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CONTEMPORARY PLANT PHYSIOLOGY: SYNERGY OF BIOLOGY, ARTIFICIAL INTELLIGENCE, AND THE INTERNET OF THINGS FOR SUSTAINABLE AGRICULTURE

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ABSTRACT

Plant physiology is a cornerstone of agronomic science, revealing mechanisms through which plants respond to stress factors such as drought, salinity, and extreme temperatures. These responses involve changes in gene expression, metabolic pathways, and phenological stages, affecting growth and yield quality. Understanding these processes supports strategies for resilient and sustainable agriculture. Integrating Informatics, Artificial Intelligence (AI), and the Internet of Things (IoT) in plant physiology offers opportunities for optimizing production, resilience, and resource use. Combining AI/IoT with advanced imaging techniques, including hyperspectral cameras, fluorescence spectroscopy, and LiDAR, enables real-time monitoring of physiology. IoT sensors and image processing allow assessment of biomass, leaf area, and water needs, promoting precision agriculture. Plant hormones, particularly auxins and gibberellins, regulate growth from germination and root–shoot development to fruit maturation. Their dynamics, along with interactions with abscisic acid (ABA), jasmonic acid (JA), and salicylic acid (SA), shape stress resilience. Quantitative models and computational tools clarify these processes, while AI facilitates analysis of genomic and phenotypic data, enabling stress prediction and productivity optimization. AI in yield, irrigation, and pest/disease control supports resource management. Combining traditional practices like crop rotation with digital tools strengthens resilience. Despite challenges such as energy demand and adaptation to varied environments, integrating plant physiology, AI, and IoT fosters sustainable, productive, climate-resilient agriculture. Overall, integrating biological knowledge with cutting-edge technologies allows understanding, predicting, and improving plant growth and resilience, laying the foundation for modern, sustainable, and efficient agriculture.

Keywords: Quantitative Plant Biology, Crop Physiology, Plant Hormones, Climate Resilience, Interdisciplinary Applications.

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1. INTRODUCTION

Understanding plant physiology constitutes a fundamental pillar of agronomic science, as it reveals how plants respond to dynamic environmental conditions, particularly climatic stress. The investigation of these mechanisms is not limited to academic interest but has direct applications in developing strategies to enhance crop resilience and optimize plant growth. Various environmental stress factors, such as drought, salinity, and extreme temperatures, trigger specific physiological responses in plants. These include changes in gene expression, adjustments in metabolic pathways, and modifications in phenological stages, which significantly affect crop yield and quality (Fahad et al., 2017). Understanding these complex processes is a key tool for implementing practices that support sustainable agriculture in an ever-changing environment.

The application of informatics to experimental data analysis has highlighted new approaches in agricultural management, with an emphasis on decision support systems. Integrating plant physiology with informatics advances knowledge of plant functioning, optimizes production, enhances resilience to climate change, and supports the transition to more sustainable agricultural systems. In this context, interdisciplinary synergy between biology and digital technologies becomes critical for the development of innovative solutions.

This work contributes to scientific knowledge by combining plant physiology with AI and IoT technologies, enabling non-invasive monitoring, quantification, and prediction of growth and stress responses, providing tools for sustainable precision agriculture.

Understanding the integration of plant physiology with the capabilities of Artificial Intelligence (AI) and the Internet of Things (IoT) through smart management practices creates a powerful pathway for addressing the challenges of climatic stress. This synergy is not limited to theoretical knowledge but actively enhances the resilience and efficiency of agricultural systems, supporting sustainable plant productivity. Simultaneously, it contributes to the rational use of resources, ensuring that plant physiological needs are met with minimal losses.

The intersection of plant physiology and informatics forms a new scientific domain where AI, Machine Learning (ML), Deep Learning (DL), and Transfer Learning (TL) play a decisive role in studying plant growth and stress responses. Intelligent data analysis enables understanding of complex biological interactions and the creation of predictive models, strengthening scientifically informed decision-making and sustainable crop management. This work links fundamental plant knowledge with digital technologies, promoting sustainable agriculture and addressing contemporary production challenges.

