A.; SCHROEDER, A.; GRIMAUDO, J.: "IT as enabler of sustainable farming: An empirical analysis of farmers' adoption decision of precision agriculture technology", *Decision Support Systems*, 54(1): 510-520, 2012, ISSN: 0167-9236, DOI: http://doi.org/10.1016/j.dss.2012.05.048.

BAYIH, A.; MORALES, J.; ASSABIE, Y.; DE BY, R.: "Utilization of Internet of Things and Wireless Sensor Networks for Sustainable Smallholder Agriculture",

Sensors, 22(9): 3273, 2022, ISSN: 1424-8220, DOI: http://doi.org/10.3390/s22093273.

BENCHALLAL, F.; HAFINE, A.; RAGOT, N.; CANALS, R.: "ConvNeXt based semi-supervised approach with consistency regularization for weeds classification", *Expert Systems with Applications*, 239: 122222, 2024, ISSN: 0957-4174, DOI: http://doi.org/10.1016/j.eswa.2023.122222.

BOSCÁN BOSCÁN, A.C.; BOSCÁN BOSCÁN, A.J.: "Artificial intelligence in agriculture: A view from a sustainable development perspective", *Agrociencia Uruguay*, 29: e1502, 2025, ISSN: 2730-5066, DOI: http://doi.org/10.31285/AGRO.29.1502.

CHLINGARYAN, A.; SUKKARIEH, S.; WHELAN, B.: "Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review", *Computers and Electronics in Agriculture*, 151: 61-69, 2018, ISSN: 0168-1699, DOI: http://doi.org/10.1016/j.compag.2018.05.012.

COLAÇO, A.F.; BRAMLEY, R.G.: "Do crop sensors promote improved nitrogen management in grain crops?", *Field Crops Research*, 218: 126-140, 2018, ISSN: 0378-4290, DOI: http://doi.org/10.1016/j.fcr.2018.01.017.

COMPARETTI, A.; FAGIOLINI, A.; FOUNTAS, S.; CASCIO, V.: "Field robots for precision agriculture", *AIMS Agriculture and Food*, 10(4): 885-916, 2025, ISSN: 2471-2086, DOI: http://doi.org/10.3934/agrfood.2025046.

CORTEZ, A.; PRO, L.; MAMANI, N.; LOZADA, P.; PARIONA, J.: "Precision agriculture: transforming traditional agriculture with technology", *Revista de Investigación de Sistemas e Informática*, 17(2): 51-63, 2024, ISSN: 1816-3823, DOI: http://doi.org/10.15381/risi.v17i2.29917.

CRAVERO, A.; SEPÚLVEDA, S.: "Use and adaptations of machine learning in big data-applications in real cases in agriculture", *Electronics*, 10(5): 552, 2021, ISSN: 2079-9292, DOI: http://doi.org/10.3390/electronics10050552.

DOMÍNGUEZ, C.; CISNEROS, E.; HERRERA, J.; RUIZ, M.; MIRANDA, A.; PANEQUE, P.; MARTIN, R.A.: "Enfoques para la gestión y uso eficiente del agua en el cultivo de arroz", *Revista Ciencias Técnicas Agropecuarias*, 34: e03, 2025, ISSN: 2071-0054.

DOMÍNGUEZ, C.; MIRANDA, A.; GUILHERME DE ARAÚJO, A.; MOREJÓN, Y.; PANEQUE, P.: "Management of Agricultural Machinery in Cuba to Enhance Ecosystem Services and Mitigate Climate Change", *Agricultural Mechanization in Asia, Africa and Latin America*, 55(3): 27-31, 2024, ISSN: 0084-5841.

ELHOSENY, M.; JAHID, K.; LATIF, R.; SADDIK, A.; ATASSI, R.: "Recent advances in IoT-driven crop monitoring and precision irrigation: Technologies, models, and future challenges", *Scientific African*, 2026, (en prensa), ISSN: 2468-2276, DOI: http://doi.org/10.1016/j.sciaf.2026.e03222.

ELIJAH, O.; RAHMAN, T.A.; ORIKUMHI, I.; LEOW, C.Y.; HINDIA, M.N.: "An overview of Internet of Things (IoT) and data analytics in agriculture: Benefits and challenges", *IEEE Internet of Things Journa*l, 5(5): 3758-3773, 2018, ISSN: 2327-4662, DOI: http://doi.org/10.1109/JIOT.2018.2844296.