The modern agricultural challenge is summarized as the need to increase plant production sustainably, without expanding cultivated land and ideally reducing inputs. This must be achieved

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under conditions of climatic instability and in increasingly marginal geographical areas (Barbosa et al., 2024). Addressing this challenge requires technologies that empower plants to yield more with fewer resources while increasing resilience. This challenge lies at the heart of crop science and drives the development of new tools.

The combination of AI and IoT with advanced imaging techniques has transformed the monitoring of plant physiology and development (Zapata-Londoño et al., 2025). Optical sensors, such as hyperspectral cameras, fluorescence spectroscopy, and LiDAR technology, when integrated with AI models, enable non-invasive real-time monitoring of key physiological parameters (Lu et al., 2020; Arya et al., 2024). The integration of IoT sensors with image processing techniques allows accurate estimation of biomass and leaf area, providing new opportunities for crop monitoring (Varas et al., 2024; Wu and Zhao, 2020).

Meanwhile, plant hormones such as auxins and gibberellins emerge as central regulators of plant growth and development. Quantitative approaches have significantly contributed to decoding their signaling networks. For example, auxin gradients maintained through feedback loops, such as the WOX5-IAA17 module, are critical for determining the identity and function of root stem cell niches (Tian et al., 2014; Galvan-Ampudia et al., 2020). Quantitative plant biology, utilizing mathematical models, computational tools, and high-resolution data, offers the ability to uncover the principles governing these biological systems (Autran et al., 2021). Thus, traditional plant physiology is now reinforced by AI and IoT technologies, creating new research and applied perspectives.

Beyond fundamental biological inquiries, artificial intelligence emerges as a powerful catalyst for practical agricultural applications. AI leverages advanced algorithms to recognize complex patterns in large datasets, playing a central role in maximizing agricultural productivity (Malhotra and Khan, 2022). Through predictive models, AI facilitates strategic planning of crop rotation and planting periods, optimizing land use and increasing annual yields. Additionally, AI-based smart irrigation can mimic adaptive decisions, ensuring precise allocation of water resources (Adeyemi et al., 2018). Specifically, artificial neural networks (ANNs) are used to determine crop water requirements considering meteorological and soil data (Ahmed et al., 2023).

Moreover, AI methods enhance predictive modeling, optimize resource allocation, and accelerate plant breeding processes. Through the analysis of large volumes of genetic, environmental, and phenotypic data, rapid assessment of high-yield and stress-tolerant varieties becomes possible (Farooq et al., 2024). Deep learning algorithms and ensemble methods have proven more effective than traditional statistical approaches in predicting complex biological outcomes such as crop yield (Azrai et al., 2024).

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Techniques such as convolutional neural networks (CNNs) and support vector machines (SVMs) automate the classification of phenotypic traits and stress responses, while their integration into predictive analyses reduces dependence on extensive field trials (Yoosefzadeh Najafabadi et al. 2023; Vieira et al., 2025). In precision agriculture, AI increases the level of automation and operational efficiency, enhancing crop monitoring and management (Sharma and Shivandu, 2024). Synergy with IoT allows data storage and analysis in the cloud, leveraging satellite imagery, soil sensors, and AI algorithms to provide real-time information (Muhammed et al., 2024; Adewusi et al., 2024).

Additionally, AI-based crop protection tools provide capabilities for timely and intelligent detection of pests, diseases, and weeds, integrating remote sensing, imaging techniques, and predictive modeling for precise and sustainable interventions (Ye et al., 2025; Jafar et al., 2024).

Overall, modern plant physiology can no longer be considered an isolated scientific field; rather, it evolves into an interdisciplinary sphere where biological knowledge, AI, and IoT coexist and mutually reinforce each other. This interaction creates new opportunities for sustainable agriculture, minimizing environmental footprint and increasing productivity while protecting ecosystems.

The main objective of this study is to investigate how the synergy of plant physiology with Artificial Intelligence and the Internet of Things can contribute to sustainable agriculture, focusing on improving plant growth and resilience, rational resource use, and the creation of efficient and climate-resilient agricultural systems.