ESCRIBÀ, M.; LIANG, S.; VAN SCHALKWYK, P.; FISK, I.; LONG, N.V.D.; HESSEL, V.: "Digital twins in agriculture: orchestration and applications", *Journal of Agricultural and Food Chemistry*, 72(19): 10737-10752, 2024, ISSN: 0021-8561, DOI: http://doi.org/10.1021/acs.jafc.4c01934.

GETAHUN, S.; KEFALE, H.; GELAYE, Y.: "Application of Precision Agriculture Technologies for Sustainable Crop Production and Environmental Sustainability: A Systematic Review", *The Scientific World Journal*, 2024: 2126734, 2024, ISSN: 2356-6140, DOI: http://doi.org/10.1155/2024/2126734.

GOAP, A.; SHARMA, D.; SHUKLA, A.K.; RAMA KRISHNA, C.: "An IoT based smart irrigation management system using machine learning and open source technologies", *Computers and Electronics in Agriculture*, 155: 41-49, 2018, ISSN: 0168-1699, DOI: http://doi.org/10.1016/j.compag.2018.09.040.

GUPTA, G.; KUMAR, S.: "Applications of AI in precision agriculture", *Discover Agriculture*, 3: 61, 2025, ISSN: 2731-9598, DOI: http://doi.org/10.1007/s44279-025-00220-9.

GUZMÁN, J.G.; MATUZ, M.; ARANA, J.Y.; LÓPEZ, E.; GÓMEZ, V.; GONZÁLEZ, N.: "Advances and prospects of precision agriculture for agricultural sustainability", *XIKUA Boletín Científico de la Escuela Superior de Tlahuelilpan*, 12(24): 01-06, 2024, ISSN: 2007-4940, DOI: http://doi.org/10.29057/xikua.v12i24.12790.

HUANG, W.; LAMB, D.W.; NIU, Z.; ZHANG, Y.; LIU, L.; WANG, J.: "Identification of yellow rust in wheat using in-situ spectral reflectance measurements and airborne hyperspectral imaging", *Precision Agriculture*, 8: 187-197, 2007, ISSN: 1385-2256, DOI: http://doi.org/10.1007/s11119-007-9038-9.

ISLAM, M.R.; OLIULLAH, K.; KABIR, M.M.; ALOM, M.; MRIDHA, M.F.: "Machine learning enabled IoT system for soil nutrients monitoring and crop recommendation", *Journal of Agriculture and Food Research*, 14: 100880, 2023, ISSN: 2666-1543, DOI: http://doi.org/10.1016/j.jafr.2023.100880.

JAWAD, H.M.; NORDIN, R.; GHARGHAN, S.K.; JAWAD, A.M.; ISMAIL, M.: "Energy efficient wireless sensor networks for precision agriculture: A review", *Sensors*, 17(8): 1781, 2017, ISSN: 1424-8220, DOI: http://doi.org/10.3390/s17081781.

JIANG, P.; CHEN, Y.; LIU, B.; HE, D.; LIANG, C.: "Real-time detection of apple leaf diseases using deep learning approach based on improved convolutional neural networks", *IEEE Access*, 7: 59069-59080, 2019, ISSN: 2169-3536, DOI: http://doi.org/10.1109/ACCESS.2019.2914929.

KAMILARIS, A.; PRENAFETA-BOLDÚ, F.X.: "Deep learning in agriculture: A survey", *Computers and Electronics in Agriculture*, 147: 70-90, 2018, ISSN: 0168-1699, DOI: http://doi.org/10.1016/j.compag.2018.02.016.

KARYDAS, C.; CHATZIANTONIOU, M.; STAMKOPOULOS, K.; IATROU, M.; VASSILIADIS, V.; MOURELATOS, S.: "Embedding a precision agriculture service into a farm management information system - ifarma/PreFer", *Smart Agricultural Technology*, 4: 100175, 2023, ISSN: 2772-3755, DOI: http://doi.org/10.1016/j.atech.2023.100175.

KOCH, B.; KHOSLA, R.; FRASIER, W.M.; WESTFALL, D.G.; INMAN, D.: "Economic feasibility of variable-rate nitrogen application utilizing site-specific management zones", *Agronomy Journal*, 96(6): 1572-1580, 2004, ISSN: 0002-1962, DOI: http://doi.org/10.2134/agronj2004.1572.

KUSHWAHA, M.; SINGH, S.; SINGH, V.; DWIVEDI, S.: "Precision Farming: A Review of Methods, Technologies, and Future Prospects", *International Journal of Environment, Agriculture and Biotechnology*, 9(2), 2024, ISSN: 2456-1878, DOI: http://doi.org/10.22161/ijeab.92.27.

LI, Y.; CHAO, X.: "Semi-supervised few-shot learning approach for plant diseases recognition", *Plant Methods*, 17: 68, 2021, ISSN: 1746-4811, DOI: http://doi.org/10.1186/s13007-021-00770-1.

LIAKOS, K.G.; BUSATO, P.; MOSHOU, D.; PEARSON, S.; BOCHTIS, D.: "Machine learning in agriculture: A review", *Sensors*, 18(8): 2674, 2018, ISSN: 1424-8220, DOI: http://doi.org/10.3390/s18082674.

LIU, X.; ZHAO, Z.; REZAEIPANAH, A.: "Intelligent and automatic irrigation system based on internet of things using fuzzy control technology", *Scientific Reports*, 15: 14577, 2025, ISSN: 2045-2322, DOI: http://doi.org/10.1038/s41598-025-98137-2.

MACHLEB, J.; PETEINATOS, G.G.; KOLLENDA, B.L.; ANDÚJAR, D.; GERHARDS, R.: "Sensor-based mechanical weed control: present state and prospects", *Computers and Electronics in Agriculture*, 176: 105638, 2020, ISSN: 0168-1699, DOI: http://doi.org/10.1016/j.compag.2020.105638.

MAHLEIN, A.K.: "Plant disease detection by imaging sensors - parallels and specific demands for precision agriculture and plant phenotyping", *Plant Disease*, 100(2): 241-251, 2016, ISSN: 0191-2917, DOI: http://doi.org/10.1094/PDIS-03-15-0340-FE.

MARQUES, J.R.; TERRÓN, J.M.; DOMÍNGUEZ, F.J.; PAIXÃO, L.: "Agricultura de Precisión con Imágenes de Satélite", en: Manual de Buenas Prácticas Agrícolas, cap. II, pp. 25-48, 2020, ISBN: 978-989-33-0549-2.

McFADDEN, J.; ERICKSON, B.; LOWENBERG, J.; MILICS, G.: "Global Adoption of Precision Agriculture: An Update on Trends and Emerging Technologies", en: Proceedings of the 16th International Conference on Precision Agriculture, Manhattan, Kansas, USA, 21-24 July 2024, pp. 1-16.

McFADDEN, J.; NJUKI, E.; GRIFFIN, T.: "Precision agriculture in the digital era: recent adoption on U.S. Farms", *Economic Information Bulletin* No. 248, U.S. Department of Agriculture, Economic Research Service, 2023, Disponible en: https://www.ers.usda.gov/webdocs/publications/105894/eib-248.pdf [Consulta: 17 de abril de 2026].

MINAG: *Anuario Estadístico Agropecuario 2022*, Ministerio de la Agricultura, La Habana, Cuba, 2023.

MORCHID, A.; QJIDAA, H.; ALAMI, R.E.; MOBAYEN, S.; SKRUCH, P.; BOSSOUFI, B.: "Smart irrigation-based internet of things and cloud computing technologies for sustainable Farming", *Scientific Reports*, 16: 5293, 2026, ISSN: 2045-2322, DOI: http://doi.org/10.1038/s41598-026-35810-0.

MUNZ, J.; SCHUELE, H.: "Influencing the Success of Precision Farming Technology Adoption-A Model-Based Investigation of Economic Success Factors in Small-Scale Agriculture", *Agriculture*, 12(11): 1773, 2022, ISSN: 2077-0472, DOI: http://doi.org/10.3390/agriculture12111773.

NICOLOPOULOU-STAMATI, P.; MAIPAS, S.; KOTAMPASI, C.; STAMATIS, P.; HENS, L.: "Chemical pesticides and human health: the urgent need for a new concept in agriculture", *Frontiers in Public Health*, 4: 148, 2016, ISSN: 2296-2565, DOI: http://doi.org/10.3389/fpubh.2016.00148.

OJHA, T.; MISRA, S.; RAGHUWANSHI, N.S.: "Wireless sensor networks for agriculture: The state-of-the-art in practice and future challenges", *Computers and Electronics in Agriculture*, 118: 66-84, 2015, ISSN: 0168-1699, DOI: http://doi.org/10.1016/j.compag.2015.08.011.