2. METHODS

Data and Sources

This analysis was based on an extensive collection and processing of available scientific publications retrieved from databases such as PubMed (Medline), Google Scholar, and Scopus. The selection focused on studies relevant to plant physiology, stress responses, plant hormones, quantitative plant biology, and applications of Artificial Intelligence (AI) and the Internet of Things (IoT) in agriculture.

Methodological Approach

The study relied on a systematic compilation and thematic analysis of international literature, emphasizing the following focal points: crop physiology and climate change, the role of phytohormones, plant stress responses, quantitative plant biology, and AI/IoT applications in agriculture. This approach enabled the identification of current trends, technological advances, and interdisciplinary integration in plant science.

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Data Collection and Processing

The collection process included peer-reviewed articles, case studies, and theoretical frameworks, with inclusion criteria based on their relevance to AI utilization in plant physiology. All selected studies were critically evaluated for methodological rigor, relevance, and the quality of data reporting. Bibliometric analysis and citation tracking were employed to ensure comprehensive coverage of recent and seminal works.

Data Analysis

A thematic analysis was applied to group and interpreted findings into key thematic axes, including crop physiology, plant hormone regulation, growth and stress adaptation, and quantitative plant biology. Emphasis was placed on the integration of computational tools and AI-based methodologies, as well as the incorporation of IoT technologies for real-time monitoring and data acquisition. Quantitative and qualitative data were synthesized to identify patterns, mechanisms, and technological applications that can support sustainable agriculture and precision crop management.

3. RESULTS

Nature The analysis of the international literature revealed that advances in agricultural engineering, data science, Artificial Intelligence (AI), and the Internet of Things (IoT) have significantly transformed plant physiology research. The integration of smart sensors and AI algorithms enables the monitoring of growth, phenology, nutrition, and stress resilience, promoting precision agriculture and rational resource management (Espinel et al., 2024) (Table 1).

Table 1: Summary of the main literature review findings across three thematic axes: (a) Plant Physiology, (b) AI and IoT Technologies, and (c) Applications and Prospects for Sustainable Agriculture.

Domain	Findings	References
Plant Physiology	**Phytohormones (Auxins & Gibberellins):** Regulate growth, root/shoot development, and stress responses. Auxin gradients (e.g., WOX5-IAA17) are critical for cell formation.	Yetgin et al., 2025; Mukherjee et al., 2022; Tian et al., 2014; Galvan-Ampudia et al., 2020
	Gibberellins: Associated with stem elongation and interaction with DELLA proteins. Their	Ezer et al., 2017; Hamant et al., 2008;

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	integration into mechanical models reveals effects across multiple scales.	Nakayama et al., 2012
	Fruit Development: In early stages, high concentrations of auxins and gibberellins enhance cell division. During ripening, their decrease is combined with an increase in ABA and ethylene.	Depuydt et al., 2016; Gill et al., 2023; Shakya and Lal, 2018
	Drought Response: Hormonal balance shifts: decrease in auxins, enhancement of ABA signaling. Impact of JA and SA on senescence and defense.	Guo et al., 2024; Margay et al., 2024; Yoshida and Fernie, 2024; Giordano et al., 2021
AI & IoT Technologies	**AI & Bioinformatics:** Analysis of genomic sequences and gene expression for understanding stress responses.	Singh and Sunita, 2024.
	Smart Sensors & IoT: Monitoring growth, nutrition, and resilience for precision agriculture and rational resource management.	Espinel et al., 2024
	Quantitative Plant Biology: Mathematical models and computational tools decode plant operational principles.	Sa et al., 2018; Yu et al., 2021; Wu et al., 2022
Sustainable Agriculture	**Crop Physiology:** Linking fundamental science with applied agronomy through technologies like IRGA and chlorophyll fluorometers.	Autran et al., 2021
	Holistic Transformation: The integration of AI and IoT transforms the study of growth and promotes sustainable and resilient agriculture.	Beyschlag and Ryel, 2007
	Quantitative Plant Biology: Mathematical models and computational tools decode plant operational principles.	Maiti et al., 2024; Zapata-Londoño et al., 2025

The table presents the categorization of the main findings based on the analysis of international literature. The findings were grouped into three main thematic axes: (a) Plant Physiology, with an

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emphasis on phytohormone dynamics and stress responses, (b) Artificial Intelligence (AI) and Internet of Things (IoT) Technologies, focusing on their applications in agricultural production, and (c) Applications and Prospects for Sustainable Agriculture, highlighting the importance of quantitative plant biology and crop physiology. For each finding, the corresponding bibliographic references are provided.