ONUDI (Organización de las Naciones Unidas para el Desarrollo Industrial): *Programa de modernización tecnológica y empresarial en el sector de producción de agroquímicos y maquinaria agrícola* (Mejora y modernización industrial en Cuba, fase II), ID 230317, 51 p., 2024.

PADHIARY, M.; KUMAR, A.; NARAYAN, L.: "Emerging technologies for smart and sustainable precision agriculture", *Discover Robotics*, 1: 6, 2025, ISSN: 3004-9157, DOI: http://doi.org/10.1007/s44430-025-00006-0.

PAGE, M.J.; MCKENZIE, J.E.; BOSSUYT, P.M.; BOUTRON, I.; HOFFMANN, T.C.; MULROW, C.D.; SHAMSEER, L.; TETZLAFF, J.M.; AKL, E.A.; BRENNAN, S.E.: "The PRISMA 2020 Statement: An Updated Guideline for Reporting Systematic", Reviews. *J. Clin. Epidemiol. 134*, 178-189, 2021. DOI: http://doi.org/10.1016/j.jclinepi.2021.03.001.

PARAFOROS, D.S.; VASSILIADIS, V.; KORTENBRUCK, D.; STAMKOPOULOS, K.; ZIOGAS, V.; SAPOUNAS, A.A.; GRIEPENTROG, H.W.: "Multi-level automation of farm management information systems", *Computers and Electronics in Agriculture*, 142: 504-514, 2017, ISSN: 0168-1699, DOI: http://doi.org/10.1016/j.compag.2017.11.022.

PARTEL, V.; CHARAN KAKARLA, S.; AMPATZIDIS, Y.: "Development and evaluation of a low-cost and smart technology for precision weed management utilizing artificial intelligence", *Computers and Electronics in Agriculture*, 157: 339-350, 2019, ISSN: 0168-1699, DOI: http://doi.org/10.1016/j.compag.2018.12.048.

PIERPAOLI, E.; CARLIA, G.; PIGNATTI, E.; CANAVARI, M.: CDrivers of precision agriculture technologies adoption: A literature review", *Procedia Technology*, 8: 61-69, 2013, ISSN: 2212-0173, DOI: http://doi.org/10.1016/j.protcy.2013.11.010.

PNDES (Plan Nacional de Desarrollo Económico y Social hasta 2030): *Propuesta de Visión, Ejes y Sectores Estratégicos*, La Habana, Cuba, Ministerio de Economía y Planificación (MEP), Resolución 30/2018 MINCEX, D-L 02/2019, 2019.

POTAMITIS, I.; RIGAKIS, I.; FYSARAKIS, K.: "The electronic McPhail trap", *Sensors*, 14(12): 22285-22299, 2014, ISSN: 1424-8220, DOI: http://doi.org/10.3390/s141222285.

PRADO, M., ÁVILA, B., QUIÑONEZ, J.: "Uso de tecnologías de agricultura de precisión en la optimización de sistemas de riego en pequeñas y medianas fincas de la comunidad El Cristal, Parroquia Alto Tambo, Cantón San Lorenzo". *Revista Social Fronteriza* 5(3): e723, 2025. DOI: http://doi.org/10.59814/resofro.2025.5(3)723

PURCELL, W.; NEUBAUER, T.: "Digital Twins in Agriculture: A State-of-the-Art Review", *Smart Agricultural Technology*, 3: 100094, 2023, ISSN: 2772-3755, DOI: http://doi.org/10.1016/j.atech.2022.100094.

QUAN, L.; JIANG, W.; LI, H.; LI, H.; WANG, Q.; CHEN, L.: "Intelligent intra-row robotic weeding system combining deep learning technology with a targeted weeding mode", *Biosystems Engineering*, 216: 13-31, 2022, ISSN: 1537-5110, DOI: http://doi.org/10.1016/j.biosystemseng.2022.01.019.

SAHA, S.; KUCHER, O.D.; UTKINA, A.O.; REBOUH, N.Y.: "Precision agriculture for improving crop yield predictions: a literature review", *Frontiers in Agronomy*, 7: 1566201, 2025, ISSN: 2673-3218, DOI: http://doi.org/10.3389/fagro.2025.1566201.

SCHIMMELPFENNIG, D.: "Farm profits and adoption of precision agriculture", Economic Research Report No. 217, U.S. Department of Agriculture, *Economic Research Service*, 2016, DOI: http://doi.org/10.22004/ag.econ.249773.

SCHIMMELPFENNIG, D.; EBEL, R.: "Sequential Adoption and Cost Savings from Precision Agriculture", *Journal of Agricultural and Resource Economics*, 41(1): 97-115, 2016, ISSN: 1068-5502, DOI: http://doi.org/10.22004/ag.econ.230771.

SINGH, S.; GUPTA, S.: "Apple scab and marsonina coronaria diseases detection in apple leaves using machine learning", *International Journal of Pure and Applied Mathematics*, 118(9): 1151-1166, 2018, ISSN: 1311-8080.

SUÁREZ, J.; RÍOS, A.: "A diagnosis on existence and use of agricultural machinery in Cuba", *Ingeniería Agrícola*, 9(4): 69-77, 2019, ISSN: 2227-8761.

TEJEDA, V.; HERRERA, J.; RÍOS, A.; LÓPEZ, R.: "Agricultural Engineering in the System of the Cuban Agriculture, a Challenge in the Current Times", *Ingeniería Agrícola*, 15, 2025, ISSN: 2227-8761.

TESKE, A.L.; CHEN, G.; NANSEN, C.; KONG, Z.: "Optimised dispensing of predatory mites by multirotor UAVs in wind: a distribution pattern modelling approach for precision pest management", *Biosystems Engineering*, 187: 226-238, 2019, ISSN: 1537-5110, DOI: http://doi.org/10.1016/j.biosystemseng.2019.09.009.

TSOUROS, D.C.; BIBI, S.; SARIGIANNIDIS, P.G.: "A review on UAV-based applications for precision agriculture", *Information*, 10(11): 349, 2019, ISSN: 2078-2489, DOI: http://doi.org/10.3390/info10110349.

VELUSAMY, P.; RAJENDRAN, S.; MAHENDRAN, R.K.; NASEER, S.; SHAFIQ, M.; CHOI, J.G.: "Unmanned Aerial Vehicles (UAV) in Precision Agriculture: Applications and Challenges", *Energies*, 15(1): 217, 2022, ISSN: 1996-1073, DOI: http://doi.org/10.3390/en15010217.

VRCHOTA, J.; PECH, M.; ŠVEPEŠOVÁ, I.: "Precision Agriculture Technologies for Crop and Livestock Production in the Czech Republic", *Agriculture*, 12(8): 1080, 2022, ISSN: 2077-0472, DOI: http://doi.org/10.3390/agriculture12081080.

WOLFERT, S.; GE, L.; VERDOUW, C.; BOGAARDT, M.J.: "Big Data in Smart Farming-A Review", *Agricultural Systems*, 153: 69-80, 2017, ISSN: 0308-521X, DOI: http://doi.org/10.1016/j.agsy.2017.01.023.

WOLTERS, S.; SÖDERSTRÖM, M.; PIIKKI, K.; STENBERG, M.: "Near-real time winter wheat N uptake from a combination of proximal and remote optical measurements: How to refine Sentinel-2 satellite images for use in a precision agriculture decision support system", Proceedings of the 12th European Conference on Precision Agriculture, Montpellier, France, 8-11 July 2019, Wageningen Academic Publishers, pp. 415-421, 2019, ISBN: 978-90-8686-337-2.

XU, J.; GU, B.; TIAN, G.: "Review of agricultural IoT technology", *Artificial Intelligence in Agriculture*, 6: 10-22, 2022, ISSN: 2589-7217, DOI: http://doi.org/10.1016/j.aiia.2022.01.001.

ZAIN, M.; MA, H.; CHAUDHARY, S.; NURUZAMAN, M.; AZEEM, I.; MEHMOOD, F.; AIWANG, D.; SUN, C.: "Nanotechnology in precision agriculture: Advancing towards sustainable crop production", *Plant Physiology and Biochemistry*, 2006: 108244, 2023, ISSN: 0981-9428, DOI: http://doi.org/10.1016/j.plaphy.2023.108244.

ZHANG, X.; CAO, Z.; DONG, W.: "Overview of edge computing in the agricultural internet of things: key technologies, applications, challenges", *IEEE Access*, 8: 141748-141761, 2020, ISSN: 2169-3536, DOI: http://doi.org/10.1109/ACCESS.2020.3013005.