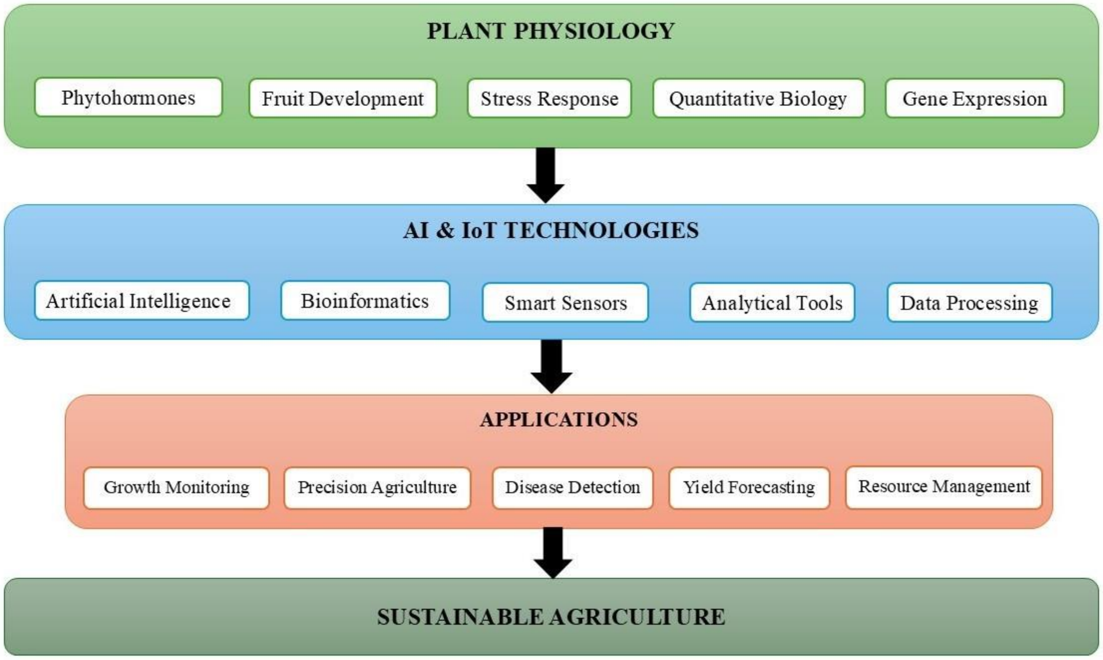

Fig. 1: Representation of the interactions between AI and IoT technologies in advanced plant physiology research for sustainable agriculture.

This diagram shows how plant physiology research integrates with AI and IoT technologies to enable practical agricultural applications, ultimately supporting sustainable agriculture through improved growth monitoring, precision farming, disease detection, yield forecasting, and resource management.

Special emphasis was placed on phytohormones. Auxins and gibberellins are recognized as central regulators of plant growth, controlling critical stages such as seed germination, root and shoot development, and responses to environmental stimuli (Yetgin et al., 2025; Mukherjee et al., 2022). Their dynamics are elucidated through quantitative models, demonstrating that auxin gradients, for example, the WOX5-IAA17 loop, are essential for defining the identity and function of root stem cell niches (Tian et al., 2014; Galvan-Ampudia et al., 2020). Similarly, gibberellins are linked to stem elongation and interactions with DELLA proteins, and their integration into mechanistic

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models reveals multi-scale developmental effects (Ezer et al., 2017; Hamant et al., 2008; Nakayama et al., 2012).

Significant insights were also obtained regarding fruit developmental phases: in early stages, high concentrations of auxins and gibberellins promote cell division and expansion; during ripening, their decrease is coupled with increased ABA and ethylene levels, leading to final differentiation (Depuydt et al., 2016; Gill et al., 2023; Shakya & Lal, 2018).

Studies on drought responses highlighted substantial shifts in hormonal balance: auxin levels decrease while ABA signaling is enhanced to conserve energy (Guo et al., 2024; Margay et al., 2024). Additionally, jasmonic acid (JA) and salicylic acid (SA) influence senescence and defense mechanisms (Yoshida and Fernie, 2024; Giordano et al., 2021).

In the domain of quantitative plant biology, the interdisciplinary nature of the field became evident: mathematical models, computational tools, and high-resolution datasets decode the principles underlying plant functioning (Autran et al., 2021). AI, in combination with bioinformatics tools, facilitates the analysis of genomic sequences and gene expression patterns, offering novel opportunities to understand stress responses (Singh and Sunita, 2024).

Crop physiology emerged as a critical link between fundamental science and applied agronomy, incorporating technologies such as Infrared Gas Analyzers (IRGA) and chlorophyll fluorometers for in situ analysis (Beyschlag and Ryel, 2007). The integration of AI and IoT supports advanced monitoring and prediction, enabling smart irrigation, early disease detection through convolutional neural networks (CNNs), and yield forecasting with transfer learning algorithms (Sa et al., 2018; Yu et al., 2021; Wu et al., 2022).

Overall, the research confirmed that the integration of AI and IoT into plant physiology is transforming the study of growth, stress responses, and productivity, promoting sustainable and resilient agriculture (Maiti et al., 2024; Zapata-Londoño et al., 2025).

4. DISCUSSION

The results indicate that contemporary plant physiology can no longer be approached as an isolated scientific field. The integration of AI and IoT technologies enables quantification, prediction, and automation at levels previously unattainable. The central role of phytohormones in regulating growth and stress resilience is consistently confirmed across multiple studies (Depuydt et al., 2016; Gill et al., 2023).

AI contributes by processing massive datasets, revealing hidden interactions and dynamics that are not directly observable with traditional methods. This capability facilitates rapid crop improvement, targeted input application, and loss prevention.

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The discussion also emphasizes agricultural adaptability, as IoT provides a continuous flow of data, enhancing real-time management. Cloud capabilities and the integration of optical sensing techniques create "digital twins" of crops, allowing the design and simulation of various scenarios (Rahman et al., 2024). These developments translate into practical tools for farmers, such as smart irrigation systems (Roopaei et al., 2017) and automated crop management platforms (Gul and Banday, 2024).

The contribution of crop physiology is further strengthened by the agroecological dimension, as traditional practices such as crop rotation remain necessary, but their combination with digital tools enhances resilience (Romero et al., 2022; Bowles et al., 2020).

Moreover, the integration of predictive modeling enables the utilization of large volumes of data to forecast plant growth and stress responses, supporting timely decision-making, sustainable crop management, and increased productivity with reduced environmental inputs.

Overall, the interdisciplinary approach that combines physiology, AI, and IoT highlights new opportunities for promoting sustainable agriculture. It generates tools that enhance crop resilience, reduce losses, and support adaptation to conditions of climatic instability.

5. CONCLUSIONS

This study demonstrated that phytohormones, particularly auxins and gibberellins, are central regulators of plant growth, while their interaction with ABA, JA, and SA critically determines responses to environmental stress. Quantitative plant biology and computational modeling provide a framework for understanding growth dynamics and formulating predictive strategies for practical agricultural applications. Furthermore, the integration of AI and IoT technologies enables non-invasive monitoring, diagnosis, and prediction of plant growth, laying the foundations for sustainable agriculture. Crop physiology acts as a catalyst linking fundamental science with applied practices, while the synergy of biology, AI, and IoT creates a new scientific and technological paradigm. Future research should focus on energy efficiency, adaptation across diverse agroecosystems, and dissemination of expertise at all levels of production to ensure widespread implementation and optimized outcomes.

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